An empirical analysis of Total Factor Productivity (TFP) in Mexico, 1993-2018: determinants, decomposition and convergence

RAMIREZ-GUERRA, EMMANUEL,ALEJANDRO

An empirical analysis of Total Factor Productivity (TFP) in Mexico, 1993-2018: determinants, decomposition and convergence

Emmanuel Alejandro Ramirez-Guerra

A thesis presented for the degree of
Doctor of Philosophy

Department of Economics and Finance
Durham University
United Kingdom
June 2023

Statement of Copyright

To my parents, Cristina and Antonio.

Acknowledges

I want to express my gratitude to the National Council of Science and Technology (CONACYT) for the scholarship I received to complete my PhD studies in Economics at Durham University. I am very privileged to have this scholarship, and I took this opportunity to deliver a research topic relevant to the Mexican economy. I developed this research thinking of my country: Mexico.

I am deeply indebted to Professor Richard Harris and Dr John Moffat. Their guidance and support improved this research at every stage of my PhD studies. From Professor Harris and Dr Moffat, I learnt better research skills and new ways to understand Economics. They have made me a better economist. I also want to acknowledge the enriching suggestions of my examiners, Professor Sai Ding and Dr Michael Nower; they contributed to improving the quality of this PhD thesis. I want to thank Durham University, the Business School and the Department of Economics and Finance for reinforcing and improving my academic knowledge. I also want to thank St Aidan's College and the Mexican Society in Durham, where I shared moments of happiness and friendship. I have great memories of all of them.

This PhD thesis would not be possible without the support of the microdata lab of the National Institute of Statistics and Geography (INEGI). This institution allowed me to access the microdata and generate estimations for this research. During Covid-19, the support of the microdata lab was crucial in aiding me to work remotely with the microdata and generate results. I want to thank Dr Natalia Volkow and Lidia Hernandez for helping to complete this research, and I sincerely appreciate your support.

This thesis is to my parents, Cristina and Antonio. They are my inspiration and my motivation. To my mom, thank you for those long calls that have made me happy and close to you. To my dad, thank you for your advice and wisdom. To my sisters, Ana and Cristina, thank you for sharing unforgettable moments when you visited me. Every time that you visit me, you make me feel at home. To my parents and sisters, the time and space have made me love you even more.

To my beloved Samantha. Thank you for your support and for being my happiness during this journey. I have discovered with you the bright side of the United Kingdom. Thank you to the Daley family, who opened their home. Dinners, parks, barbecues and walks have been part of the lovely memories.

Abstract

This research estimates TFP at the establishment level in Mexico at 5-year intervals from 1993 to 2018. The production function used to estimate TFP includes a mark-up correction to overcome the omitted price bias, and the Wooldridge (2009) approach overcomes the endogeneity bias. The TFP analysis is divided into three categories: determinants, decomposition and convergence. The first category of the research identified six TFP determinants at the establishment level. The main findings are: (i) firm age positively impacts TFP, indicating a learning-by-doing effect; (ii) managerial and organisational efforts to reduce costs increase TFP; (iii) higher industrial concentration positively impacts TFP, suggesting that higher competition does not necessarily lead to higher TFP (i.e. Schumpeterian models); (iv) MAR externalities positively impact TFP due to localised economies of scale; (v) Jacobian externalities negatively affect TFP as a result of potential urbanisation costs; (vi) population density negatively affects TFP due to potential congestion costs in most sectors. The second category of the research analysed TFP decomposition by geographical locations, economic sectors and the contribution of firm selection to TFP growth. The geographical dimension of TFP indicates three clusters of states with high TFP: (i) some states in the North of Mexico, with potential productivity spillovers due to proximity with the U.S; (ii) states with high agglomeration economies, including Mexico City, Jalisco and contiguous states; and (iii) states in the Southeast, including Campeche and Tabasco, which are states mainly dedicated to oil extraction (i.e., natural advantages). The sectoral dimension of TFP accounts can be classified in three sectors with high TFP: (i) mining, quarrying, and oil and gas extraction, (ii) wholesale and retail trade, (iii) finance and insurance. Overall, services and oil extraction had a high TFP during 2018 while manufacturing activities had a low TFP performance. The Mexican economy had a negligible TFP growth of 0.10% from 1998 to 2018, and there was calculated the TFP growth decomposition regarding the contribution of surviving, entering and exiting establishments. The TFP growth decomposition shows a positive contribution of net entrants but a negative contribution of survivors. The condition of survival has deteriorated its contribution to TFP growth since the financial crisis (2008-2009). Conversely, business creation has been a driver of TFP growth. The third category of the research analysed TFP convergence across Mexican states and municipalities. There is no evidence of TFP convergence across states due to a potential aggregation bias. However, there is evidence of TFP convergence at the municipality level, which is associated with a reduction of TFP disparities across municipalities. Mexican municipalities had an absolute convergence rate of 0.21% per annum (1998-2018), and it would take around 323 years to eliminate 50% of the TFP gap across municipalities (i.e. half-life period). This thesis concludes with recommendations for an industrial strategy to increase TFP in Mexico.

Keywords: Total Factor Productivity, Panel Data Models, Regional Economics

JEL: D24, C23. P25

Contents

List of Figures

List of Tables

Introduction

Total factor productivity (TFP) is a key variable in growth accounting because it measures the contribution of efficiency and technical progress to economic growth. TFP has a central role in the economic literature to understand the performance of an economy in the short and the long-term. In addition, TFP can explain disparities in income per capita across economies (Klenow & Rodriguez-Clare 1997). In the short-term, TFP is an element that influences economic fluctuations to determine phases of recession or expansion (Kydland & Prescott 1982). In the long-term, TFP is a source of sustainable economic growth, and in many economies, TFP has become the ultimate engine of Gross Domestic Product (GDP) growth (Solow 1956, OECD 2015). Therefore, research on TFP analysis is relevant to derive policies oriented to increase efficiency and improve economic living standards over time and across space (e.g., countries, regions, cities).

The availability of disaggregated databases has shifted TFP estimation from the macro level (e.g., countries, regions) to the micro level (i.e., firms, plants, establishments). Disaggregated databases are defined in the literature as microdata. TFP estimation at the micro level allows a deeper analysis of productivity derived from individual TFP measurements at the production unit level (e.g. firm, establishment and plant). The literature accounts for the large TFP dispersion at the firm level, which reflects the wide productivity heterogeneity across firms. There can be summarised two branches in the literature which explain TFP dispersion. There is a branch which explains TFP dispersion as the result of distortions at the firm level. Those distortions cause misallocations and dispersion in the marginal productivity of the factors of production (Hsieh & Klenow 2009). Another branch in the literature accounts that TFP dispersion results from the fact that some firms have better production practices than others. Better production practices are caused by a combination of different attributes, which are referred to as the X-efficiency factor (Bartelsman & Wolf 2017). This branch of the literature is dedicated to identifying the X-efficiency factor, or TFP determinants, as the underlying nature of the TFP heterogeneity across firms.

TFP dispersion is also persistent over time. Some studies have explained that TFP dispersion is due to firm selection and competition. For instance, Martin (2008) found a negative relationship between the level of competition and TFP dispersion. According to Kehrig (2011), the Schumpeterian 'creative destruction' in relation to the business cycle shows a high TFP dispersion during recessions but low TFP dispersion during economic booms. For that reason, the Schumpeterian theory associates productivity at the micro level with the condition of firm survival in a competitive environment. Then, more productive firms generally have higher output, revenue and profits, as well as lower prices (Olley & Pakes 1996, Hopenhayn 1992, Melitz 2003). Firm selection explains the dynamics in an economy with firms entering, continuing and exiting the market. Therefore, analysing the firm selection on TFP growth is relevant to determine to what extent entrants and surviviors contribute to TFP growth in a competitive environment (Haltiwanger 1997, Melitz & Polanec 2015).

There are not many studies that analyse TFP using microdata in middle-income countries (Ding et al. 2016, Dias et al. 2020, Levy-Algazi 2018). Empirical research on TFP in middle-income economies using microdata usually emphasises the importance of the manufacturing sector at the expense of omitting the service sector in determining aggregated productivity (Puggioni 2019, Rodríguez-Castelán et al. 2020, López-Noria 2021). In recent decades, the structural change has reallocated production factors (i.e., capital, employment, intermediate inputs) from manufacturing to services. Therefore, TFP measurement at the firm level across all economic sectors is necessary to provide empirical evidence on productivity differences across economic sectors, the structural transformation of middle-income economies, and its effect on aggregated TFP.

This thesis estimates with parametric methods TFP in Mexico at the establishment level by using microdata of the Economic Census of Mexico collected by the National Institute of Statistics and Geography (INEGI, by its acronym in Spanish). The microdata used in this research consists of a comprehensive and unusual panel dataset for a middle-income country that covers 20.77 million establishments from 1993 to 2018 at 5-yearly intervals. Establishments are categorised by national industry group at the 6-digit North American Industrial Classification System (NAICS) code. [1] The microdata was recently linked longitudinally by Busso, Fentanes Téllez & Levy Algazi (2019), which makes suitable to track Mexican establishments over time. Thus, TFP at the establishment level is estimated with panel data models. Few middle-income countries have microdata available with a high disaggregation at the establishment level. Therefore, data from the Economic Census in Mexico is outstanding because it provides a high granularity for productivity analysis in a middle-income country.

Productivity analysis for Mexico is important because macroeconomic estimations of TFP show evidence that TFP has contributed negatively to economic growth. INEGI estimated that TFP had a negative average growth of -0.45% per annum (p.a.) from 1991 to 2020. The literature on growth accounting indicates two ways to stimulate economic growth: increasing the factors of production or increasing the TFP. However, an economy based on productivity as the engine of growth provides more sustainable economic growth in the long term (Chen 1997). If the economic

[1] The results of this research have been verified by INEGI's staff in order to fulfill the confidentiality policy on the use of the Economic Census microdata.

growth in Mexico is input-driven instead of TFP-driven, the Mexican economy must make the transition to TFP-driven growth. This transition might allow the Mexican economy to overcome the middle-income trap of economic growth (Tran 2013). In the end, TFP-driven economic growth reflects the capacity of an economy to increase its technological capacity and allocate resources efficiently, which contributes to increasing the income per person in the long-term.

Mexico has had a pattern of sluggish economic growth in the last two decades, defined in the literature as a trap of slow economic growth (Ros-Bosch 2013). The average GDP growth in Mexico was 1.78% p.a. during 2003-2021, which is lower than the average GDP growth of 2.1% p.a. in the period 1982-2002, and both rates are significantly lower compared with the average GDP growth of 6.2% p.a. in the period 1932-1981. The impact of Covid-19 has had an unprecedented negative effect on GDP and productivity growth in the global economy, and Mexico is not the exception. According to INEGI's estimations, TFP in Mexico had one of its deepest decreases in the last 30 years during the Covid-19 crisis in 2020, with a drop of -3.69% associated with an output decrease of -9.29%. For that reason, there has been a renewed interest in implementing industrial strategies to increase productivity and hence economic growth in Mexico.

The recent consensus in the literature is that low productivity in Mexico results from the entry and subsistence of unproductive establishments in the Mexican economy, which creates dysfunctional firm dynamics instead of a Schumpeterian 'creative destruction' (Ros-Bosch 2019, Levy-Algazi 2019). Establishments that have survived in the Mexican economy are characterised as informal, small in employment, and with a low stock of capital per worker. The misallocation in Mexico implies that workers and capital are allocated to low-productivity activities, particularly in the informal service sector (Levy-Algazi 2018). Therefore, reallocating resources to activities with higher productivity is necessary to boost aggregate TFP growth in Mexico.

In recent years, the number of studies focusing on TFP analysis in Mexico with a microeconomic approach has increased. Most empirical studies of productivity at the establishment level can be divided into two groups according to their methodology. The first group replicates the Hsieh & Klenow (2009) model to measure TFP at the establishment level in Mexico to account for productivity heterogeneity, distortions, and misallocations (Busso et al. 2012, Martínez-Alanís 2011, Misch & Saborowski 2018, Levy-Algazi 2018). These studies usually estimate TFP gains without the presence of misallocations through the elimination of distortions at the establishment level. However, the limitation of estimating TFP with the model of Hsieh & Klenow (2009) is that this approach does not explain the sources of TFP (i.e. determinants). In addition, there is a bias in the measurement of TFP with the methodology of Hsieh & Klenow (2009) due to the price pass-through, as Haltiwanger et al. (2018) explained. The second group of studies using microdata applies parametric methods to estimate TFP at the establishment level. These studies investigate TFP determinants such as market structure, management quality, and trade liberalisation by implementing the control function approach, following Olley & Pakes (1996) and Levinsohn & Petrin

(2003). However, the second group of empirical literature mainly focus on the manufacturing sector, and those studies do not conduct productivity analysis across economic sectors or geographical locations.

This research can be classified in the second group of empirical literature in Mexico that quantifies TFP at the establishment level with parametric methods to analyse TFP determinants. Moreover, this research extensively uses the microdata of the Economic Census across all economic sectors. The extensive use of microdata is a research contribution because most existing studies in Mexico only use manufacturing sector data (Blyde & Fentanes 2019, Puggioni 2019, Rodríguez-Castelán et al. 2020, López-Noria 2021). The study of Levy-Algazi (2018), measured TFP at the establishment level across all economic sectors in Mexico but using the Hsieh & Klenow (2009) model. Thus, the latter does not explain the sources of TFP heterogeneity across Mexican establishments, and the TFP measurement can be biased (Haltiwanger et al. 2018). In addition, Levy-Algazi (2018) does not provide measurements of TFP at a different level of aggregation to account for the TFP disparity across geographical locations and economic sectors. Even though there is a significant research contribution by Levy-Algazi (2018) in the analysis of distortions, misallocations, TFP gains, and firm selection, the productivity analysis of Mexican establishments can be extended. Recently, Iacovone et al. (2022) estimated TFP at the establishment level in Mexico using the Control Function Approach of Ackerberg et al. (2015), but the lack of parametric results in the estimation of the production functions leaves a gap in the literature to analyse the magnitude, direction and significance of the TFP determinants included in the production function (See the online appendix in Iacovone et al. (2022). In comparison to Iacovone et al. (2022), this thesis uses the Economic Census (1993-2018) extensively to make a deeper analysis of the parametric estimation of the production function and the TFP determinants as the underlying causes of the productivity heterogeneity across establishments in Mexico.

This research focused on the transition of the TFP analysis in Mexico through the channel micro-meso-macro, which reflects the economic 'pointillism' of the productivity analysis of the Mexican economy.[2] Thus, this research intends to fill the gap in the TFP analysis of the Mexican economy by contributing to the literature on empirical productivity analysis from the particular to the general, particularly in emergent economies.

This thesis has seven chapters. Chapter 1 is the research overview of this PhD thesis, including the description of the research problem, research objectives, research contributions, and policy implications. Chapter 2 is a literature review that includes three necessary components for this research: the concept of productivity, methodologies to measure TFP and TFP determinants.

[2] 'Pointillism' is a painting technique in art that links dots to a big picture. The economic 'pointillism' is a metaphor which refers to how measurements at the micro level can be linked to calculate measurements at the macro level. Then, economic 'pointillism' is the channel micro-macro in the economic analysis. The term meso refers to an intermediate stage in the micro-macro channel, which can include the analysis of measurements disaggregated by regions, sectors, etc.

Chapter 3 describes the data and methodology used to estimate TFP at the establishment level in Mexico. This chapter defines a methodological strategy of estimation divided into two stages. The first stage uses a subset of the Economic Census, which comprises medium and large establishments in the manufacturing sector. The main purpose of the first stage is to compare the parametric results with different methodologies and to define whether different parametric approaches lead to different TFP estimates. The second stage of the estimation strategy consists of estimating a Cobb-Douglas function with a mark-up correction to overcome the omitted price bias, as Klette & Griliches (1996) proposed. In this stage, production functions are estimated with mark-up corrections by economic sector using the Wooldridge (2009) model as the preferred parametric approach. The second stage has two objectives (i) to correct the price bias in the production function and (ii) to quantify the effect of TFP determinants at the establishment level.

The results are divided into three chapters examining three interrelated topics with TFP in Mexico. The topics comprise TFP determinants, TFP decomposition and TFP convergence. Chapter 4 presents the parametric results of the production functions with the mark-up correction and the estimation of TFP at the establishment level. The relevance of Chapter 4 is the analysis of the TFP determinants in Mexico at the establishment level to examine what factors make Mexican establishments to be more productive than others. Chapter 5 presents results of TFP decompositions presented into two sections. The first section presents a geographical and sectoral dimension of productivity in Mexico that consists of TFP decomposition by geographic locations (i.e., states and municipalities) and economic activities (i.e., sectors and subsectors). The TFP decomposition sheds light on the productivity disparity across geographical locations and sectors in Mexico. The second section presents the TFP growth decomposition in Mexico using the Haltiwanger (1997) and Melitz & Polanec (2015) methods to examine the firm selection contribution to the aggregated TFP growth. The relevance of the TFP growth decomposition is to measure the contribution of surviving, entering and exiting establishments to aggregated TFP growth in Mexico. Chapter 6 uses measurements of TFP at the state and municipality levels to analyse regional TFP convergence in Mexico. Two metrics are used in the TFP convergence analysis: beta-convergence (Barro & Sala-i Martin 1992) and sigma-convergence (Quah 1993, Sala-i Martin 1996). In particular, beta-convergence is measured with the traditional cross-section approach but also includes the measurement of a spatial TFP convergence model using techniques of Spatial Econometrics to account for the effect of spillovers in the determination of TFP convergence across geographical locations in Mexico (Anselin 1988). Finally, Chapter 7 presents the conclusions of this research, which summarise the main findings and purposes of policy recommendations related to the research findings.

Chapter 1

Research overview

1.1 Overview of Chapter 1

Chapter 1 provides the research overview of this PhD thesis. This Chapter consists of four sections. Section 1.2 focuses on the definition of the research problem: the productivity problem that affects the economic growth in Mexico. In addition, section 1.2 provides initial evidence of stylised facts about the productivity problem in Mexico using labour productivity at different levels of disaggregation: national, geographical, sectoral and the establishment level. Section 1.3 presents the research objectives of this thesis. Section 1.4 presents the different research contributions of this research. Finally, section 1.5 presents the policy implications of this thesis, which aims to guide the implementation of industrial policies oriented towards increasing productivity in Mexico. Table 1.1 provides an overview of this Chapter.

Table 1.1: Overview of Chapter 1

Concept	Description
Research problem.	• The examination of the productivity problem in Mexico that affects economic growth.
Research objectives	• To identify the TFP determinants that cause productivity heterogeneity in Mexican establishments. • To measure the contribution of firm selection on TFP growth. • To measure TFP at different aggregation levels that account for Mexico's geographical and sectoral dimensions of productivity. • To test the hypothesis of regional convergence of productivity in Mexico.
Research contributions	• Detailed and extensive TFP estimates. • Comparison of TFP estimates derived from different methodologies. • Analysis of TFP determinants at the establishment level. • Analysis of TFP in the sectoral and geographical dimensions • Measurement of the effects of firm selection on TFP growth. • Analysis of TFP convergence across locations.
Policy implications.	• To provide information for the design of an industrial strategy oriented to boost productivity at different levels of disaggregation in Mexico (e.g., firms, sectors, geographical locations).

Source: Own elaboration

1.2 Research problem

The growth accounting literature explains that two mechanisms contribute to economic growth: the accumulation of factors of production and the increase of TFP. Overall, economic growth with TFP orientation provides the economy with a more sustainable growth that relies on the efficiency to produce more with the same or lower inputs. The increase of TFP provides sustainable economic growth as it reflects the capacity of firms and the economy to increase their technological capacity and their efficiency in allocating resources that contributes to increasing the income per person in the long term (Kumbhakar & Lovell 2003, Klenow & Rodriguez-Clare 1997, p. 15). TFP is the ultimate engine of growth in the global economy, and economic growth will increasingly depend on this variable (OECD 2015).[1]

In recent decades, Mexico has followed a series of actions to promote economic growth, including reforms and macroeconomic stabilisation policies, fiscal discipline and foreign trade. However, a faster pace of economic growth has not come. The recent literature explains the slow economic growth in the Mexican economy as the result of low productivity and declining rates of productivity growth.

Busso et al. (2012) argue that factor accumulation in Mexico was higher compared to the United States (U.S.) during 1960-2008. Busso et al. (2012, p. 2) state that "if TFP had kept pace, relative income per capita would be 24 per cent higher in 2008 vs 1960. However, the sharp fall in Mexico's TFP relative to the U.S. since 1980 more than offset the gains from factor accumulation, with the result that in 2008 Mexico's relative income per capita was 14 per cent lower." Thus, factor accumulation is not the underlying problem of modest economic growth rates in Mexico, and the real reason is the slow productivity growth.

The low productivity in Mexico is the research problem of this thesis. The literature about the productivity problem in Mexico points out the following related problems:

1. There is negative productivity growth at the national level in Mexico due to an inefficient allocation of resources.
2. There is a wide disparity of productivity across geographical locations and sectors because there are only a few geographical locations and economic sectors with high levels of productivity.
3. There is wide productivity heterogeneity, with few frontier firms with high productivity and many underperforming firms with low productivity.

[1] Several macroeconomic studies use TFP at the country level because they display the ability of an economy to grow without inflationary pressures in conditions of macroeconomic stability (Barnett et al. 2014)

The following subsections provide the main arguments in the current literature about the productivity problem in Mexico and the 'stylised facts' of productivity indicators in Mexico.

1.2.1 The low productivity in Mexico

At the international level, the long-term trend of labour productivity has had two major slowdowns in most countries after the second world war, and two economic events have generated these productivity slowdowns. The first event came during the 1970s, which was the result of the oil crisis, and the second event was during 2008-2009 due to the global financial crisis.[2] The severity of the economic crisis might lead to persistent weakness in tangible and intangible capital affecting productivity growth in the long-term (Barnett et al. 2014). In recent years, some studies have coined the concept of 'productivity puzzle' as the coexistence of the productivity slowdown with technological improvements.[3] The statistical evidence in this subsection shows that productivity decreases after a negative shock of an economic crisis. The Covid-19 crisis has had an unprecedented negative impact on the pace of productivity and economic growth. For that reason, there can be concerns that the crisis of Covid-19 affects the long-term trend of productivity.

OECD. (2020, p. 83-87) presents evidence of productivity in Mexico compared to other emerging countries, particularly in Latin America and Asia. Countries in Latin America and the Caribbean (LAC) had a sustained decreasing trend in their labour productivity in relation to the rest of the world from 1950 to 2018. In emerging countries like China, the contribution of productivity to GDP growth was 96%; in India there was 79%, and in Korea 66%. On the counterpart, in countries of LAC there was a lower contribution from productivity to GDP growth because only 24% of the GDP growth comes from productivity. Mexico is the country of LAC with the highest percentage of added value (41%) in the medium and high-tech manufacturing industry in 2017. However, the comparison of this percentage between Mexico and other emerging countries like Korea is significantly lower. In 2017, Korea had a percentage of the added value of 61% in medium and high-tech manufacturing, which is 20% higher than in Mexico. In summary, Mexico has had a better productivity performance than other countries in LAC, but productivity in the Mexican economy has underperformed compared to emerging countries in Asia over the recent years, like Korea and China.

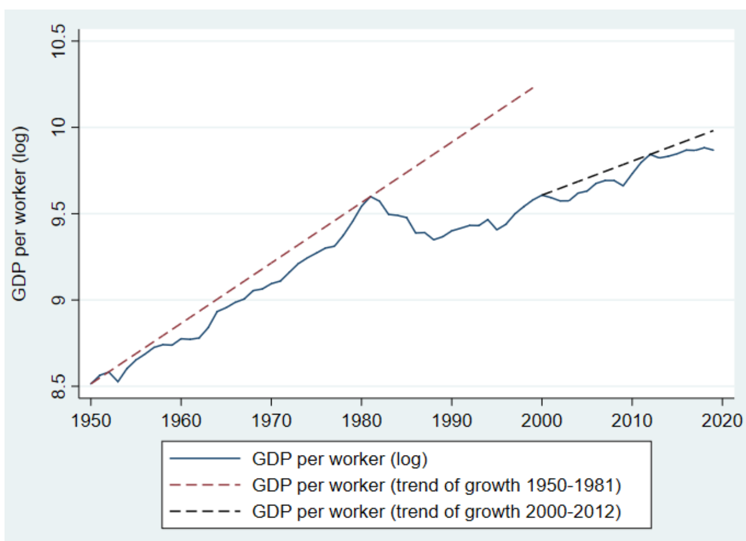
[2] In the case of the U.S., Nordhaus (2004) indicates that there were between four and six major productivity slowdowns in the period 1889-2004, but the 1970s productivity slowdown was longer as it lasted about a decade. The oil crisis mainly caused this slowdown. After the 1970s slowdown, the levels of productivity in the U.S. rebounded during the mid-1990s to recover its initial level, mainly driven by the computer and the information technology sector (Romer 2018, p. 30-32)

[3] 'Productivity puzzle' is used in the United Kingdom (U.K.) to describe the productivity slowdown caused by the global financial crisis 2008-2009. Riley et al. (2018) found that financial industries, the manufacture of pharmaceuticals, and the manufacture of machinery and equipment had a negative contribution to TFP growth in the U.K. after the global crisis 2008-2009, and the weak productivity in these sectors contributed to the productivity puzzle in the U.K. Then, the financial crisis of (2008-2009) affected the productivity of services and manufacturing activities.

This subsection provides preliminary evidence about productivity underperformance in Mexico by examining the evolution of labour productivity and TFP estimated with the KLEMS model at the national level. In addition, this section explains the causes of the low productivity in Mexico according to the literature.

The evidence of labour productivity in Mexico has displayed periods of rapid increase while others of contraction. Figure 1.1 displays labour productivity measured in natural logarithms (ln) in Mexico from 1950 to 2019. Labour productivity in the Mexican economy increased rapidly from 1950-1981, but its trend reverted in 1982 due to a slowdown.[4] Labour productivity in Mexico had its lowest level in 1988; from that year, labour productivity recovered until 2000. From 2000 to 2012, labour productivity displayed a trend with a lower slope than the period covering 1950-1981. In particular, labour productivity showed a sluggish pace of growth after 2012. According to Figure 1.1, there can be identified four periods of the labour productivity evolution in Mexico: (i) rapid increase (1950-1981), (ii) productivity slowdown (1982-1999), (iii) increase (2000-2012) and (iv) sluggish growth (2012-2019). The periods of labour productivity evolution coincide with the international experience, but it seems that Mexico has a time lag compared to the labour productivity evolution compared to high-income countries.[5]

Figure 1.1: Labour productivity (GDP per capita in log) in Mexico, 1950-2019 [a/] [b/]



[a/] Real GDP chained at PPPs (in mil. 2017 U.S. Dollars). [b/] The growth trends were calculated from peak to peak for the periods 1950-1981 and 2000-2012.
Source: Own elaboration with data of Penn World Table

There is a limitation in the use of labour productivity as the measure of productivity analysis because the increase in labour productivity can reflect the increase of capital and intermediate

[4]Labour productivity data is collected from the Penn World Table, which is updated periodically. This data was initially collected and presented in the paper of Feenstra et al. (2015).

[5]In Figure 1.2, the phase of slowdown and sluggish increase of labour productivity was years after the oil crisis in the 1970s and the global financial crisis of 2008-2009.

inputs without rising efficiency.[6] Therefore, the literature recognises that TFP, also known as Multifactor Productivity, is a superior metric for productivity analysis.

Growth accounting is a disaggregated measurement of economic growth that analyses to what extent the growth results from the increase in the factors of production or the contribution of TFP (Romer 2018, p. 30-32). In recent years, offices for national statistics in different countries have included growth accounting in their catalogue to give evidence of the TFP performance at the macroeconomic and sectoral levels. INEGI (2018) measures TFP growth in Mexico using the growth accounting of the KLEMS model following the methodologies of Jorgenson et al. (2000) and Schreyer & Pilat (2001). The KLEMS model measures TFP growth as the proportion of output growth not attributed to the increase in the factors of production, including capital (K), labour (L), electricity (E), materials (M), and services (S). Then the KLEMS approach is the acronym for the five factors of production included in the production function. The growth accounting is relevant as it provides evidence of whether the economic growth in Mexico relies on the intensive utilisation of factors of production or TFP.

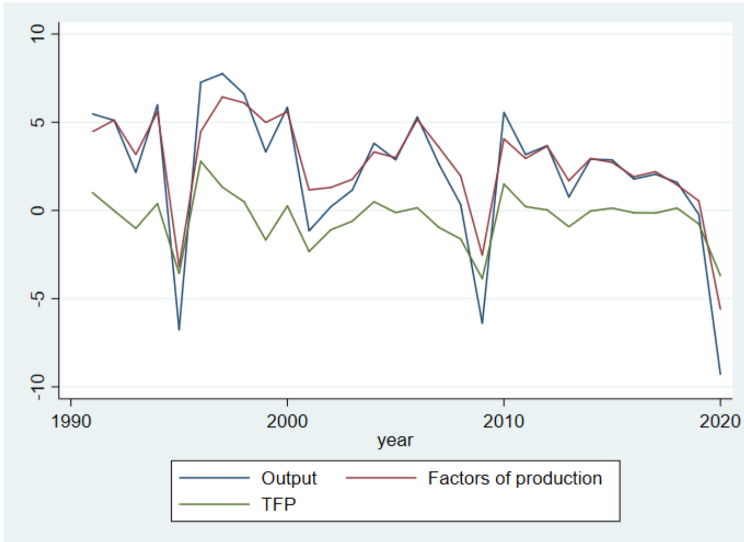
According to the evidence provided by the growth accounting statistics in Figure 1.2, the decrease in the utilisation of the factors of production and the negative rates of TFP growth over the period covering 1991-2021 explains the sluggish economic growth in Mexico. The output growth was 2.21% on average during 1991-2020; the growth of the factors of production was 2.67%, while TFP growth was -0.45%. Figure 1.2 displays that TFP growth and the growth in the factors of production are procyclical, and in periods of crisis, TFP decreases drastically. During the Mexican peso crisis in 1995, TFP decreased by -3.58%. In the global financial crisis of 2009, TFP decreased by -3.86%. Finally, the Covid-19 crisis caused the largest drop in TFP, equivalent to -3.69% in 2020.

The current literature that studies the productivity problem in Mexico can be divided into two approaches. The first approach has a microeconomic orientation. The microeconomic approach assumes firm-specific factors and context variables that determine the productivity heterogeneity across firms through adopting better production practices (Levy-Algazi 2018, López 2017, Rodríguez-Castelán et al. 2020, Bloom et al. 2022).[7] Then, horizontal industrial policies can incentive firms to adopt better production practices. In addition, some studies argue that building a simple institutional framework is necessary to eliminate institutional barriers constraining the firm's size and productivity growth.

[6] Although labour productivity is a useful metric, it is important to notice that this measurement is biased in some sectors, and thus it is not a supplement to TFP. For instance, in sectors intensive in capital, labour productivity is biased, reflecting an overestimation of productivity.

[7] A branch of the literature argues that the main cause of low productivity is the inefficient allocation of resources due to a large informal sector (Busso et al. 2012, Levy-Algazi 2018). Hanson (2010, p. 9) argues that the informal sector results from firms that keep small in capital accumulation to avoid onerous government regulations. Consequently, informality keeps small and unproductive firms in subsistence. Additionally, the informal sector reduces the correct functioning of the public sector as informal firms avoid tax payments.

Figure 1.2: Growth accounting of Mexico estimated with the KLEMS model, 1991-2020



Source: Own elaboration with data of the KLEMS model estimated by INEGI

The second approach of the literature about the productivity problem in Mexico has a macroeconomic approach. This approach argues that the availability of capital and the growth of capital is the major problem for productivity in Mexico. The reason is that the relative lack of capital per worker and obsolete technology have allowed Mexico's informal and unproductive sector to grow extensively. The previous idea is in line with theories of economic development. For that reason, this branch of the literature argues that capital accumulation is necessary so that the formal sector can absorb workers from the informality (Ros-Bosch 2013, 2019).[8] Another argument for this approach is that the structural change in Mexico has generated slower growth in the manufacturing sector. As predicted by Kaldor's laws, slower growth in the manufacturing sector has generated sluggish growth in the whole economy (Loría et al. 2019). Then, the declining share of manufacturing production in the GDP is one of the major causes of the decrease in capital stock. For instance, Padilla-Perez & Villarreal (2017) concluded that labour has moved from activities where productivity is growing faster towards those with a lower pace of productivity growth. Then, the structural change in Mexico has allocated labour to less productive activities.[9] For that reason, the Mexican economy has had two parallel processes: a structural change with an increasing share of services and a decrease in aggregated productivity.

[8]This idea is consistent with the two-sector model of Arthur Lewis (Hunt 1989).

[9]Structural change is the shift of economic resources from secondary and primary to tertiary activities. According to Padilla-Perez & Villarreal (2017), structural change in Mexico has occurred jointly with low economic growth and sluggish productivity growth.

1.2.2 The wide disparity of productivity across economic sectors and geographical locations

A growing part of the literature proposes that industrial strategies have to be oriented to increase productivity as an engine of recovery post-Covid-19. These policies should define specific interventions to target the productivity of key industries. The definition of key industries has been flexible and has changed over time. During the 1970s, industrial policies focused on strengthening the 'National Champions' in key industries such as high-tech manufacturing firms or in key industries that provided better benefits for the national economies. However, the economic composition has changed, and the service sector has gained a decisive role in economic performance. Successful industrial strategies build bridges of cooperation between the manufacturing and the services sector to increase efficiency in both sectors. For instance, digital services that include automation and Artificial Intelligence (AI) increase efficiency in the manufacturing and the services sector (Monahan & Balawejder 2020).

One of the challenges of industrial policies is to target specific interventions in sectors with a large proportion of firms with low TFP so that industrial policies support underperforming firms and the aggregated TFP of the economic sector increases. Recent studies argued that there is a larger proportion of underperforming firms in the TFP distribution of the services sector compared to the manufacturing sector; as a result, there is potential to increase TFP in the services sector (Monahan & Balawejder 2020, Dias et al. 2020).

In recent decades, a substantial body of theoretical and empirical research has measured TFP at different levels of disaggregation to understand the insights of TFP as a driver of economic growth. The main findings in the literature have documented a wide heterogeneity of productivity across firms, which reflects a differential in productivity across economic sectors and geographical locations. For that reason, the financial crisis (2008-09) and the Covid-19 crisis have intensified the debate about the renewal for the implementation of industrial policies oriented to rebalance the economy not only across sectors but also across geographical locations (Gardiner et al. 2013). An understanding of the differentials of productivity is crucial to target strategic locations and economic sectors to increase aggregated productivity by applying selective industrial policies. The following subsections provide statistical evidence and a literature review of the wide disparity in productivity across sectors and geographical locations in Mexico.

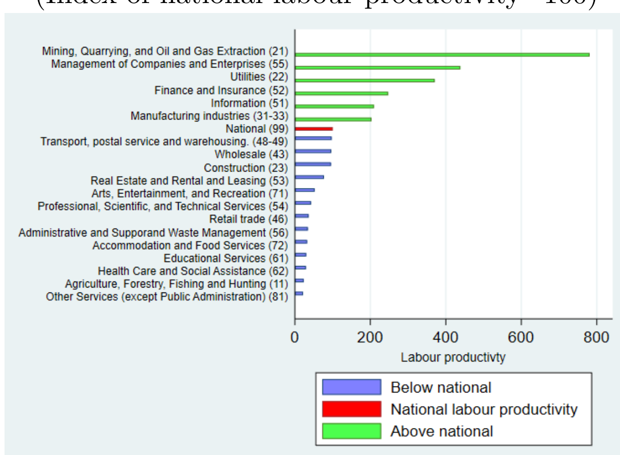
Sectoral productivity

The empirical evidence and the literature mention that manufacturing activities are more productive than services. However, economic activities in the tertiary sector can show high productivity, such as financial services and services of Information and Communications Technology (ICT). This subsection presents evidence of the wide disparity in labour productivity across economic sectors at 2-digit of the North American Classification System (NAICS) using data from the Economic Census of Mexico.

Figure 1.3 displays the labour productivity by economic sectors in Mexico during 2018. There are three sectors of services with higher labour productivity above the national level: Management of Companies and Enterprises, Financial and Insurance, and Information. However, eleven economic sectors in the tertiary sector are below the national labour productivity. On the contrary, most economic sectors dedicated to transforming raw materials into goods are above the national level —the only exception is the Construction sector—. Figure 1.3 displays three economic sectors above the national level, including Mining, Quarrying, Oil and Gas Extraction, Utilities, and Manufacturing industries. The disaggregated data by the economic sector indicates a wide disparity of productivity across economic sectors, with higher levels of labour productivity in activities of the secondary sector while lower labour productivity in the tertiary sector. In addition, Figure 1.3 provides evidence that there are only a few economic sectors with a high productivity level because only 6 of 19 economic sectors are above the average labour productivity at the national level.[10]

Figure 1.3: Labour productivity by economic sectors, 2018.

(Index of national labour productivity=100)



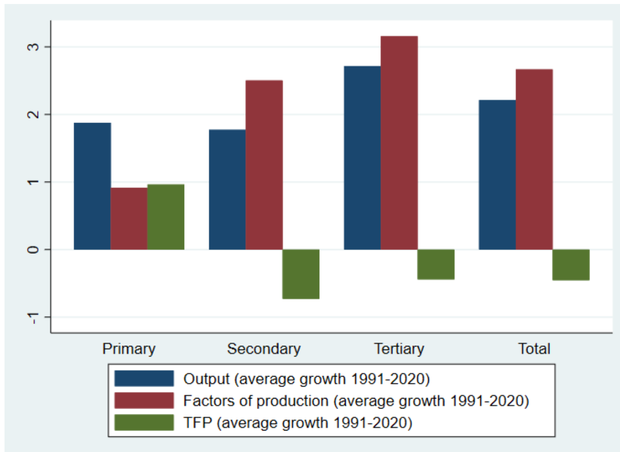
Source: Own elaboration using microdata of the Economic Census of Mexico (INEGI)

The growth accounting statistics aggregated by the three major sectors (i.e., primary, secondary and tertiary) provide evidence that the secondary sector had the lowest TFP average growth during 1991-2020, followed by the tertiary sector. Figure 1.4 displays that the primary sector does not represent a current problem for the aggregated TFP in Mexico because the average TFP growth was positive (0.96% p.a.) while the secondary and tertiary sectors had a negative TFP growth of -0.73% p.a. and -0.44% p.a., respectively, during 1991-2020. TFP in the secondary and tertiary sectors are relevant to the economy as both explain the negative TFP growth in the Mexican economy. In

[10]In this case, there are considered 19 economic sectors because INEGI concentrates the manufacturing industries with the NAICS code 31-33 and the transport and postal services with the NAICS code 48-49.

addition, the output growth in the Mexican economy is mainly driven by the growth of the factors of production.

Figure 1.4: Growth accounting by three sectors: primary, secondary and tertiary, 1991-2020



Source: Own elaboration with data of the KLEMS model estimated by INEGI

Geographical productivity

Although some studies have found an economic convergence between Mexican states, the convergence rate has been slow. Esquivel (1999) estimated that the regional convergence growth within Mexico was equivalent to 1.1% during 1940-1995, lower than other countries. As a result of the slow economic growth, high economic disparities across Mexican regions have persisted (Esquivel 1999, 2003). Mexico reflects a high disparity across geographical locations between OECD countries, characterised by high levels of GDP inequality between regions (OECD 2018).

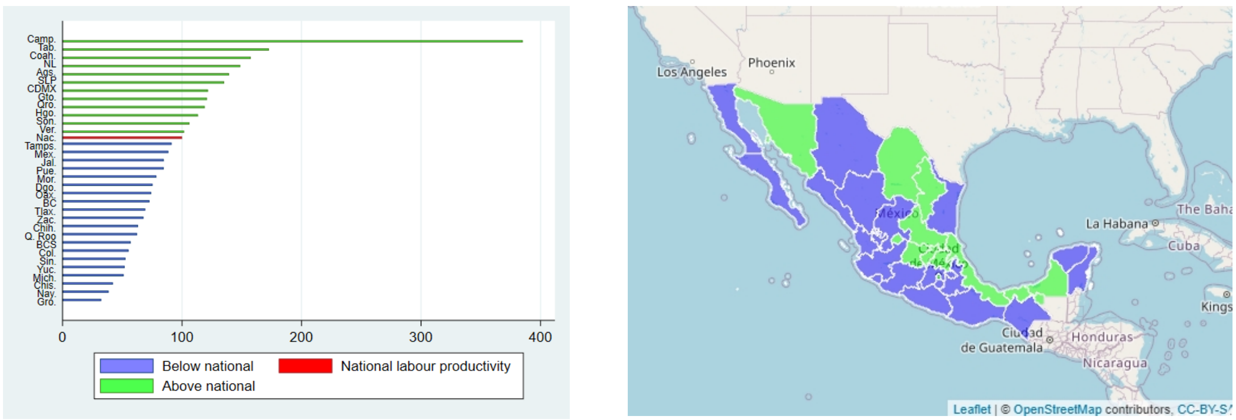
In recent years, there has been a renewed interest in the literature for implementing policies oriented to tackle geographical inequality and spatial 'rebalancing'. Some regions have better opportunities, and spatial inequality reflects the wide productivity disparity across geographical locations. In some countries, these inequalities can be explained by the decline of manufacturing industries and the uneven growth of services, mainly in large cities. In Mexico, firms with higher productivity levels are clustered in particular regions, which is more likely related to economic dynamism and better performance of socioeconomic variables (e.g. externalities).

There is a wide disparity in productivity across geographical locations within Mexico. Figure 1.5 displays an index of labour productivity by Mexican states in relation to labour productivity at the national level. Figure 1.5a shows a total of 32 Mexican states; only 12 have higher labour productivity than the national level (Nac). Particularly, Campeche (Camp.) and Tabasco (Tab.) have large labour productivity because those states are mainly dedicated to the extraction and production of oil. States with a high level of productivity, such as Coahuila (Coah.) and Nuevo

Leon (NL), have a high level of labour productivity due to their large manufacturing industries that have the facility to export to the U.S. by land, as both states share a border with Texas. In addition, Figure 1.5b displays the distribution of labour productivity by Mexican states.

Figure 1.5: Labour productivity index by Mexican states, 2018

(a) (Index of national labour productivity=100) (b) (Spatial distribution of labour productivity index)



Source: Own elaboration using the Economic Census of Mexico

A branch of literature argues that better living standards result from higher productivity levels. Klenow & Rodriguez-Clare (1997) conclude that differences in their levels of TFP are the dominant cause of differences in GDP per capita across countries. According to Pritchett (1997, p. 3), "divergence in relative productivity levels and living standards is the dominant feature of modern economic history".[11] Gardiner et al. (2013) argue that it is necessary to reduce spatial inequalities for two purposes: to increase aggregated economic efficiency and to provide better social equity. There are 'stylised facts' that can show that productivity correlates with social equity variables.

In Mexico, less productive regions have been deprived of socioeconomic opportunities. The evidence shows that labour productivity correlates with the living standards of the Mexican states. For instance, Figure 1.6 is a scatter between labour productivity (ln) at the state level in Mexico and the poverty percentage within each state (ln). Figure 1.6 indicates that the larger the labour productivity is in a state, the lower the percentage of poverty within this state.[12]

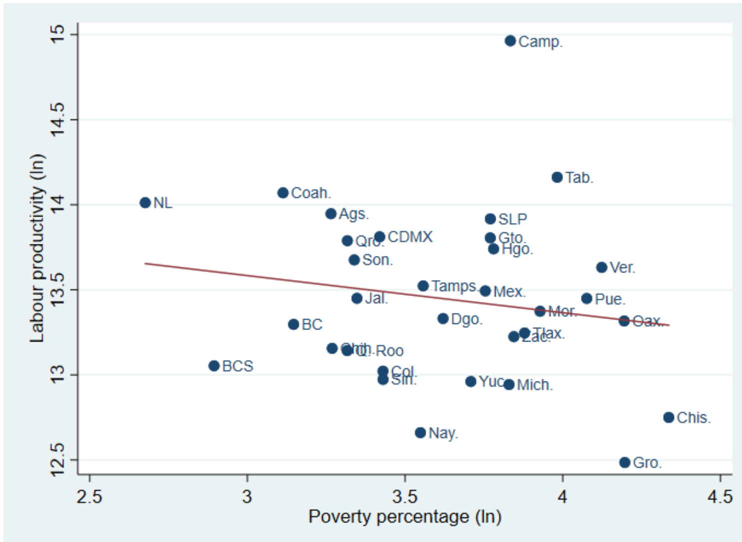
Space plays a crucial role in determining productivity in a geographical location, and studies measure how externalities generate productivity disparity across geographical locations. The literature points out that large cities are more productive than other locations due to externalities

[11] The debate about economic inequality in different dimensions has been renewed in recent years. Pritchett (1997) referred to the divergence big time as the widening gap between developed and undeveloped countries due to industrialisation that deteriorates the terms of trade. After the comparison of historical data of GDP, Pritchett (1997, p. 12) concludes that "Although there is not a great deal of historical evidence on GDP estimates in the very long-run for the less developed countries, what there is confirms the finding of massive divergence".

[12] Campeche and Tabasco can be outliers in this sample. The reason is that these states show high labour productivity because their economic activities are predominantly concentrated in the extraction and production of oil. However, poverty percentages within these states are relatively high.

Figure 1.6: Labour productivity and poverty by Mexican states, 2018.

(Horizontal: poverty percentage (ln). Vertical: labour productivity (ln))



Source: Own elaboration using microdata from the Economic Census of Mexico and data from the National Council for the Evaluation of Social Development Policy (CONEVAL)

that make firms more productive (Puga 2010). In addition, the evidence of different countries indicates that the 'place' effects are the major source of productivity that generates a wide disparity of productivity between regions. In addition, there are regional clusters of productivity which can be the effect of productivity spillover of firms residing in a particular region (Harris 2021, Harris & Moffat 2022).[13]

Tsvetkova et al. (2020, p. 7) state, "The mainstream economics research, which studies the drivers of productivity at the level of industries and firms, appears to be ill-equipped to offer solutions that would reverse the widening gap across regions. An explicit focus on the spatial (subnational) dimension of productivity is needed to better understand the recent productivity dynamics and devise policy solutions to boost aggregate productivity growth and decrease interregional inequality". For that reason, TFP estimates with a geographical dimension in Mexico are crucial to providing better measurements of productivity that allow a better perspective on the productivity disparities across regions and their underlying causes. TFP measurement by regions and their determinants can support the implementation of industrial policies committed to reducing spatial inequalities in terms of efficiency, which is ultimately a necessary condition, while not sufficient, for better performance in social equity across regions.

[13]Harris (2021) found that 'place' effects are the major source of TFP spatial differences across New Zealand geographical locations that create a wide disparity in productivity across geographical locations. Harris & Moffat (2022) estimated the geographical dimension of productivity in Great Britain, and they concluded that there is a substantial productivity difference between London and the rest of the regions. In particular, the areas with higher TFP are London and the Southeast of Great Britain.

Accurate measurements of TFP at the regional level do not currently exist in Mexico. Most regional studies in Mexico rely on labour productivity as the main analysis metric. However, TFP with a geographical dimension provides a more accurate measurement of productivity at different levels of geographical disaggregation so that governments can target regions with low TFP to implement industrial strategies to increase aggregated productivity.

1.2.3 The wide heterogeneity of productivity across establishments

The literature has recently focused on analysing productivity with a microeconomic approach because this approach accounts for a wide heterogeneity of productivity across firms. For that reason, comparing aggregated productivity levels at the macro level in Mexico can be analysed from the productivity distribution at the establishment level, which is the ultimate production unit in the productivity analysis. The analysis of the productivity distribution allows for identifying the characteristics of low levels of aggregated productivity. Harris (2021) pointed out that three characteristics of the wide TFP heterogeneity led to a low aggregated TFP.

1. Few frontier firms (i.e., global leaders) are at the top of the TFP distribution.
2. Many non-frontier firms are at the bottom of the TFP distribution (i.e., laggard firms).
3. There is an inefficient allocation of resources.

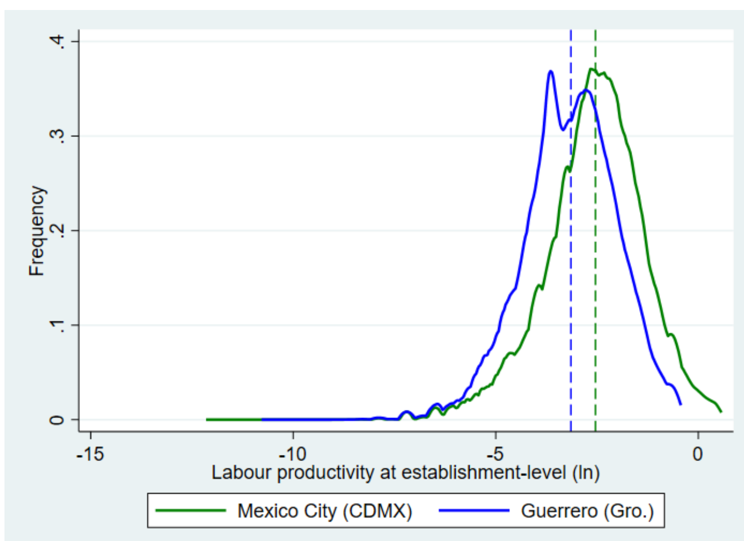
Regarding the first cause of low aggregated TFP, the literature points out that the productivity heterogeneity reflects different production practices between the frontier and non-frontier firms that lead to a wide difference in levels of efficiency. For that reason, the frontier firms with the 'best' production practices are more efficient and at the top of the TFP distribution. The literature explains why some firms have 'better' production practices than others by using productivity determinants as the underlying nature of productivity heterogeneity, also known as the X-efficiency factors (Bartelsman & Wolf 2017). Then, the minor presence of productivity determinants that positively impact TFP reveals the cause of why there are few firms concentrated at the top of the TFP distribution.

The second cause of low aggregated TFP accounts for many 'laggard' firms at the bottom of the TFP distribution because there is a lack of technological diffusion and privation of spatial drivers that impede firms from adopting 'better' practices of production. Then, the distance in levels of TFP between the frontier and laggard firms reflects the catch-up process of efficient production practices (Harris 2021). The minor presence of positive determinants to TFP and negative determinants to TFP reveals why many firms are concentrated at the bottom of the TFP distribution.

The third cause of the low aggregated TFP is an inefficient allocation of resources. The inefficient allocation of resources inhibits the allocation of resources from the less productive to the most productive. The modifications in the allocation of resources generate a firm selection that allows for the entry, subsistence and exit of firms in the market, and this process modifies the TFP distribution. The firm selection accounts that the more productive firms survive or enter the market while less productive firms exit the market.

In addition, measuring productivity at the establishment level allows for examining how productivity heterogeneity influences aggregated productivity across geographical locations or economic activities. For instance, Figure 1.5 indicates that Mexico City is in the 7th position in the ranking of labour productivity across states, while Guerrero was the state with the lowest labour productivity. Figure 1.7 uses the distribution of labour productivity at the establishment level to analyse the productivity heterogeneity across these two geographical locations. Figure 1.7 reveals that Mexico City is more productive than Guerrero because Mexico City has more establishments concentrated in the top tail of the labour productivity distribution while there are fewer establishments in the bottom tail of the labour productivity distribution. This evidence indicates that the production practices in the establishments of Guerrero are behind the 'national' frontier of labour productivity and many non-frontier establishments are stuck in low levels of labour productivity.

Figure 1.7: Distribution of labour productivity (ln) at establishment level in Mexico City and Guerrero, 2018.



Source: Own elaboration using microdata of the Economic Census of Mexico

The analysis of the productivity distribution is more reliable when the TFP distribution is analysed. For that reason, Figure 1.7 has limitations for analysing the wide heterogeneity of productivity across establishments in Mexico, but Figure 1.7 explains the micro-meso transition in the productivity analysis (i.e., establishments-regions). This thesis aims to measure TFP heterogeneity across establishments and then extrapolate the productivity analysis to measure TFP disparity across geographical locations in Mexico.

1.3 Research objectives

During the 1980s and 1990s, several empirical studies analysed TFP at the macro level. However, TFP at the macro level hides the productive heterogeneity at the micro level. Understanding this heterogeneity in productivity is crucial to account for the opportunities to increase the aggregated sectoral, regional and national productivity from the micro-level approach. This thesis analyses the productivity problem in Mexico using TFP at the establishment level as the primary analysis metric to provide a deeper productivity diagnosis. The availability of information in Mexico at the establishment level (i.e. microdata) is relevant. There are few databases in middle-income countries with this granularity of disaggregation.

There are four research questions that this thesis intends to answer using TFP as the variable of analysis in the Mexican case.

1. Why are some firms more productive than others?
2. To what extent is the TFP disparity across economic activities (e.g., sectors, subsectors) and geographical locations (e.g., states, municipalities)?
3. What is the contribution of the firm selection (i.e., entrants, continuers, exiters) to TFP growth?
4. Have the Mexican geographical locations had TFP convergence (i.e. catch-up)?

This research has four objectives to answer the previous four research questions.

1. To identify and measure empirically the TFP determinants that cause productivity heterogeneity in Mexican establishments.
2. To measure the contribution of the firm selection on TFP growth.
3. To measure TFP through different disaggregation levels that account for Mexico's geographical and sectoral dimensions of productivity.
4. To test the hypothesis of regional convergence of productivity in Mexico.

1.4 Research contributions

This research extensively uses the Economic Census's microdata to provide TFP estimates at the establishment level across all economic sectors and geographical locations in Mexico. The research contributions can be enumerated as follows:

1. Detailed and extensive TFP estimates.
2. Comparison of TFP estimates derived from different methodologies.
3. Analysis of TFP determinants at the establishment level.
4. Analysis of TFP in the sectoral and geographical dimensions
5. Measurement of the effects of firm selection on TFP growth.
6. Analysis of TFP convergence across Mexican states and municipalities.

The rest of this subsection explains in detail each research contribution.

1. Detailed and extensive TFP estimates.

   This research contributes to the literature on productivity in emergent countries by providing TFP estimations in Mexico with a high granularity of analysis at the establishment level. TFP at the establishment level provides better estimates than previous studies in Mexico because this measurement captures the productivity heterogeneity across producers. Furthermore, the high granularity of TFP estimates can extend the productivity analysis in the aggregation of TFP measurement from micro to macro.

   This research exploits the rich microdata of the Economic Census of Mexico that covers 20.77 million establishments in the period 1993-2018, with a 5-years gap collected by INEGI.[14] The national industry group categorises the establishments at the 6-digit code of the NAICS. The microdata was recently linked longitudinally, which makes it possible to track establishments over time (Busso, Fentanes Téllez & Levy Algazi 2019). The microdata used in this research is a comprehensive and unusual panel dataset for an emergent country.[15] Most of the recent studies that have used this dataset to estimate TFP using parametric methods only focus on manufacturing activities. Those studies include Blyde & Fentanes (2019), Puggioni (2019),

[14] On the INEGI's website, the Economic Census refers to the year of the data collection. For instance, the Economic Census 1994 refers to data collected in 1994 but this data refers to information from the previous year (1993). In this research, the period of the Economic Census denotes the year that the information is referred (1993-2018).

[15] There can be two reasons for the limited studies that compare TFP across sectors in middle-income countries like Mexico. The first reason is because the manufacturing sector has better data quality, and the second reason is because the economic growth of the manufacturing sector is determinant in the total GDP growth (Kaldor 1984).

Rodríguez-Castelán et al. (2020) and López-Noria (2021). Levy-Algazi (2018) provided TFP estimates for the manufacturing and service sectors using the Hsieh & Klenow (2009) model. However, these TFP estimates may be biased due to the price pass-through (Haltiwanger et al. 2018). For that reason, another contribution of this research is to provide unbiased TFP estimations across all economic sectors in the Mexican economy, not only the manufacturing industry.

Iacovone et al. (2022) is a recent paper that estimated TFP at the establishment level in Mexico (presented as TFPR), which provides a comprehensive TFP analysis from micro to macro. However, the research of Iacovone et al. (2022) needs more transparency of the parametric (econometric) results in estimating TFP at the establishment (plant) level. Iacovone et al. (2022, p. 31) explain that "TFPR is estimated using the methodology of Ackerberg, Caves, and Frazer (2015), which controls for endogeneity in the productivity estimates.". Although Iacovone et al. (2022) confirm using methods of the Control Function Approach to estimate TFPR, but there are no results about the estimation of the production functions even in the Online Appendix, which confirms "Cobb-Douglas production functions are estimated using the prodest Stata command, performing the Ackerberg-Caves-Frazer correction". The lack of parametric results to estimate the production functions in Iacovone et al. (2022) leaves a gap in the literature about TFP estimation at the establishment level in Mexico. In comparison toIacovone et al. (2022), this PhD thesis contributes to the literature with an extensive parametric (econometric) analysis of the production functions and the TFP determinants to estimate TFP at the establishment level in Mexico, as the primary analysis metric of research.

2. Comparison of TFP estimates derived from different methodologies.

   Few studies compare different parametric methodologies to measure production functions and TFP. Van Beveren (2012) reviews the parametric methodologies for estimating production functions and TFP with microdata. However, Van Beveren (2012) omitted Stochastic Frontiers models in the methodological comparison. For that reason, this research contributes to the empirical research by comparing current methods to estimate TFP with microdata.[16] The parametric methodologies included in the comparison are the Fixed Effects (FE) model, models of Stochastic Frontiers (SF) (Battese & Coelli 1995, Karakaplan & Kutlu 2017), models of Control Function Approach (CFA) (Levinsohn & Petrin 2003, Wooldridge 2009) and the System of Generalised Method of Moments (SYS-GMM) Blundell & Bond (1998).

3. Analysis of TFP determinants at the establishment level.

   In recent years, there has been an increasing number of empirical papers focusing on the determinants of TFP at the establishment level in Mexico. The recent longitudinal linkage of the microdata of the Economic Census in Mexico allows the implementation of parametric

[16] One reason for the exclusion of SF models in Van Beveren (2012) is that the literature did not account for endogeneity in SF models. In recent years, Karakaplan & Kutlu (2017) have argued that SF methods can present endogeneity issues.

methods to measure and analyse TFP determinants at the establishment level with panel data models. This empirical research is in line with the current branch of literature that identifies establishment-specific factors and context variables as TFP determinants in Mexico (Blyde & Fentanes 2019, Puggioni 2019, Rodríguez-Castelán et al. 2020, López-Noria 2021).[17] Most recent studies of the Mexican economy which analyse TFP at the establishment level are mainly dedicated to the manufacturing sector. This research contributes to the literature by implementing different parametric methodologies and specifications in the production function to investigate the TFP determinants at the establishment level across all economic sectors of the Mexican economy.

The methodological estimation strategy of the TFP estimation in this research is divided into two stages. The first stage analyses TFP determinants of medium and large manufacturing establishments as a subset of the Economic Census. A larger number of TFP determinants is analysed in the first stage because this data subset has more information available. TFP determinants of the first stage include firm's age, export activity, industrial concentration, reduction of costs, liquidity, informality, externalities (i.e., specialisation, diversification, local competition), and regional factors (i.e., population density). The second stage of the methodology strategy estimates a Cobb-Douglas production function with a mark-up correction to overcome the price bias, as Klette & Griliches (1996) proposed. The production function is estimated with the Wooldridge (2009) model by each economic sector. The microdata of the manufacturing sector covers the period 1993-2018. The rest of the economic sectors have microdata available from 1998 to 2018. There is a reduced number of TFP determinants in this stage compared to the first stage, but the TFP determinants are used extensively across establishments and sectors.

4. Analysis of TFP in the sectoral and geographical dimensions.

   The measurement of TFP at the establishment level allows the aggregation of TFP at different dimensions: geographical locations and sectors. This research provides empirical evidence about the wide productivity disparities across sectors and geographical locations in the Mexican economy. Few studies analyse TFP from a geographical dimension, and even fewer studies examine TFP across geographical locations using microdata. TFP measurements by geographical locations using microdata are not currently provided for productivity analysis in Mexico.[18] Most studies that measure and analyse TFP across regions in Mexico use aggregated data by states or municipalities instead of microdata.[19] This research is only aware of two studies comparing TFP across Mexican regions using microdata: Martínez-Alanís (2011)

[17] However, it is also relevant the role of capital accumulation and the manufacturing growth in the determination of TFP (Ros-Bosch 2013, Loría et al. 2019). These determinants related with theories of Economic Development can be considered in the future research agenda

[18] Official statistics of TFP available in Mexico can be limited in levels of disaggregation because the KLEMS model only estimates the rates of growth of TFP by economic sectors.

[19] For instance, Borrayo & Quintana (2018) and Borrayo López et al. (2019) estimated TFP using models of Stochastic Frontiers with data aggregated at the metropolitan level and states, respectively.

and Misch & Saborowski (2018). Both studies use the methodology of Hsieh & Klenow (2009) instead of parametric methods like this research.[20] Recently, Iacovone et al. (2022) provided TFP by geographical locations including states and municipalities, but that study does not provide TFP measurement by sectors and subsectors. Then, this thesis extends the current TFP evidence into geographical and sectoral dimensions.

5. Measurement of the effects of firm selection on TFP growth.

   Recent literature on productivity in Mexico has reached a consensus that dysfunctional (adverse) firm selection generates inefficient allocations of resources that lead to slow productivity growth in the Mexican economy. The dysfunctional firm selection implies that unproductive establishments entering and continuing in the market have pulled the aggregated productivity downwards in Mexico (Ros-Bosch 2019, Levy-Algazi 2019). Levy-Algazi (2018) provides evidence of the negative effect of dysfunctional firm selection on aggregate TFP. The evidence consists of descriptive statistics by comparing TFP distributions across groups of surviving, entering and exiting establishments (Levy-Algazi 2018, p. 127-258).[21] However, Levy-Algazi (2018) did not use a methodology to decompose TFP growth. This research measures the effect of firm selection on TFP growth using two methods of decomposition: Haltiwanger (1997) and Melitz & Polanec (2015). This analysis calculates the TFP growth decomposition in Mexico with two methods, while Iacovone et al. (2022) only applied the approach of Melitz & Polanec (2015). Therefore, another contribution of this research is to provide more empirical evidence about the effect of firm selection on TFP growth in an emergent economy.

6. Analysis of TFP convergence across Mexican states and municipalities.

   Aggregation of TFP to the state or municipality level allows analysis of TFP convergence (i.e., catch-up) across geographical locations in Mexico. Few studies in the literature examine the catch-up of productivity across states and municipalities using TFP as the analysis metric. In Mexico, Cabral et al. (2020) reviewed the studies that analysed regional convergence in Mexico, and the current studies have examined GDP or labour productivity convergence but not TFP convergence (Esquivel 1999, Díaz-Dapena et al. 2019, Mendoza-Velázquez et al. 2020, Castellanos-Sosa 2020). This research contributes to the literature by examining the catch-up

[20] Martínez-Alanís (2011) built a regional model with the Hsieh & Klenow (2009) approach to estimate distortions, misallocations and TFP gains by geographical locations in the manufacturing sector. The results of Martínez-Alanís (2011) indicate that distortions in the capital factor are the main cause that reduces the aggregated TFP in Mexico. The reason is that the distortions in the capital factor generate resource misallocation across establishments within the Mexican states. Misch & Saborowski (2018) estimated TFP gains by industry and state during 2013. TFP gains were included as the dependent variable in a cross-section model to explain the disparities in TFP gains between Mexican states. Misch & Saborowski (2018) concluded that the reduction of informality, reduction of crime, more access to financial services, more access to the internet and more efficient transport could increase TFP gains in Mexican states

[21] In particular, Levy-Algazi (2018, p. 143) provides a figure in which he calculated the probabilities of entry firms during 2008 to transit as surviving establishments in 2013 classified by low, medium and high productivity groups. However, Levy-Algazi (2018) did not provide integrated results that measure the contribution of surviving, entering and exiting establishments over time. This gap in the literature can be solved with the TFP growth decomposition using the approaches of Haltiwanger (1997) and Melitz & Polanec (2015)

across geographical locations in an emergent economy using TFP, which is generally regarded as a superior measure of productivity (Sargent & Rodriguez 2001). Iacovone et al. (2022) explored TFP convergence across states and municipalities. However, the analysis omits the parametrictr results, which are relevant to identify the significance of beta-convergence and estimate the convergence rate.

1.5 Policy implications

The outcome of this research will support the design of an industrial strategy in Mexico orientated to increasing TFP at different levels of disaggregation: establishment level, sectoral level, regional level, and ultimately at the country level. Particularly, this research uses TFP as the crucial variable of guidance for implementing suggestions of actions within an industrial strategy. The research outcome has an emphasis on the design of horizontal policies. For that reason, measuring TFP at different levels of disaggregation is crucial to provide suggestions for public policy. There can be enumerated four advantages of the current research to provide recommendations for industrial strategies in Mexico.

(a) Information on TFP determinants is useful to inform the design of policies to target establishments' attributes or spatial drivers that increase efficiency at the establishment level (Harris & Moffat 2022).

(b) Evidence on the contribution of firms entering, surviving or exiting the market explains whether a process of 'creative destruction' of the establishments generates a more efficient allocation of resources with positive effects on TFP growth in Mexico or whether there is a dysfunctional selection which should be mitigated by policy.

(c) TFP by geographical locations allows an understanding of regional productivity disparities, while TFP by sector provides evidence about the key sectors that contribute to a larger extent to the aggregated TFP in levels and TFP growth in Mexico. This information can guide government actions at different levels (e.g. country, state, municipality) included in the design and the implementation of industrial strategies to 'rebalance' the economy.

(d) The analysis of the catch-up effect can show whether current public policies provide an appropriate economic context for regional convergence in productivity or whether action is required to encourage the dissemination of technologies to deprived areas.

There is a long literature which accounts that industrial policies are the set of government strategies to improve the productivity of firms, sectors and regions to increase national productivity.[22] Classical theories of economic development accept that government interventions

[22]For instance, Johnson (1984) specifies that "[An] Industrial policy means the initiation and coordination of governmental initiatives to leverage upward the productivity and competitiveness of the whole economy and of

can raise productivity by increasing the accumulation of the stock of capital and updating the manufacturing infrastructure, mainly funded and coordinated by the government (Rosenstein-Rodan 1943, Lewis 1954, Rostow 1956, Leibenstein 1957). In this theoretical perspective, government interventions are essential to implement industrial strategies. In the post-pandemic period, the debate intensified about implementing industrial strategies. The current debate is about whether countries must promote global independence in strategic industries. The claim of a political front of economic independence comes from the supply chain disruption caused by the Covid-19 crisis, the economic tensions between U.S. and China and the war Rusia-Ukraine. In addition, industrial strategies have been in the debate of public policies because these strategies can be leverages to recover productivity growth.

Governments and academia have renewed interest in implementing industrial strategies as leverage of productivity that ultimately lead to sustainable economic growth (Rodrik 2008, Lin 2011, Mazzucato 2018). In Mexico, the first government self-identified as left-wing, designed and implemented an industrial strategy that was missing for decades in Mexico. In addition, there has been the construction and development of macro-projects related to infrastructure to promote the import substitution of petrol and develop regional mobility and tourism projects (Mexican-Government 2019). The creation and development of infrastructure promoted by the Mexican government implicitly accept the argument of development economists that support implementing industrial strategies. However, the question is not "why to implement industrial strategies?" but the relevant question is "how to implement industrial strategies?". This research aims to provide recommendations for public policy oriented to increase productivity in Mexico.

particular industries in it". Gual & Jódar-Rosell (2006, p. 5) argue that that the main justification for the implementation of an industrial strategy is the quest for efficiency and they defined an industrial policy as the "the set of government interventions that by way of taxes (or subsidies) and regulations on domestic products or factors of production attempt to modify the allocation of domestic resources that results from the free operation of the market".

Chapter 2

Literature review

2.1 Overview of Chapter 2

Chapter 2 is a literature review that specifies the relevant concepts of productivity in the economic literature. This literature review provides a general framework according to the theory and empirical findings related to TFP. The concepts from this literature review set the foundations to measure variables, define methodologies and analyse the results of TFP analysis in Mexico in subsequent chapters. The concepts of this literature review include the definition of TFP, its measurement, the underlying causes of TFP (i.e. TFP determinants), the impact of TFP on economic performance and the economic policy oriented to incentive TFP growth. Chapter 2 intends to answer three questions about TFP: (i) What is TFP? (ii) How to measure TFP? (iii) What are the TFP determinants in the literature? Table 2.1 summarises the structure of the content in Chapter 2 with the following sections and subsections. Section 2.2 reviews the main concepts of productivity and measurement, distinguishing between labour productivity and TFP. In addition, section 2.2 examines the main production functions to measure TFP and the importance of TFP at the macro and micro levels. Section 2.3 reviews the methodologies of TFP measurement using microdata classified in non-parametric and parametric methods. Section 2.4 identifies and classifies the TFP determinants in the literature into two categories: non-spatial and spatial determinants. Finally, Section 2.5 concludes this Chapter with the contributions that this research brings to the literature considering the gaps in the field of productivity analysis.

Table 2.1: Overview of Chapter 2

Topic	Section	Subsection
Productivity	Concepts and measurements	TFP at the macro level TFP at the micro level Production functions to measure TFP
	Methodologies of TFP measurement	Non-parametric Parametric
	TFP determinants	Non-spatial Spatial.

Source: Own elaboration

2.2 Concepts and measurement of productivity

This section examines the main concepts of productivity in three subsections. Subsection 2.2.1 defines the concept of productivity and the difference between labour productivity and TFP. Subsection 2.2.2 reviews the most relevant production functions to measure TFP. Finally, subsection 2.2.3 describes the relevance of TFP at the micro and macro levels according to the literature.

Productivity is the ratio of outputs and inputs. The productivity variation across producers and time can be attributed to technology, the scale of operation, operational efficiency and the context where the production occurs. Productivity is usually associated with efficiency. According to Neoclassical Economics, efficiency is the optimal value of inputs and output that a producer can reach as the best practice of production in allocative efficiency and technical efficiency (Farrell 1957).[1] For that reason, efficient firms reach the frontier of production (i.e. best practice of production) while firms out of the frontier of production do not reach their optimal level of efficiency (Fried et al. 2008, p. 8). Therefore, productivity measures the degree of efficiency at the micro level (i.e. firm level) and macro level (e.g. countries, regions).

There are two measures to approach productivity: labour productivity and TFP. Labour productivity is the ratio of output to labour as the only input $LP = Y/L$, while TFP is the ratio of output to inputs $TFP = Y/f(K, L, M) = A$ where $Y = A \cdot f(K, L, M)$ and A measures efficiency and technical progress: TFP. Comin (2010, p. 260) defines TFP as "the portion of output not explained by the number of inputs used in production. As such, its level is determined by how efficiently and intensely the inputs are utilized in production". The literature considers that TFP is a more reliable metric than labour productivity because labour productivity typically overestimates

[1] If a producer does not reach the highest production level with the inputs given, then the producer has technical inefficiencies. Even though a producer does not have technical inefficiency, the producer can have allocative inefficiency. Allocative inefficiency means a producer cannot minimise costs (Farrell 1957).

productivity in capital-intensive industries.

2.2.1 Production function to measure TFP

In Neoclassical Economics, the Theory of Production and the Theory of the Firm are fundamental to understanding the variables and mathematical specifications that constitute the TFP measurement. For the TFP estimation, it is necessary to specify a function $f(K, L, M)$ that relates the inputs: capital K, labour L and intermediate inputs M in a mathematical expression. The Theory of Production generally comprises three production functions: (i) the Cobb-Douglas function, (ii) the Constant Elasticity Substitution (CES) function and (iii) the Translog function.

The seminal work of Cobb & Douglas (1928) was the first step to formalise the Theory of Production with relative proportions of physical capital and labour added to production, defined as constant returns to scale. Empirically, Cobb & Douglas (1928) estimated the fitness of their production function to the American manufacturing industry from 1899 to 1922 using the specification $Y = AK^{\alpha}L^{\beta}$ where Y is the value-added. The results indicate an elasticity of substitution in the factors of production equivalent to 1. Then $\alpha + \beta = 1$ is distributed on 0.75 to labour in the elasticity β and 0.25 to capital in the elasticity α while the variable A approximates TFP measurement.

Other contributions complemented the Cobb-Douglas function, such as the CES production function proposed by Arrow et al. (1961) with the mathematical attribute to consider an elasticity of substitution different to one. Arrow et al. (1961) used a cross-country dataset with various industries to test if the first-order conditions of the Cobb-Douglas function with perfectly competitive markets fulfilled the condition that the elasticity of substitution is equal to one. The initial CES function was specified with two inputs, or factors of production, with a value-added specification $Y = A(\alpha K^{\rho} + \beta L^{\rho})^{(1/\rho)}$ where the parameter of substitution $\rho = (\sigma - 1)/\sigma$. If it is considering a CES isoquant as $K = 1/\alpha[(Y/A)^{\rho} - \beta L^{\rho}]^{(1/\rho)}$, there are three forms that the CES isoquant can take according to the magnitude in the parameter of substitution ρ. (i) If ρ approximates zero, the CES isoquant is a perfect linear substitution function. (ii) if p approximates to one, the CES isoquant is a Cobb-Douglas function. (iii) if p approximates to $-\infty$, the CES isoquant is a Leontief function.

Finally, another relevant production function in the literature is the transcendental logarithm (i.e., translog) function proposed by Christensen (1971), Christensen et al. (1973). This function allows the elasticity of substitution to vary according to factor proportions. The translog function with two factors of production and a value-added specification is $\ln(Y) = \ln(A) + \alpha \ln(K) + \beta \ln(L) + (1/2)\gamma\alpha\beta[\ln(K) - \ln(L)]^2$. Then, the translog production function can be regarded as a Taylor series expansion. A mathematical attribute of the translog function is when $\gamma = 0$. In that case, the translog function becomes a log-linear Cobb-Douglas function. The advantage of the translog function is that in the empirical application, this function can be estimated using parametric methodologies and the inclusion of more components in the production function without incorporating more factors of production.

Heathfield & Wibe (1987, p. 153-182) point out that a critique of the Theory of Production is that the assumption of a mathematical production function that relates inputs, output and TFP can be an oversimplification of the production process.[2] Johansen (1972) formalized the simplification of applying a joint production function by industries. Johansen (1972) demonstrated that industries produce a homogenous product with a single production function; as a result, it is possible to aggregate production functions from the micro to the macro level. In applied research at the micro-level, firms are grouped by industries, and then a common production function is estimated as an approach to estimate TFP. The empirical analysis examines the elasticities in the production function to quantify the effect and magnitude of the inputs to the output by the industry group. In addition, the direction and magnitude of the parameters in the control variables of the production function allow for quantifying the effect of TFP determinants.

The most common production function in applied research is the Cobb-Douglas function due to its simplicity for measuring the elasticities in the factors of production when logarithms are applied. The early paper of Ringstad (1967) compared the parametrical estimation of the Cobb-Douglas and the CES function. Ringstad (1967, p. 133) indicated that there is not a big difference between both functions because both fit the same degree to data. The CES and the Cobb-Douglas functions are similar because they share mathematical properties. Battese & Broca (1997) compared the Cobb-Douglas and the translog function using the parametric methods of the SF. Battese & Broca (1997) concluded that there are significant parametric differences between production functions and the specification of technical efficiency. Battese & Broca (1997, p. 407) recommended: "approaches in which more general model specifications and assumptions are made, and simpler formulations are formally tested". For that reason, the simplicity of the Cobb-Douglas function is generally assumed as the true functional form for the estimation of productivity. Estimating production functions with data at the micro or macro level determines the level of TFP disaggregation. On the one hand, databases disaggregated at the macro-level consider countries, states or cities as the producers. On the other hand, databases at the micro-level consider firms or plants as the producer (i.e., microdata).

A final characteristic of the production function is whether the output Y is a variable of gross output or value-added. The specification of the production function with the gross output orientation implies that the production function has three factors of production $Y = A \cdot f(K, L, M)$ while

[2] According to Heathfield & Wibe (1987, p. 177) an alternative approach to model the economic production process is the engineering approach which applies mathematical isoquants to relate inputs and output. Nonetheless, the estimation of engineering production functions can be inefficient for empirical research because "The engineering approach has, however, some serious drawbacks. The method is extremely time-consuming and a researcher has to devote perhaps years of study for the construction of isoquant for some small process".

a production function with a value-added orientation has two factors of production $Y = A \cdot f(K, L)$. Gandhi et al. (2020) state that a production function with a gross output or value-added approach leads to different productivity patterns. They concluded that estimating production functions with gross output orientation provides stronger foundations.

2.2.2 TFP at the macro level

Since the contribution of Solow (1956), TFP has been a central variable in understanding economic growth driven by technical progress and efficiency.[3] Furthermore, TFP has a perspective of economic development by explaining the differences in income per capita with TFP in levels across countries (Klenow & Rodriguez-Clare 1997). For instance, TFP at the country level in the Penn World Table, estimated by Feenstra et al. (2015), accounts for a positive relationship across countries between TFP and the GDP per capita. Caselli (2005) estimated TFP with a calibrated model in the agriculture sector for 65 countries using the World Development Indicators (WDI) in 1996. The conclusion of Caselli (2005) is that the differences in TFP across countries mainly explain the income per capita differences in agriculture. Therefore, the consensus at the macro-level is that TFP is as important as the factors of production to explain variations of income per capita across countries. The evidence related to TFP is relevant as it aims to understand the improvements and the differentials of economic living standards over time and across space (e.g. countries, regions, cities).

At the macroeconomic level, TFP is crucial for understanding the productivity gap between high-income and middle-income countries to implement policies that improve productivity. Daude & Fernández-Arias (2010) concluded that the low income and the growth stagnation of Latin American countries in relation to developed countries are predominantly caused by the low TFP instead of the low factor accumulation. Then, closing the gap in productivity between countries is crucial for the catch-up (i.e., convergence) process between high-income and middle-income countries.

In recent years, the offices for national statistics in different countries have included the growth accounting approach as additional statistics that give evidence about the role of TFP in economic performance at the macro and sector levels. Growth accounting is a disaggregated measurement of economic growth that analyses to what extent economic growth is the result of the increase in the factors of production or the increase of TFP (Romer 2018, p. 30-32). Therefore, growth accounting is relevant as it provides a perspective on whether economic growth relies on the intensive utilisation of factors of production or TFP. Ultimately, the increase of TFP provides sustainable economic growth as it reflects the capacity of an economy to increase its technological capacity and its efficiency in allocating resources that contribute to increasing income per person in the long-

[3] Related to this empirical evidence, Kydland & Prescott (1982) argue that TFP is an element that influences the economic fluctuations, which determines the phases of recession or expansion of an economy.

term (Chen 1997, Klenow & Rodriguez-Clare 1997).[4] In the coming decades, TFP will become the ultimate engine of GDP growth (OECD 2015).

2.2.3 TFP at the micro level

The empirical evidence has shown wide TFP heterogeneity across firms at the microeconomic level. TFP heterogeneity reflects the different degrees of success that producers achieve in allocating available inputs and output to achieve efficiency in cost, revenue, or profits (Kumbhakar & Lovell 2003, p. 15). Fried et al. (2008, p. 12) gives three reasons for the interest in measuring TFP at the microeconomic level: (i) the identification and separation of controllable and uncontrollable sources of productivity heterogeneity, (ii) micro performance drives macro performance, (iii) the ultimate success of productivity is profits; then productivity is an indicator of financial performance. The importance of productivity at the microeconomic level is that TFP is commonly associated with a condition of firm survival in a competitive environment because more productive firms generally have higher output, revenue and profits, as well as lower prices (Hopenhayn 1992, Olley & Pakes 1996, Melitz 2003).

Harris & Moffat (2015*a*) pointed out that there is wide heterogeneity in TFP at the firm level as productivity distributions are significantly 'spread' out with large 'tails' of low-productive firms. In addition, TFP distribution is persistent as firms typically spend long periods in the same part of the TFP distribution. The analysis of the TFP distribution is an approach to measure the productivity gap between the firms in the productivity frontier and the laggard firms. This analysis supports the design of policies that incentive laggard firms to push their TFP to increase aggregated TFP.

The dynamic of TFP at the firm level is relevant for understanding the evolution of the aggregated TFP growth. For instance, Nishimizu & Page (1982) measure the aggregated TFP growth in three components using TFP at the firm level. The first component refers to technical efficiency, which is calculated as the distance from a firm's output in relation to the output with the best practice of production. The second component is the growth of the technological progress that represents the firms' TFP growth in the technological frontier. The third component is the change of inputs according to changes in output, which measures Hick's neutrality.

It is commonly argued in the literature that the micro-level performance drives the macro performance of productivity through the firm selection, creating a Schumpeterian process on the TFP growth. This process generates a 'creative destruction' in the market in which the entering firms contribute positively to the aggregated TFP while the exiting firms contribute negatively (Haltiwanger 1997).

[4] Macroeconomic studies use TFP statistics at the country level because they display the ability of an economy to grow without inflationary pressure in conditions of macroeconomic stability (Barnett et al. 2014).

2.3 Methodologies to measure TFP with microdata

The methodologies presented in this subsection are generally part of the empirical literature, which can be applied to microdata in different countries with a statistical orientation to accept or reject hypotheses according to existing economic theories. Methodologies in the empirical literature differ substantially from TFP estimations in the theoretical literature that generally implements calibrated models, which are mathematical constructions with a high content of formalisation and economic theory. The empirical literature is often associated with econometrics, and theoretical literature is associated with calibrated models.[5]

In general, replicating calibrated models in different databases can be difficult due to the initial database's particularities or the theoretical researcher's set of assumptions and constraints to calibrate the model. However, in the last decade, the calibrated model of Hsieh & Klenow (2009) became influential and popular in estimating TFP using microdata and replicated in several industries and economies. TFP measurement with the Hsieh & Klenow (2009) model seems attractive to several researchers because its calibration is manageable due to the few parameters in the model.[6]

The replication of TFP measurement with Hsieh & Klenow (2009) model does not increase knowledge to understand the underlying causes of TFP differences across firms. The reason is that the Hsieh & Klenow (2009) model assumes that distortions mainly explain TFP differences across producers. The role of the distortions in this model are constraints of firms to reach their optimal marginal revenue in production and their optimal level of profits. The limitation of the Hsieh & Klenow (2009) model is the omission of variables that explain these distortions, and it does not derive potential solutions to misallocations (Restuccia & Rogerson 2013, 2017). Studies that replicate the Hsieh & Klenow (2009) model in different economies generally measure the aggregated TFP gains in an economy without distortions and misallocations (Busso et al. 2012, Levy-Algazi 2018, Dias et al. 2020).

The methodology of Hsieh & Klenow (2009) has been criticised due to TFP measurement biases. From their theoretical model, Hsieh & Klenow (2009) make the difference between TFP

[5] Therefore, empirical literature uses methodologies or models to be estimated, while theoretical literature uses models to calibrate. Econometrics is related to the 'data generation process' because the estimation process is the search for the independent variable(s) that can generate a dependent variable according to statistical criteria. Calibration models assume that data is appropriate to represent reality, and it has to be determined by specifications and variables of the theory. Then, calibration is the search for the correct magnitude and sign of the parameters in the model to represent reality. Cooley (1997, p. 60) argues that "calibration and estimation are complements, not substitutes" in economic research.

[6] For instance, the Hsieh & Klenow (2009) model considered a production function at industry level with value-added orientation and constant returns to scale. In order to measure TFP of Quantity (TFPQ), the parameters needed to calibrate the model are the elasticity of the capital factor α_s and the elasticity of substitution between plants σ, which generally takes a value of three according to Hsieh & Klenow (2009). For the measurement of distortions and marginal revenue of labour and capital, the parameters needed to calibrate are the interest rate R —price of the capital factor— and the wage w -price of the labour factor-

of Revenue (TFPR) and TFP of Quantity (TFPQ).[7] The measurement of TFPR represents the productivity that includes the price at the firm level, while TFPQ represents the real productivity measurement without price influence. In Hsieh & Klenow (2009), the measure of TFPQ derives from TFPR through parametric calibration. However, Haltiwanger et al. (2018) argue that the Hsieh & Klenow (2009) model presents problems because the price is embodied in the TFPQ measurement. Haltiwanger et al. (2018) argue that TFPQ and TFPR are positively correlated rather than uncorrelated.[8] This positive correlation reflects the price pass-through from TFPR to TFPQ. This price pass-through yields spurious distortions and mismeasurement of misallocations in the Hsieh & Klenow (2009) model. As a result, the TFP dispersion results from idiosyncratic mark-up or shift in the demand rather than true TFP differences across firms (Foster et al. 2008).

De Loecker & Syverson (2021)) distinguish two concepts in the literature between TFPQ and TFPR. TFPR is a metric that measures TFP using data quantified in monetary value, which implies that output is typically measured as revenue (e.g. sales or net sales). On the other hand, TFPQ measures TFP using data in which output is measured in quantity instead of monetary values. De Loecker & Syverson (2021) are aware that output data measured in quantity at the establishment level is more precise to measure TFPQ, but the availability of this data is rare. Thus, measuring TFPQ using microdata is not common in the literature. The measurement of TFPR is the most common in the literature as microdata quantified in monetary values is usually available in the national agencies of statistics. In the literature, TFPR is usually labelled as TFP. As this research measures TFP with revenue microdata, the analysis metric in this thesis is TFPR, which is simplified to be labelled as TFP in the rest of this thesis.

The complication of measuring TFPR implies deflating revenue data and approximating the measurement of TFPQ. The restriction of using price indices to deflate data implies that prices at the industry level do not capture the heterogeneity of prices in the economy. As a result, data deflated with price indices do not incorporate imperfect competition in which establishments are price takers. De Loecker & Syverson (2021) account that the recent literature in the productivity analysis has incorporated a demand system and demand shifters to include imperfect competition (with price heterogeneity) in the TFPR measurement to approximate the measurement of

[7] Bils et al. (2021) developed a methodology to correct the measurement bias in Hsieh & Klenow (2009). The TFP correction focuses on removing the error measurement of idiosyncratic distortions, which leads to the correction of misallocations. Bils et al. (2021) applied their model to manufacturing in India and the U.S. Their results indicate that after removing error bias, the correction lowers potential gains from reallocation by 20% in India and 60% in the US. Then, the initial approximation of resource reallocation estimated by Hsieh & Klenow (2009) in India and the U.S. might be overestimated.

[8] Haltiwanger et al. (2018) measured the elasticity of prices and TFPQ to test empirically if the value of this elasticity is equal to one, as Hsieh & Klenow (2009) sustain. The results indicate that the elasticity is less than the unity in eleven economic sectors, and the assumptions of Hsieh & Klenow (2009) do not hold in data. Haltiwanger et al. (2018) proposed a decomposition of TFPR into six components: three of them –the most relevant– imply mark-ups, non-constant returns to scale and distortions. The latter is the crucial variable to measure the aggregated TFP gains without distortions. The Haltiwanger et al. (2018) decomposition is convenient, but this decomposition is fitted to the data separated by prices and quantities, and in practice, this type of data is difficult to obtain.

TFPQ more accurately. The incorporation of imperfect competition in the TFPR measurement —henceforth TFP— consists of the specification in the production function, including a mark-up correction.[9] This production function specification was first derived from the model of Klette & Griliches (1996). This thesis accounts for the recommendation of De Loecker & Syverson (2021) to include imperfect competition in the productivity analysis and, thus, the necessity to incorporate the mark-up correction in the functional form of the production function using the framework of Klette & Griliches (1996). The explanation of the production function estimation with mark-up correction is described in detail in Chapter 4 and Appendix C.

De Loecker & Syverson (2021) provide a survey that analyses productivity analysis's implications and application in Industrial Organization (I.O.). This survey considers that the literature in I.O. accounts that market power leads to the inefficient allocation of resources (i.e., misallocation) and ultimately to productivity loss. De Loecker & Syverson (2021) consider that misallocation research has grown since the initial contribution of Hsieh & Klenow (2009). The approach of Hsieh & Klenow (2009) considers that the dispersion of TFP across firms leads to larger misallocations (because the larger presence of distortions affecting output and input(s) leads to larger TFP dispersion across firms). However, De Loecker & Syverson (2021) consider that TFP dispersion is not, per se, a sufficient condition to measure TFP loss due to misallocations. There are two challenges this branch of literature faces. The first challenge is that specification of models in the line of Hsieh & Klenow (2009) have several assumptions to hold (which were discussed in Haltiwanger et al. (2018)), and the assumptions used to compute marginal revenue products and infer misallocations are the centre of attention. The second challenge is that TFP dispersion reflects not only misallocations but also adjustments costs (which leads to the dispersion of marginal revenue product of capital) and uncertainty about their sales per input process (which leads to dispersion in the inputs' marginal revenue products). The effect of adjustment costs and uncertainty (i.e. volatility) on TFP dispersion is investigated by Asker et al. (2014).

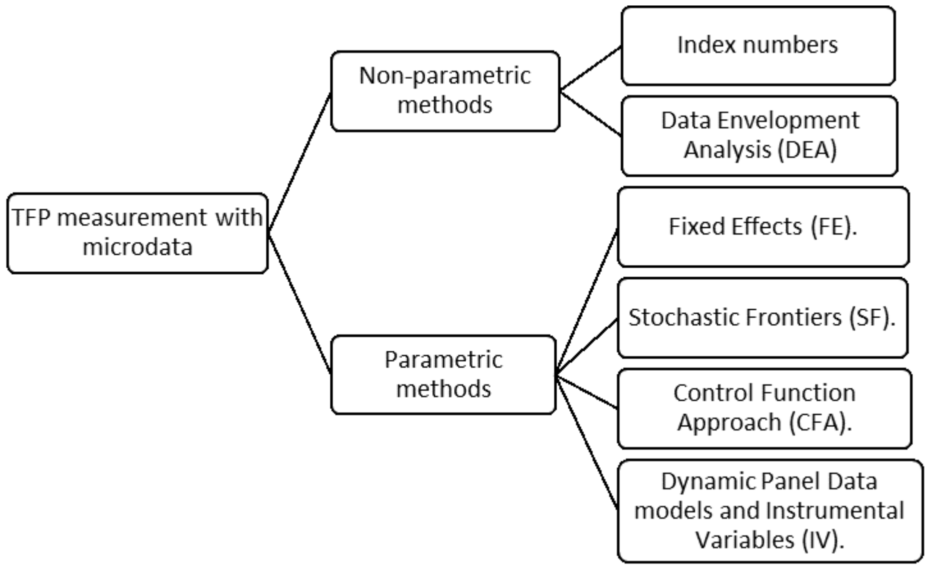
This subsection mainly reviews the surveys of Del Gatto et al. (2011) and Van Beveren (2012) that explain the empirical methodologies to measure TFP using microdata (i.e., firm, establishment, plant-level). Methodologies to measure TFP in empirical research using microdata are classified into non-parametric and parametric methods.[10] The main difference between both classifications is that parametric methods use econometric techniques to estimate the elasticities of the factors of production and the empirical identification of TFP determinants. In contrast, non-parametric methods apply other mathematical approaches for the TFP estimation (i.e. linear programming, index numbers). Figure 2.1 shows a classification of the parametric and non-parametric methods

[9] De Loecker & Syverson (2021) account that several papers in the empirical research estimate TFP using a log Cobb-Douglas as the specification of the production function. However, this function does not account for the fact that establishments are price takers. Therefore, the specification of a log Cobb-Douglas function assumes perfect competition.

[10] Even though these methods can also be applied to TFP measurement at the macro-level, this section does not review the growth regression, which is the primary methodology to measure TFP at the macro-level (Del Gatto et al. 2011). The review of methods to estimate TFP at the macro-level is beyond the research's objectives.

to measure TFP at the firm level. The following two subsections review in detail the content of Figure 2.1.

Figure 2.1: Methodologies to measure TFP with microdata



Source: Own elaboration

2.3.1 Non-parametric methods

The non-parametric methods include two methodologies: Index numbers and Data Envelopment Analysis (DEA). However, the review of non-parametric methods can be limited in this research because this thesis is primarily dedicated to reviewing and implementing parametric methods to measure TFP with microdata.

Index numbers

An index number is a real number that measures changes in one variable in relation to some variables over a given period. This method is appropriate for time-series. Laspeyres and Paasche formulae are the best-known methods to construct index numbers because these methods are generally applied to calculate price indexes. The Fisher and Tornqvist index formulae are also widely popular as index numbers (Coelli et al. 2005). Then, a TFP index number measures the output change in relation to inputs over a base period. The most accepted method to measure TFP is the Fisher and Tornqvist index (Diewert 1992).

Data Envelopment Analysis (DEA)

DEA is a metric that attempts to estimate production efficiency using the Theory of the Firm as a background. Farrell (1957) was the precursor to measuring efficiency with the DEA method. The basic assumption of Farrell (1957) is that a group of firms' output in the same industry share a common isoquant and its optimized isocost. Firms out of the isoquant function face inefficiencies due to imperfect competition. According to Farrell (1957), there are three components included in efficiency: Technical Efficiency (TE), Allocative Efficiency (AE) and Economic Efficiency (EE). TE measures the efficiency of output to reach the maximum use of inputs, AE measures the efficiency of output to reach the minimum costs, and EE is the product of TE and AE.

The model described previously has input-orientation. However, there is an extension to this model known as the output-oriented model to measure efficiency proposed by Fare et al. (1994). The DEA output-oriented model measures TE, AE and EE using a Possibility of Production Frontier (PPF) and its isorevenue line. In that model, TE measures the efficiency of inputs used to reach the maximum output, and AE is the efficiency metric of output to maximise revenues. The estimation of average TE is with the solution of a linear programming problem to capture the efficiency of the DEA output-oriented model with the nature of scale economies.

For the empirical measurement of TFP at the firm level using the DEA method, Ji & Lee (2010) and Lee et al. (2011) proposed that the DEA with input-orientation or output-orientation can be applied to longitudinal data in STATA. For this application, the assumption is that firms have a common production function with Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) to measure firm-level efficiency. The variation of efficiency over time calculated with the VRS is equivalent to the technical efficiency change. In contrast, the variation in time of the efficiency calculated with the CRS is equivalent to the efficiency change. The multiplication of the efficiency change and the technical efficiency change is equivalent to the TFP change at the firm level. TFP can be aggregated using the Malquimist productivity index.

2.3.2 Parametric methods

Parametric methods assume a production function (e.g. Cobb-Douglas, CES, translog) in which the coefficients related to the factors of production are estimated with econometric models. A standard specification in the production function is a Cobb-Douglas function. The application of this production function to a panel of firms i where $i = 1, \ldots, N$ in the period t where $t = 1, \ldots, T$. and the dimension of the panel data is NT. Equation 2.1 shows the specification of the Cobb-Douglas function:

$$Y_{it} = A_{it} M_{it}^{\beta_m} L_{it}^{\beta_l} K_{it}^{\beta_k} \tag{2.1}$$

where, A_{it} is TFP in levels, and this variable can be expressed as follows

$$A_{it} = \beta_0 e^{\beta_T t} \mathrm{X}^{\beta_{\mathrm{x}}} e^{\varepsilon_{it}} \tag{2.2}$$

Equation 2.2 shows that TFP (A_{it}) at the firm level i in the year t is a function of an initial level (constant) of TFP represented by β_0, and this initial level of TFP evolves over time t at the pace β_T. Then, the parameter β_T represents the disembodied exogenous increase/decrease of efficiency over time that the literature defines as Hicks-neutral technical change. In addition, matrix X comprises the variables that determine TFP, known as efficiency shifters (i.e., X-efficiency factor). The vector β_{x} represents the direction in which the efficiency shifters influence TFP. Finally, the variable ε_{it} is the random shocks to TFP. If ln is applied to equation 2.1, then the production function takes the form of a log-linear Cobb-Douglas function expressed in equation 2.3.

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t + \varepsilon_{it} \tag{2.3}$$

In equation 2.3, the variables y, m, k, l refer to the ln of the real gross output, intermediate inputs, capital stock and employment, respectively. Parameters β_m, β_k, and β_l are the elasticities in the factors of production. The specification of ln TFP is the part of the production function in equation 2.3 not attributed to the factors of production, and this specification is expressed in equation 2.4.

$$\ln\left(TFP_{it}\right) = y_{it} - \beta_m m_{it} - \beta_l l_{it} - \beta_k k_{it} = \beta_0 + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t + \varepsilon_{it} \tag{2.4}$$

Harris & Moffat (2017) argue that some studies measure TFP at the firm level and then regress TFP with potential determinants. However, the estimation of TFP with a two-stage strategy generates a problem of omitted variables in the production function in equation 2.3.

The parameters β's of the production function in equation 2.3 can be estimated with Ordinary Least Squares (OLS). However, estimating the production function with OLS causes endogeneity of inputs (i.e., simultaneity bias). The literature points out that the endogeneity of inputs leads to inconsistent and biased OLS parameters due to the correlation of the error term ε_{it} and the factors of production in equation 2.3 (i.e. m_{it}, l_{it}, k_{it}).[11] The endogeneity of inputs implies that a proportion of TFP is embodied in the factors of production, and then TFP measurement is biased. In addition to the endogeneity of inputs, Van Beveren (2012) points out additional biases using parametric methods: selection bias, omitted price bias and multi-product firms.

The selection bias, or endogeneity of attrition, accounts for a correlation between the error term ε_{it} and the capital factor k_{it}. The selection bias leads to the elasticities bias because the firms'

[11] For instance, if V is a matrix that contains the vectors of inputs in (2), the endogeneity of inputs implies that $E\left(\mathrm{V}'\varepsilon\right) \neq 0$. The consistency of the OLS parameter is given by $\hat{\beta}_{OLS} = \beta + \left(\mathrm{V}'\mathrm{V}\right)^{-1}\ \mathrm{V}'\varepsilon$, as a result of the endogeneity of inputs, the OLS estimator is not equal to its real value because $\hat{\beta}_{OLS} \neq \beta$. Therefore, the endogeneity of inputs in the production function leads to an inconsistent OLS estimation because the asymptotic distribution of the estimator is biased (Cameron & Trivedi 2005, p. 72).

survival condition is omitted. According to Hopenhayn (1992), productivity shocks are associated with a probability of exit, and Bartelsman & Doms (2000) argue that large firms have a higher probability of survival. Then, the omission of the survival condition means the exclusion of a relevant variable associated with TFP. Empirical studies find that the parametric estimation of the production function with balanced panel data causes endogeneity of attrition. The issue with balanced panel data is that this data structure does not deal with the survival condition of entry and exit of firms in the market. Olley & Pakes (1996) found that the estimation of a balanced Panel Data Model led to higher elasticities of capital and lower elasticities in labour compared to an unbalanced Panel Data Model (i.e. full sample).

An additional issue of TFP estimation with parametric methods is the omitted price bias. The origin of this issue is that most firms' production databases are not disaggregated in prices and quantities, and the production statistics are presented in monetary values. Therefore, TFP is typically estimated with statistics in monetary values and then deflated using a producer price index at the industry level. However, production-deflated values do not reflect the real production at the firm level because usually, the price index at industry-level ρ_{st} is different to the price index at the firm level ρ_{it}. In perfect competition, there is no difference between the price index at the industry level and the price index at the firm level. However, in an imperfect competition market, the difference $\rho_{st} - \rho_{it} \neq 0$ is the omitted price bias that leads to biased TFP estimations.

Finally, the product mix is the firms' use of different technologies applied to various inputs and prices across products produced by a single firm. For that reason, Van Beveren (2012) argues that having disaggregated data by the firm's products is necessary to have consistent TFP estimation in the presence of multi-product firms. In practice, it is rare to find databases with the product mix level of disaggregation. However, there are some exceptions, such as the research of Foster et al. (2008, 2016) and Haltiwanger et al. (2018) that use a database with prices and quantities separated by single firms.

In summary, according to Van Beveren (2012), there are four issues for the TFP estimation with parametric methods that include: (i) endogeneity of inputs —simultaneity bias—, (ii) endogeneity of attrition —selection bias—, (iii) omitted price bias and (iv) multi-product firms. In particular, this section reviews the parametric methods that overcome simultaneity and selection bias. For the correction of the omitted price bias, Klette & Griliches (1996) constructed a model that estimates TFP at the firm level with a specification that incorporates a mark-up factor of correction. Chapter 3 explains the production function with mark-up correction to overcome omitted price bias (Klette & Griliches 1996). However, the multi-product firm bias is generally omitted in the empirical literature because this issue requires the microdata to be separated by prices, quantities and products. This microdata is usually unavailable. For that reason, a potential solution for the multi-product firm is beyond the scope of this work because the data used to estimate TFP in Mexico does not have information disaggregated by product mix.

Table 2.2 presents relevant parametric methodologies in the literature included in four categories: (i) FE model, (ii) SF models, (iii) CFA models and (iv) Dynamic Panel Data Models with Instrumental Variables (IV).

Table 2.2: Parametric methods: categories and models to measure TFP using microdata

Parametric methods.	**Selected models**	**Estimator[a/]**
FE model		WE
SF models.	Battese & Coelli (1988)	ML
	Battese & Coelli (1992)	ML
	Battese & Coelli (1995)	ML
	Karakaplan & Kutlu (2017)	ML
CFA models.	Olley & Pakes (1996)	FS: OLS. SS: GMM
	Levinsohn & Petrin (2003)	FS: OLS. SS: GMM
	Ackerberg et al. (2015)	FS: OLS. SS: GMM
	Wooldridge (2009)	GMM
Dynamic Panel Data Models with IV	SYS-GMM (Blundell & Bond 1998)	GMM

[a/] Abbreviation of the estimators. Within Estimator (WE). Maximum Likelihood (ML). First Stage (FS): Ordinary Least Squares (OLS). Second Stage (SS): Generalized Method of Moments (GMM)
Source: Own elaboration

Fixed Effects (FE) model

This category only comprises the FE model as the basic specification in a production function to obtain consistent and unbiased parameters that overcome the endogeneity of inputs. Mundlak & Hoch (1965) were precursors in applying the FE model to production functions. The FE model considers two components in the error term. The first is the factor of efficiency, which is time-invariant and establishment-specific u_i, and the second is a component of the productivity shock v_{it}, which follows a normal distribution with zero mean. Then, the FE model specifies this composite residual: $\varepsilon_{it} = u_i + v_{it}$. The log-linear Cobb-Douglas function with FE takes the following specification in equation 2.5.

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t + u_i + v_{it} \tag{2.5}$$

The FE model can be estimated either with Least Squares Dummy Variables (LSDV) or the Within Estimator (WE). The latter is preferred because the WE avoids potential computational complications in finding the parameters in the production function. Additionally, the LSDV estimator should be biased due to the incidental parameters that lead to a correlation between the fixed effects and the explanatory variables (Van Beveren 2012). The main drawback of this model is the limitation in the assumption that the idiosyncratic efficiency is invariant over time.

Stochastic Frontiers (SF) models

Similar to the FE model, the models in the category of SF also have a composite residual $\varepsilon_{it} = -u_{it}+v_{it}$, which is also known in the literature as the two-sided error. SF models are relevant in the literature because these models can separate productivity into two components: technical efficiency and random shock to efficiency. The first component $-u_{it}$ is the efficiency term in logarithms, while the second component v_{it} is the random shock. The difference in the composite error between SF and the FE model is that SF models assume a particular distribution in the efficiency component, but the FE considers a free distribution in the idiosyncratic efficiency component. For that reason, the SF models consider a joint likelihood function that includes the probability distribution in the efficiency component and the stochastic shock. The estimation of the parameters in the SF is through numerical optimization using techniques such as Newton-Raphson and Gauss-Newton to obtain the Maximum Likelihood (ML) estimator. A general specification of the production function with the SF model is expressed in equation 2.6

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t - u_{it} + v_{it} \tag{2.6}$$

The efficiency component can assume a particular distribution according to the specification of the SF model (e.g. half normal, exponential, truncated normal). Some SF models assume that the efficiency component can be time-invariant for each establishment (Schmidt & Sickles 1984, Pitt & Lee 1981, Battese & Coelli 1988) or time-variant (Battese & Coelli 1992, 1995). The technical efficiency component either invariant in time (u_i) or variant (u_{it}) can be disentangled from the residual ε_{it} using the method of Jondrow et al. (1982) and Battese & Coelli (1988). These methods obtain technical efficiency as $TE_{it} = \exp(-u_{it})$; then the values of technical efficiency are bounded between 0 and 1 with mean μ_{TE} and variance σ^2_{TE}. The random shock variable follows a normal distribution $v_{it} \sim N(0, \sigma_v)$ and this variable is independent to u_{it}. The STATA routine of Belotti et al. (2013) can estimate the popular SF models of Battese & Coelli (1988, 1992, 1995).

A disadvantage in the Battese & Coelli (1995) model is that the SF presents an endogeneity bias. Karakaplan & Kutlu (2017) propose an SF model that corrects for potential endogeneity of inputs. The endogenous SF model includes an auxiliary regression in which one factor of production (or various) is (are) the dependent variable(s). The auxiliary regression is parametrised by including instrumental variables. Then the residual of the auxiliary regression is included as an independent variable in the SF. The inclusion of the error term from the auxiliary regression in the SF corrects the endogeneity of inputs (Karakaplan & Kutlu 2017). The SF model of (Karakaplan & Kutlu 2017) can be estimated with the STATA routine of Karakaplan (2017). However, a limitation in the routine of Karakaplan (2017) is that the estimation of the auxiliary regression can only include a reduced number of inputs with presumed endogeneity. Furthermore, the auxiliary regression in Karakaplan (2017) has to include exogenous instruments that account for additional data not included in the factors of production or TFP determinants.

The main purpose of the SF models is to estimate the technical efficiency and the random shocks using the components of the composite residual. This particularity of the SF allows measuring the technical efficiency with a particular distribution through the ML estimator. However, there are computational difficulties in applying the SF models in large databases of microdata. These computational difficulties avoid the convergence of the numerical optimization to calculate the ML estimator in the production function. Cameron & Trivedi (2005, p. 350) enumerate four computational difficulties of the ML estimation: (i) problems reading data (e.g. anomalies in the data like many missing values), (ii) variables with different scales, (iii) multicollinearity and (iv) dummy traps (i.e., most of the observations with values of zero or one). For those reasons, the estimation of SF models can be problematic when these models are applied to large databases.

Control Function Approach (CFA).

Mollisi & Rovigatti (2017) use the category of CFA to refer to those models that overcome the endogeneity of inputs by using a proxy and a state variable to express them as a function of productivity. In the CFA models, the parameter of the state variable, typically the capital, is corrected through an algorithm that uses the proxy variable as a correction variable.

The Olley & Pakes (1996) model, henceforth the OP model, uses capital as the state variable and investment as the proxy variable. The control function assumes that investment decisions (i) is a function of capital (k) and current idiosyncratic productivity (ω_{it}).[12] Olley & Pakes (1996) assume that the investment function is expressed as $i_{it} = f(k_{it}, \omega_{it})$ where the investment function $f(\cdot)$ is monotonically increasing in capital and productivity. This function is invertible, so idiosyncratic productivity is expressed as a function of capital and investment $\omega_{it} = f^{-1}(k_{it}, i_{it})$. The OP model assumes that $f^{-1}(\cdot)$ is a polynomial of the state and the proxy variables. The term $\omega_{it} = f^{-1}(k_{it}, i_{it})$ is considered in the literature as the control function.

Levinsohn & Petrin (2003), hereafter LP model, found that using the investment at the firm or establishment level (i_{it}) is inappropriate because, in practice, several investment values are reported in data as zero or null.[13] This lack of data leads to a bias in the estimation because establishments without reporting data on investment are excluded from the estimation sample.[14] Therefore, the LP model considers a control function in which the intermediate inputs are a function of capital and productivity $m_{it} = f(k_{it}, \omega_{it})$.[15] The purpose of using the intermediate inputs as a proxy variable in

[12] In the original paper of Olley & Pakes (1996), the algorithm also included the age of the establishment in the investment function.

[13] The literature also recognises that the OP and LP algorithms are semi-parametrical models because the productivity is expressed as a polynomial, non-linear function, of the state and the proxy variables (Van Beveren 2012).

[14] The exclusion of observations with null values in the variable of investment causes a sample bias, which leads to an estimation bias in the production function.

[15] In the seminal paper, the LP model suggests that the intermediate inputs can be related to inputs of energy consumption (e.g. oil, diesel, electricity). Then the function in the LP model implies that more use of intermediate

the LP model is to overcome the sample bias of the OP model because the variable of intermediate inputs is available in most of the observations in the sample.[16] The LP model can invert the function of intermediate inputs to obtain a control function that expresses the idiosyncratic productivity as a function of the capital and intermediate inputs $\omega_{it} = f^{-1}(m_{it}, k_{it})$.[17]

The estimation of the OP and LP models uses OLS in the first stage, and it can be implemented with Generalized Methods of Moments (GMM) when the routine of Mollisi & Rovigatti (2017) is applied.[18] In the second stage of the OP and LP models, the routine of Mollisi & Rovigatti (2017) includes the polynomial of the state and proxy variable in $f^{-1}(\cdot)$ in the matrix of instruments of the GMM estimator. Either the OP and LP models comprise a two-stage algorithm for estimating the parameters $\beta' s$ in the production function. In the first stage, the parameter of the free variable is estimated, typically labour. The second stage estimates the parameters of the state variable, the proxy variable, the TFP determinants and the productivity component (Mollisi & Rovigatti 2017). The specification of the production function in the OP and LP models is expressed in equation 2.7.

$$y_{it} = \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t + \omega_{it} + v_{it} \tag{2.7}$$

The routine of Mollisi & Rovigatti (2017) includes the constant term (β_0) of the production function in the idiosyncratic productivity. Therefore, the estimation of the OP model implies that $\omega_{it} = \beta_0 + f^{-1}(k_{it}, i_{it})$ and $\omega_{it} = \beta_0 + f^{-1}(k_{it}, m_{it})$ in the LP model. Equation 2.7 can also be expressed as $y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f^{-1}(k_{it}, i_{it}) + v_{it}$, in the OP model and $y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f^{-1}(k_{it}, m_{it}) + v_{it}$ in the LP model. The component v_{it} is the residual of the first stage, also considered as the random shocks to productivity, which follows a normal distribution $v_{it} \sim N(0, \sigma_v)$. The idiosyncratic productivity time-variant ω_{it}, and the parameters β_{x} are estimated in the second stage of the OP and LP models.[19]

Ackerberg et al. (2015), henceforth ACF, developed a correction to the OP and LP algorithms. This correction indicates that either the OP or LP models have a functional dependence on the free variable due to the two-stage estimation in the OP and LP models. Then the ACF correction considers estimating jointly the state, the proxy and the free variable as well as the TFP determinants in the second stage of the algorithm. The production function specification in the ACF correction considers a value-added orientation with only two factors of production: labour and capital.[20] How-

inputs is associated with a higher stock of capital and a higher level of idiosyncratic productivity.

[16] If the variable of intermediate inputs is not reported, this variable can be calculated as the difference between the gross output and the value-added.

[17] The literature also recognises that the OP and LP algorithms are semi-parametric models because the productivity is expressed as a polynomial, non-linear function of the state and the proxy variables (Van Beveren 2012).

[18] In addition, the routine of Yasar et al. (2008) and Petrin et al. (2004) use Non-linear Least Squares (NLS) in the second stage to estimate the OP and the LP model, respectively.

[19] In the second stage estimation, ω_{it} includes a polynomial function of the proxy and the state variable, the constant term and the residual of the second stage. Typically, the polynomial function includes variables of capital, investment and in the original paper of Olley & Pakes (1996) it is also included the probability of survival condition.

[20] However, the intermediate inputs are included in the estimation of the polynomial function of ω_{it} in the ACF

ever, the estimation with the ACF algorithm leads to different results than the OP and LP models because the later models consider a production function with gross output orientation compared to the ACF specification that accounts for a value-added production function.[21] Therefore, there is no comparability between production functions estimated with the ACF model and the rest of the CFA model. The limitation of the ACF model is that the value-added production function cannot determine whether an economy is intensive in using intermediate inputs. Usually, there is a large magnitude in the estimated elasticity of the intermediate inputs in the production function.

The Wooldridge model is another approach classified in the CFA category (Wooldridge 2009). This model estimates the parameters of the production function in one single stage using a system of two equations estimated with the GMM framework. The estimation of the Wooldridge model in one single stage overcomes the dependence on the free variable that the algorithms of OP and LP present due to the two-stage estimation. Wooldridge (2009) proposes that idiosyncratic productivity follows an autocorrelated process, and this process is equal to the inverse function in the LP model using the lags of the control and proxy variables. Wooldridge (2009) assumes that in the first equation $\omega_{1it} = E\left(\omega_{1it} \mid \omega_{1i,t-1}\right) = f^{-1}\left(k_{1i,t-1}, m_{1i,t-1}\right)$ and in the second equation $\omega_{2it} = E\left(\omega_{2it} \mid \omega_{2i,t-1}\right) = h\left(f^{-1}\left(k_{2i,t-1}, m_{2i,t-1}\right)\right)$. The function $f^{-1}(\cdot)$ is the polynomial of the state and proxy variables, and the function $h(\cdot)$ is a polynomial over the polynomial of $f^{-1}(\cdot)$.[22]

The limitation of the Wooldridge model is that this model can exclude a significant number of observations in the sample. If the Wooldridge model is estimated in panel data with a large number of establishments N and a short number of periods T, a significant number of observations are excluded due to the missing dynamic instruments in the polynomial of the state and proxy variables (Mollisi & Rovigatti 2017). Then there is more extensive coverage in the estimation sample when the Wooldridge model is estimated in panel data with a small number of establishments N a large number of periods T. For the estimation of the Wooldridge model, Mollisi & Rovigatti (2017) stacked the two equations proposed by Wooldridge (2009) and included the components of $f^{-1}(\cdot)$ and $h(f^{-1}(\cdot))$ in the matrix of instruments to generate the GMM estimator. The Wooldridge model's reduced form, which includes two stacked equations, is specified in equation 2.8.

$$y_{it} = \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}_{it}' \beta_{\mathrm{x}} + \beta_T t + \varepsilon_{it} \tag{2.8}$$

The estimation of the Wooldridge model using the GMM framework with the routine of Mollisi & Rovigatti (2017) produces the residual ε_{it} in equation 2.8. The residual ε_{it} includes the constant term, idiosyncratic productivity and random productivity shocks. Then, the residual ε_{it} is a stacked

model.

[21]The estimation of the ACF model with the STATA routine of Mollisi & Rovigatti (2017) is more efficient and less time-consuming than the routine of Manjón & Manez (2016).

[22]The function of the idiosyncratic productivity implies $h\left(f^{-1}\left(k_{it}, m_{it}\right)\right) = \rho_0 + \rho_1 h + \rho_2 h^2 + \cdots + \rho_G h^G$. The implementation of the Wooldridge (2009) model with the routine of Mollisi & Rovigatti (2017) assumes that $\rho = 1$ And $G = 1$. This simplification avoids computational issues in the calculation and use of the instrumental variables in the Wooldridge model.

vector $\varepsilon_{it} = (\varepsilon_{1it}, \varepsilon_{2it})$ in which the first vector is $\varepsilon_{1it} = \beta_0 + \omega_{1it} + v_{it}$ and the second vector is $\varepsilon_{2it} = \beta_0 + \omega_{2it} + u_{it}$. The variables v_{it} and u_{it} are the random shocks to productivity in the first and second equations.

In summary, the CFA models use the theoretical foundations of Olley & Pakes (1996) to approximate the estimation of idiosyncratic productivity at the producer level using a state and a proxy variable. The CFA models have been modified over time to overcome estimation issues (i.e. sample bias and dependence on the free variable). The modification of the CFA models has evolved from the OP model to LP, ACF and finally, the Wooldridge model. The estimation of the CFA models with the STATA routine of Mollisi & Rovigatti (2017) avoids computational difficulties by implementing the GMM estimator, which makes this routine more efficient compared to other routines that implement NLS estimated with ML. A drawback in Mollisi & Rovigatti (2017) is the absence of a test to examine the overidentification of instruments in the polynomial function. This gap in the empirical literature could open the debate about the estimation of CFA models using the GMM estimator.

Dynamic Panel Data Models and Instrumental Variables (IV)

The IV and the two-stage least squares (2SLS) are early approaches to overcoming input endogeneity in the production function. Those approaches use instruments as variables correlated with the factors of production but uncorrelated with the random error term. The instruments overcome the endogeneity bias of inputs by correcting the elasticities of the factors of production. As a result, the inputs are uncorrelated with the random error when a correct set of instruments is implemented.

The Dynamic Panel Data Models recover the idea of IV models to use the lags of the factors of production and the TFP determinants in levels and differences to correct the parametric bias due to simultaneity. The limitation of the IV estimators is that these models cannot be estimated because there are more instruments than variables in the production function. Then, the GMM is a convenient estimator because it can include more instruments than variables in the production function by using a weighting matrix (Baum et al. 2003).

Roodman (2009) catalogued the Difference GMM (Arellano & Bond 1991) and the SYS-GMM model (Blundell & Bond 1998) in the category of Dynamic Panel Data Models with IV. These models are catalogued as dynamic because the variables in the production function, including the gross output, the factors of production and the TFP determinants, can follow a dynamic process by using their lags for accounting the short-run and long-run effects in the production function. If the production function does not include lagged variables, only contemporaneous, then the Difference GMM and the SYS-GMM models have a static specification.

The Difference GMM is a model that uses variables in the production function in the first differences, and the instruments are lagged variables in levels. The SYS-GMM model is an extension of the Difference GMM model because this is a system of two equations in differences and levels that improve the efficiency of the GMM estimator. The use of instruments provides the SYS-GMM model with high flexibility in parametric identification by exploiting the moments of orthogonality between the instruments and the random error term (Blundell & Bond 1998).

The matrix of instruments in the equation in differences of the SYS-GMM model is $\mathrm{z}_{1it} = (\Delta \mathrm{x}_{it}, m_{i,t-1}, l_{i,t-1}, k_{i,t-1}, \ldots, m_{i,t-T}, l_{i,t-T}, k_{i,t-T})$. In the matrix z_{1it}, the difference in the TFP determinants $\Delta \mathrm{x}_{it}$ are the exogenous instruments, while the rest of the variables are the endogenous instruments.[23] The command of Roodman (2009) allows for varying the number of lags in the endogenous instruments of the matrix z_{1it}. The matrix of instruments in the equation of levels of the SYS-GMM model is $\mathrm{z}_{2it} = (\mathrm{x}_{it}, t, \Delta m, \Delta l, \Delta k)$ in which x_{it} and t are the exogenous instruments, and the rest of the variables are the endogenous instruments. The advantage of the SYS-GMM approach is that it overcomes the endogeneity and selection bias by using a set of dynamic instruments. The parametric identification of the SYS-GMM model uses dynamic instruments generated from the current database.

The literature usually simplifies the equation in levels and differences of the SYS-GMM model into one single equation. This simplification implies that both equations are stacked. Therefore, the matrices of instruments are also stacked, which can be expressed as a single matrix of instruments $\mathrm{z}_{it} = (\mathrm{z}_{1it}, \mathrm{z}_{2it})$. Then, the SYS-GMM model can be specified as follows.[24]

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t + \varepsilon_{it} \tag{2.9}$$

The SYS-GMM model shares some features with the Wooldridge model as both models are a system of two equations, and in practice, both are estimated with the GMM estimator. The difference is that the specification of the SYS-GMM model accounts for one equation in levels with fixed effects and one in differences; the Wooldridge model has both equations in levels and specifies idiosyncratic productivity as a polynomial function of control and state variables. In addition, the matrix of instruments in the SYS-GMM and the Wooldridge model has different specifications when they are estimated with the routines of Roodman (2009) and Mollisi & Rovigatti (2017), respectively.

The advantage of the SYS-GMM model is to allow for high flexibility in the parametrization by using a different set of lags in the endogenous instruments (i.e. factors of production). The flexibility of the SYS-GMM allows using dynamic instruments from the initial database, and it is not necessary to collect more data or calculate more variables. The choice of lags in the endogenous variables can be specified according to the researcher's criteria. There can be two criteria for choosing an

[23]It is important to notice that the time-trend is not included as an exogenous instrument because the difference of the time-trend is a constant. As a result, including a constant as an instrument is not appropriate to overcome the endogeneity bias.

[24]The fixed effects in the SYS-GMM model are included in the variable ε_{it}.

appropriate set of lags. The first criterion is to overcome the overidentification of instruments and autocorrelation of errors.[25] The second criterion can be to obtain an appropriate parametrization of the production function with credible magnitudes in the elasticities of the factors of production and TFP determinants.[26] However, the controversy about using the SYS-GMM model is that this approach can be sensitive to the instruments used. The sensitivity of the SYS-GMM model implies that a different set of instruments lead to different parametrization in the presence of weak instruments (i.e. marginally valid). Therefore, when the SYS-GMM is estimated, it is appropriate to define a robustness check to validate parametrical results with different instruments.

2.4 TFP determinants

The specification of the log Cobb-Douglas production function in equation 2.3 includes a matrix of covariates and the parameters that measure the effect and the magnitude of these variables on TFP ($\mathrm{x}'_{it}\beta_{\mathrm{x}}$). The literature refers to the inclusion of covariates in the production function as TFP determinants because these variables are channels of transmission responsible for efficiency shifts across producers. Then, TFP determinants are the underlying causes of productivity heterogeneity across producers (i.e. firms, establishments, plants). This section reviews the variables considered TFP determinants according to the theoretical literature. This review includes empirical studies that test the significance, direction and magnitude of TFP determinants.

According to Tsvetkova et al. (2020), TFP determinants can be classified as Non-Spatial and Spatial determinants. On the one hand, TFP determinants catalogued as Non-Spatial include characteristics that benefit or directly affect the producers' production process; these variables are related to theories of non-competitive markets, institutional economics and endogenous growth (Del Gatto et al. 2011). This classification includes variables such as Research and Development (R&D), technology, knowledge diffusion, business churning, human capital, institutions (both formal and informal, such as culture), policies and regulations and demographic profiles. On the other hand, the Spatial TFP determinants are related to regional and urban science research that identifies the spatial productivity drivers related to producers' externalities, economic geography variables, and public policy. This classification includes variables of geography and borders, agglomeration economies and plants' geographic distribution. In the following two subsections, there is a review of theoretical and empirical contributions to the categories of Non-Spatial and Spatial TFP determinants.

In a similar classification, Syverson (2011) argues that TFP determinants can be divided into production practices and producers' external operating environments. Those categories can also be labelled as within and between TFP determinants. In the category of production practices,

[25] According to the Hansen/Sargan test and AR(2) test.

[26] Credible parameters might come from economic theory.

Syverson (2011) identified: (i) managerial practice/talent, (ii) higher quality of labour and capital inputs, (iii) IT and R&D, (iv) product innovation and (v) firm structure decisions. In the category of producers' external operating environments, Syverson (2011) identified: (i) productivity spillovers, (ii) competition, (iii) regulation and (iv) input markets.

Table 2.3 categorises Non-Spatial and Spatial TFP determinants and the economic theories in each classification (Tsvetkova et al. 2020). Three economic theories are included in the category of Non-Spatial TFP determinants. The first theory is the endogenous growth theory which emphasises that knowledge is a driver of productivity. The second is the theory of the non-competitive market which accounts for market power and information asymmetries among agents that generates productivity heterogeneity across producers. Finally, the institutional economics theory explains the role of institutions in shaping the economic structure and the firm's productivity. Each category includes the theoretical mechanism of transmission that benefit or affect productivity, while empirical studies test the effect and magnitude of these mechanisms using proxy variables. Additionally, the category of Spatial TFP determinants includes Spatial Economics as a theoretical framework which explains the allocation of economic activity in space. This category also includes the mechanism of transmission and proxy variables.

Table 2.3: Classification of TFP determinants

Categories of TFP determinants	**Economic theories**	**Mechanism of transmission**	**Proxy variables**
Non-Spatial	Endogenous growth theory	Learning-by-doing	Firm's age
		Learning-by-exporting	Export index
	Non-competitive markets	Market concentration	Herfindahl index
		Managerial capabilities	Fixed cost index
		Firms' funding	Liquidity index
	Institutional economics	Informality	Informality index
Spatial.	Spatial Economics	MAR externalities	Agglomeration index
		Jacobian externalities	Diversity index
		Porter's externalities	Firms entering the market
		Place effects	Demographic characteristics

Source: Own elaboration

2.4.1 Non-spatial TFP determinants

Endogenous growth theory

During the 1980s and 1990s, the endogenous growth theory consolidated in Macroeconomics as an approach to explain TFP disparities between countries. The endogenous growth theory defines knowledge as a variable emerging from the self-economic structure that determines economic growth. Endogenous growth models emphasise that learning-by-doing, R&D, innovation and human capital increase TFP and thus promote economic growth (Nelson & Phelps 1966, Romer 1986, Mankiw et al. 1992).[27]

Early theoretical approaches focused on micro-dynamics to understand the relationship between the learning-by-doing effect and TFP at the firm level through firms' investments in intangible assets (Griliches 1981). Harris & Moffat (2015*b*) categorised the variables based on knowledge as internal and external creation of knowledge. Internal knowledge refers to the firms' capacity to increase their intangible capabilities. Consequently, 'active learning' allows firms to increase external knowledge, which is more likely to increase their competitiveness. Two transmission mechanisms are analysed in this research as TFP determinants categorised in the endogenous growth theory. The first transmission mechanism is the learning-by-doing effect, which is associated with the firm's age proxy variable. In addition, the second transmission mechanism is the learning-by-exporting effect, which is associated with an export index.

Learning-by-doing: firms' age

A firm's age is related to the external knowledge that represents the exogenous gains or losses over time, and this variable has two opposite effects on productivity. On the one hand, older firms can positively impact productivity by reflecting a learning-by-doing process that generates an endogenous improvement in technical efficiency. On the other hand, older firms can negatively impact productivity due to the vintage capital effect, which represents an exogenous deterioration of capital that reduces the firm's technical efficiency. Harris & Moffat (2015*a*) and Ding et al. (2016) found that a firm's age affected TFP negatively at the plant-level in Great Britain and China, respectively. As a result, these studies conclude that a firm's age creates a vintage effect on TFP of Chinese and British firms.

Hsieh & Klenow (2014) provided evidence of the life cycle and TFP at the establishment level using data from the U.S., India and Mexico.[28] Hsieh & Klenow (2014) concluded that endowments of factors of production and productivity increase with age. However, in high-income countries, the life cycle tends to be higher as those countries may benefit to a larger extent from a process in which firms grow at an accelerated pace. The main finding of Hsieh & Klenow (2014) is that older plants in Mexico and India are less productive and smaller than their counterparts in the U.S.. Hsieh & Klenow (2014) indicated that greater taxation on the most productive manufacturing

[27] On the one hand, the concept learning-by-doing refers to increasing workforce productivity through practice (Arrow 1962, Lucas 1988, Young 1991). On the other hand, human capital refers to workers' education as essential in adopting and adapting techniques and technologies that improve productivity. Mankiw et al. (1992) extended the neoclassical Solow's growth model and incorporated the human capital as a factor in the production function that explains the differential of production across countries.

[28] Hsieh & Klenow (2014) referred to the establishments' life cycle as the accumulation of the factors of production and TFP in relation to firms' age.

establishments inhibits their potential to grow and increase their productivity over their life cycle.

Learning-by-exporting: export capacity and trade liberalisation

Another TFP determinant related to external knowledge is exporting, which is associated with gains in productivity due to the learning-by-exporting effect post-entry (Greenaway & Kneller 2007). The expected effect of export on firms' TFP is that firms with export activity have higher TFP due to access to knowledge and resources from foreign activities, partnerships or subsidiaries. Empirical studies such as Bernard & Jensen (1999) found limited evidence that export activity induces faster productivity growth in the American manufacturing sector at the firm level. Bernard & Jensen (1999) argue that this finding can be explained by the fact that highly productive firms enter into exporting in foreign markets, and the causality comes from productivity to export capacity. However, Bernard & Jensen (1999) also found that within industries, exporters have a high reallocation of resources because these firms have higher employment and output growth rates in comparison to non-exporters firms. The productivity growth disaggregation shows that the reallocation of resources significantly contributes to productivity increase. As a result, Bernard & Jensen (1999) conclude that exporters firms contribute indirectly to productivity growth by reallocating resources.

De Loecker (2013) provides a framework in which learning by exporting is a mechanism that affects/improves a firm's future productivity. The framework for estimating the learning by exporting is applied to manufacturing microdata in Slovenia. De Loecker (2013) found that there are productivity gains that come from export entry, and exporting has a heterogeneous effect on productivity across firms. Empirical research has also shown a positive correlation between R&D and export activities. Aw et al. (2011) developed a framework in which the firm decides to have R&D activities and then enter the global market. This relationship affects the firm's productivity and reinforces the self-selection in favour of highly productive firms in the market. Aw et al. (2011) provide a model that relates R&D and export, such as the effect of learning by exporting.

De Loecker (2013) argues that there is not much evidence in the empirical literature of learning by exporting due to misspecification in measuring the effect of export on productivity. De Loecker (2013, p. 7) argues that firms decide to export, and in the next period, their productivity increase. As a result, productivity follows a dynamic process in which future productivity depends on current export activity levels. This expression specifies that future productivity is a CFA determined by export (Olley & Pakes 1996, Levinsohn & Petrin 2003). De Loecker (2013) defines this estimation as a non-parametric approach. Alternatively, De Loecker (2013) detected the effect of learning by exporting using an approach of difference in difference. This approach measures the difference between the productivity growth (difference) of exporters versus non-exporters. De Loecker (2013) concluded that with his productivity two measurement methods, there are findings of learning by exporting on productivity.

Ding et al. (2016) found limited evidence to support the hypothesis that exporter Chinese firms have higher TFP. Dai et al. (2016) argue that for the analysis of exporters, it is necessary to distinguish between processing/assembly exporters and non-processing/trade exporters because processing exporters are less productive in comparison to non-processing exporters and non-exporters. Then, countries with large processing exporters, such as China, Mexico and Taiwan, are focused on the assembly production process with a low value-added. Thus, the processing exporters in these countries may have lower productivity.

The literature accounts that apart from learning by exporting, open trade can benefit/affect productivity through two other channels: quality of inputs and self-selection. The first channel explains that importing high-quality inputs can improve efficiency by promoting technology transfer and enabling firms to specialise in their core competencies. The second channel explains that self-selection consists of the entry and exit of firms in export activity to generate an aggregated positive effect on productivity. Some papers on open trade, like Amiti & Konings (2007) and Yu (2015) analysed the effect of quality inputs on productivity, while Melitz (2003) analysed the effect of self-selection on productivity.

Amiti & Konings (2007) measured productivity gains by estimating production functions at three digits of SIC and using the parametrical method of Olley & Pakes (1996). The microdata analysed covers the manufacturing census in Indonesia for 1991 and 2011. Amiti & Konings (2007, p. 28) concluded that the decrease of inputs tariffs increases productivity, and this effect is higher than reducing output tariffs. Yu (2015) has a similar conclusion explaining that reducing tariffs on output and inputs leads to productivity gains in China. Melitz (2003) developed an equilibrium model of heterogeneous firms to investigate the effects of trade on self-selection within industries and the resulting impact on aggregate productivity. Melitz (2003, p. 1714) describes that exposure to trade generates a type of Darwinian evolution of self-selection in which firms enter, survive and exit the market. The findings of Melitz (2003) account that (i) firms with high productivity tend to export and survive in the market, (ii) firms with lower productivity produce in the domestic market, (iii) and this effect generates that the least productive firms exit the market. Melitz (2003) adopts the Hopenhayn (1992) model in an open market in which there is a stationary equilibrium between the average profits and productivity in a distribution of heterogeneous firms. The entry of firms to export comes after the productivity level is known, and the entry process is a shock to the equilibrium that generates productivity gains in the aggregated industry, which describes the welfare-enhancing properties of trade.

In particular, Melitz (2003, p. 1707-1718) argues that the positive correlation between productivity and export can suggest the inverse causality in which productivity leads to export activity. This argument in the model of Melitz (2003) assumes that firms know their productivity levels (to reduce their uncertainty), and after they decide to enter the export market. Therefore, productivity levels for incumbents are the condition for successful entry. Subsequently, a firm that exports increase its share of industry revenue in the internal market and its profits. As a result, high productivity levels incentivise the entry decision to export markets and a dynamic process in which exposure to the open trade market leads to a larger size (e.g. larger industry share) and higher profits.

In the Mexican case, the literature points out that trade liberalisation and export capacity are positive and significant variables that explain TFP heterogeneity across producers in the manufacturing sector. López-Noria (2021) made a productivity analysis of the effect of trade liberalisation on TFP in the automobile industry from 1994 to 2014.[29] The results indicate a positive association between trade liberalisation and TFP in medium-size establishments but not for small and large establishments. Therefore, trade liberalisation benefits some firms but not all of them. Puggioni (2019) analysed the export capacity in the Mexican manufacturing sector using microdata for the period 1984-1990. The results indicate that intensive exporters (i.e., a high percentage of output exported) have a mark-up premium even after netting the productivity effect. Therefore, international exposure induces firm selection to modify the intra-industry composition. Puggioni (2019) argues that productivity is a channel for survival, as more productive firms are also more profitable.[30]

Iacovone (2012) and Blyde & Fentanes (2019) analysed the competition effect on Mexican manufacturing establishments with trade liberalisation. On the one hand, Iacovone (2012) developed a Schumpeterian model to study the impact of the NAFTA liberalisation on Mexican manufacturing establishments. Iacovone (2012) concludes that trade liberalisation spurred productivity growth among manufacturing plants, but NAFTA has a heterogeneous productivity effect. The reason is that firms with advanced technology benefited to a large extent from trade openness because these firms promote an innovative production process and managerial efforts. On the other hand, Blyde & Fentanes (2019) estimated TFP at the establishment level using the Levinsohn & Petrin (2003) model to study the competition shock that Mexican manufacturing plants had from the Chinese exporter competitors. The findings are that there is an overall negative productivity shock to the Mexican manufacturing establishments from Chinese competition but with a heterogeneous effect. The trade liberalisation generated the productivity gap between large and small Mexican establishments over time because the reallocation of resources is productivity-enhancing.

Global Value Chains (GVC) is the division of labour (activities and tasks) across countries to share the production process in particular industries. Iacovone et al. (2022, p. 73-87) argue that

[29] López-Noria (2021) used data at establishment level and the methodology consisted in two stages. The first stage consisted of estimating a Cobb-Douglas function to measure TFP with the Levinsohn & Petrin (2003) model. The second stage consisted in the analysis of the effect of trade liberalisation on TFP using the SYS-GMM model. In an alternative exercise, it was used the methodology of Ackerberg et al. (2015).

[30] Puggioni (2019) measured TFP by estimating a Cobb-Douglas function with the Olley & Pakes (1996) model using the investment as the proxy variable with the GMM framework (Mollisi & Rovigatti 2017). Finally, Puggioni (2019) measured the mark-up at industry and plant-level.

there is a link between GVC and productivity in Mexico. GVC provides benefits of productivity to enter the global market. The mechanism of transmission to increase productivity by GVC includes the adoption of technology and knowledge transfer. Iacovone et al. (2022) noted that GVC has increased in Mexico, but the process still needs to generate less asymmetrical effects across regions and sectors. GVC in Mexico has been characterised as having backward participation, which consists of a large contribution of foreign firms to the added-value of the product. This result infers that Mexico has incorporated mainly tasks of assembly in the GVC. Iacovone et al. (2022) provided evidence that GVC in Mexico has focused primarily on manufacturing industries (e.g. automotive, electronics) and GVC has been spatially concentrated in states with proximity to the U.S. Particularly, states with proximity to the U.S have higher productivity, and GVC can be an explanatory variable. In terms of public policy, Iacovone et al. (2022) recommended that it is necessary the integration of more firms, sectors and regions into the GVC. The recent trade agreement with the U.S. provides Mexico with opportunities to incorporate disconnected regions into the GVC and to upgrade the workers' skills to generate a more balanced process in which GVC increase productivity in more sectors and regions in Mexico.

Previous studies to Iacovone et al. (2022) support the argument that manufacturing productivity in northern Mexico has experienced improvements as a result of its proximity to the U.S. and policies promoting open trade. In particular, the manufacturing sector in the North of Mexico has experienced larger productivity gains due to the GVC. For instance, Fuentes & Fuentes (2002) concluded that productivity gains in the northern region could be attributed to implementing outward-oriented policies, such as establishing a free-trade zone along the US-Mexico border and developing the assembly exporting industry. In addition, Díaz Bautista (2017) argued that trade liberalisation has led to a reallocation of economic activity, favouring the northern states. In summary, GVC is crucial for enhancing TFP through various channels, which include specialisation, access to inputs, promoting knowledge, technology transfer, market expansion, and export diversification. The improvement of GVC leads to higher levels of productivity.

Non-Competitive markets

A market is non-competitive when there is imperfect competition. In this situation, there are producers with the capacity to influence the market price of equilibrium directly as price-makers. As a result, price-makers can follow their strategies independently from the other producers.[31] The economic theory usually refers to non-competitive markets as monopolistic and oligopoly structures. Economic factors of non-competitive markets are reflected in producers' asymmetries in market conditions. This research analyses three mechanisms of transmission related to the theory of Non-

[31] Georgantzís & Attanasi (2016) survey non-competitive markets, focusing on results of labouratory experiments. Their results show that limited agents with no experience, limited cognitive ability and insufficient information on the market conditions can reach a price equilibrium by using a strategy of learning by trial and error.

Competitive markets that determine TFP. The first transmission mechanism is market concentration, commonly measured with the Herfindahl-Hirschman Index (HHI). The second transmission mechanism is the managaerial capabilities and one variable to measure successful capabilities considers the organisation's capacity to reduce costs. The third transmission mechanism is the firms' funding that represents the non-neutrality of money to increase TFP in the short-term.

Market concentration

The HHI is a well-known proxy of market power or market concentration that accounts for competition effects. One argument favouring a positive effect of competition on TFP is that higher competition pushes firms to adopt new technologies and operate more efficiently; thus, aggregated TFP grows (Nickell 1996). On the contrary, another view based on Schumpeterian theory accounts for a negative relation between the level of competition and TFP. The reason is that the grant of innovators' monopoly rights incentivises investment in R&D and innovation through a patent system, which increases productivity (Aghion et al. 2001, Aghion & Howitt 1990, Grossman & Helpman 1991). For that reason, high levels of competition do not necessarily reflect high levels of productivity. In addition, under some conditions, high competition can lower the expected income of managers, and their effort can lead to reductions in productivity levels (Hermalin 1992). In empirical studies, Ding et al. (2016) found that in most industries, higher competition leads to lower TFP in Chinese firms. Harris & Moffat (2015*a*) found that British plants operating in more concentrated industries have significantly higher TFP, reflecting that monopoly rents encourage innovation.[32] Either the theoretical or the empirical literature describes the mixed effects of competition on TFP.

Aghion et al. (2015) argue that the prediction in Schumepterian models is that there is an inverted-U relationship between the level of competition and productivity growth. Aghion et al. (2015) relate productivity growth with innovation. Therefore, the main argument is that there are two extremes in the inverted U-shape between competition and innovation. On one extreme, the competition and innovation are low. This extreme point incentives competition and innovation to increase to a maximum level. On the other extreme, high competition disincentives laggard firms to innovate. For that reason, in Schumpeterian models, higher competition does not necessarily reflect higher productivity levels.

Rodríguez-Castelán et al. (2020) analysed the effect of market concentration and trade exposure on firms' TFP in the Mexican manufacturing sector. Market concentration was calculated with the HHI at the 3-digits level of NAICS. The productivity analysis of Rodríguez-Castelán et al. (2020) is in two stages. The first stage estimates a Cobb-Douglas production function at 3-digits of

[32] However, Harris & Moffat (2015*a*) do not reject the argument that the HHI may reflect problems as a measure of competition.

NAICS in the manufacturing sector for the period 1993-2013 to obtain TFP at the establishment level.[33] The sample of Rodríguez-Castelán et al. (2020) consisted of 884,823 observations. TFP at the establishment level is estimated by comparing three models: a pooled model, a pooled model with fixed effects for years and sectors and the Olley & Pakes (1996) model.[34] Overall, Rodríguez-Castelán et al. (2020) reported that the elasticities in the factors of production are similar across models. In the second stage of the analysis, TFP is regressed with the variables of market concentration and trade exposure using an approach of instrumental variables following the procedure of Bartik (2002). The results indicate that a decline in local industry concentration by 10 points in the HHI (on a scale of 0-100) causes TFP to increase by 1 per cent. Then, there is a negative and statistically significant impact of the HHI on TFP in 10 of 20 subsectors. On the contrary, the positive effect of international exposure on TFP in some sectors can neutralise or reverse the negative impact of market concentration on TFP. Then, there are establishments in Mexican manufacturing that do not face local but international competition.[35]

Managerial capabilities

Financial variables can account for the managers' efforts and capabilities in a non-competitive market. For instance, Ding et al. (2016) measured fixed costs as the percentage of selling and distribution expenses to sales as a proxy variable of managerial efficiency and corporate governance problems (e.g. discretionary spending, self-aggrandisement, organisational slack). Ding et al. (2016) and Harris & Li (2019) found a negative effect of the fixed costs index on TFP in China; consequently, the higher the fixed costs are, the lower TFP is in Chinese firms.

Bloom et al. (2022) made a productivity analysis using microdata in Mexico's manufacturing and services activities.[36] Bloom et al. (2022) found that manufacturing establishments with better managerial practices have larger firm sizes. However, the size-management relationship is lower in Mexico than in the U.S. Bloom et al. (2022) argue that greater misallocation results from deficient managerial practices. In addition, the relationship size-management is lower in the manufactur-

[33] The production function has a revenue orientation, and it includes three factors of production (i.e. capital, intermediate inputs and labour) as well as dummy variables for regions, sectors and years.

[34] Rodríguez-Castelán et al. (2020) are aware that the estimation of TFP can have a price bias estimation, and they produced two strategies of correction. The first strategy estimates the OP model, and the second implies a control measure of firm level mark-up defined as revenues over total costs. They argued that both approaches are robust to these checks to overcome the mark-up bias.

[35] The trade exposure is calculated as the level of external exposure of metropolitan areas to international markets using data from the Mexican Atlas of Economic Complexity. Rodríguez-Castelán et al. (2020) concluded that most of the exports in Mexico are calculated at the metropolitan level because there is no information available on international competition at a lower level of disaggregation.

[36] Bloom et al. (2022) used the National Survey on Productivity and Competitiveness microdata in Mexico (ENAPROCE 2015, 2018). A section in the ENAPROCE replicates the U.S. Census Management and Organisational Practices Survey (MOPS). The data sample in Bloom et al. (2022) did not consider micro-enterprises to have full comparability between the Mexican and American surveys. This sample included 16,100 firms. According to Bloom et al. (2022), the ENAPROCE 2015 survey takes data of 2013 collected in the Economic Census as a framework, and around 90% of the firms have only one establishment.

ing sector compared to the services sector.[37] Bloom et al. (2022) developed a theoretical model to explain their findings on the relation size-management. This theoretical model includes heterogeneous firms, imperfect product market competition, and regulatory/institutional distortions to formalise the proposition that a firm's size increases with management quality. However, the size-management relationship is attenuated when distortions are higher and competition is weaker. The key idea of this model is that as frictions increase, the impact of better management on a firm's size will decline.[38]

Bloom et al. (2022) empirically tested the relationship size-management by separating the data into three samples: (i) U.S. manufacturing, (ii) Mexican manufacturing, and (iii) Mexican services. Their findings are that the slope of the relationship size-management is 3.4 for U.S. Manufacturing, 2.7 for Mexican Manufacturing, and 1.6 for Mexican services. Bloom et al. (2022) used those results to conclude that there is a lower reallocation of resources in Mexican manufacturing and services if compared with the relationship size-management of U.S. manufacturing as a benchmark. Bloom et al. (2022) documented that management scores are associated with greater labour productivity, profitability, exporting, R&D expenditure per worker, patenting, and size. Furthermore, Bloom et al. (2022) estimated a TFP as a Törnqvist index, and TFP index was regressed with the management score. The results indicate that management quality has a positive and statistically significant effect on TFP.

Firms' funding

As the New Keynesian macroeconomic theory suggests, variation in the money supply can generate a positive effect on both production growth and aggregated demand due to the non-neutrality of money in the short term (Akerlof & Yellen 1985).[39] In addition, macroeconomic theory accounts that the credit channel influences economic activity. According to the New Keynesian perspective, banking credit is a monetary channel of transmission that influences variations in the money supply, causing an effect on the real interest rate, inflation, and production level in the short-term (Howells 2009).[40] Microeconomic studies have focused on the impact of credit and funding on firms' pro-

[37]Bloom et al. (2022) pointed out that there are higher regulations barriers to entry in the services sector than in manufacturing for international competition in the Mexican institutions. This factor can partly explain why the relationship size-management is larger in Mexican manufacturing than in services.

[38]Bloom et al. (2022) modelled the distortions as an implicit revenue tax and the level of employment measures the establishments' size.

[39]New Classics and New Keynesians have opposite views about the variations of money supply in the short term. New Classics purpose that there is the neutrality of money in the short-term and then variations in money supply go to the increase of prices while the New Keynesians argue that there are positive effects on production due to the presence of sticky prices (Akerlof & Yellen 1985). However, New Classics and New Keynesians coincide that in the long-term, the money supply is neutral, and then the economy is totally determined by productivity and sterile to monetary imbalances Blanchard (2006, p. 543).

[40]Howells (2009) develop an equilibrium model that includes the commercial banking sector to the macroeconomic New Keynesian model of Carlin & Soskice (2005). Then, this model has a graphical exposition of a banking circuit with an effect on the real economy.

ductivity. These studies argue that the financial sector plays a crucial role in funding the upgrade of technological infrastructure that contributes to higher productivity (Levine 1997). A virtuous circle between bankers and entrepreneurs is when the credit funds innovative projects to encourage the Schumpeterian process of creative destruction of products (Festré & Nasica 2009).

Capital structure theories explain the firms' leverage decisions on profitability (e.g. firm's value). The reason for the relevance of capital structure theories is that empirical research has evaluated the relationship between variables of leverage and TFP (e.g., debt). Frank & Goyal (2009) reviewed the capital structure theories in three branches: trade-off theory, pecking order theory and market timing theory. The trade-off theory explains that firms balance the benefits and costs of debt to reach an optimal debt level. The advantages of acquiring debt include tax benefits, while the disadvantages include bankruptcy costs. Firms increase their debt until reaching an optimum leverage level; beyond that level, costs overweight benefits. The pecking order theory explains that firms have a choice preference according to funding sources available. The pecking order indicates that firms prefer funding from profits. If profits are unavailable, firms choose debt as a leverage source and equity as a last resort. The market timing theory explains that managers evaluate the market conditions and decide whether to fund from equity (i.e. stocks) or debt. If market conditions are unusually favourable, firms will raise funding even though the financial resources are not needed currently.

Blažková & Dvouletỳ (2018) evaluated the effect of debt-to-equity and labour productivity on firms' profitability in the Czech food processing industry from 2003 to 2014. The results of Blažková & Dvouletỳ (2018) indicated that labour productivity positively impacted Czech firms' profitability in the food industry, while debt-to-equity has a negative effect. Blažková & Dvouletỳ (2018) explained that the more productive a firm is, the more profitable the firm becomes. Therefore, labour productivity indicates firms' financial success. In addition, higher debt reflects financial distress and lowers firm profitability. Dvouletỳ & Blažková (2021) extended the analysis and found a negative effect from the debt ratio to TFP in Czech firms. Dvouletỳ & Blažková (2021, p. 1536) explained that "high debt ratios lead to financial distress and high proportion of debt may lead to financial distress due to the paying of high interests, and subsequently to managerial decisions restricting new investment and technological development as risky activities, usually increasing the need for external sources of financing".[41] Those results are consistent with the empirical work of Coricelli et al. (2012), which evaluated the effect of debt on TFP growth using firm-level data for a group of Central and Eastern European countries from 1998 to 2008. Coricelli et al. (2012) estimated a threshold regression model and evaluated different funding indicators sectioned by levels as an explanatory variable of TFP growth. The results of Coricelli et al. (2012) indicated that the increase in debt had a positive effect on TFP growth until a critical level; beyond that

[41] A critique of the methodological approach of Blažková & Dvouletỳ (2018) and Dvouletỳ & Blažková (2021) is that both papers used OLS, and there can be the presence of endogeneity. Even though these works included fixed effects for sectors and geographical locations, the fixed effects are not present at the firm level. Thus, endogeneity can still be present at the firm level.

level, debt negatively impacted TFP growth.

Misallocation of resources is a hypothesis that has taken relevance in emerging economies because this hypothesis explains that low-income countries have a large proportion of firms with low productivity while there is a small proportion of firms with high levels of productivity that remain small in size. Then, unproductive firms have a large proportion of resources; if those resources were used to enlarge productive firms (i.e. economies of scale), they would generate larger productivity benefits for the aggregated economy (Midrigan & Xu 2014). A branch in the literature has investigated financial frictions (i.e. obstacles or constraints) as a transmission channel that generates distortions at the firm level, misallocations and TFP losses in the economy.[42] Financial frictions include limited access to credit, high borrowing costs, asymmetric information between lenders and borrowers, transaction costs, or regulatory barriers. Although the literature points out that increasing access to credit in developing countries will increase aggregated productivity, Midrigan & Xu (2014) found that even in the case of large financial frictions, there are modest aggregated TFP losses (4-5%) from misallocations. Frictions are obstacles that affect aggregated productivity, and ongoing theoretical and empirical research identifies those frictions and measures the magnitude of which they affect aggregated productivity.

Other studies evaluated the effect of liquidity on TFP. Chen & Guariglia (2013) focused on cash flows as a variable that reflects firms' funding and its importance in determining Chinese firms' productivity growth. Therefore, Chen & Guariglia (2013) derived a TFP measure at the firm level and regressed TFP with a liquidity index and control variables.[43] Chen & Guariglia (2013) concluded that the role of liquidity is fundamental for financing and funding projects and activities that determine a shift in the efficiency frontier; as a result, firms' funding impacts TFP positively, but the effect of liquidity on TFP is higher on private and foreign firms.[44] Ding et al. (2016), Harris & Li (2019) estimated a production function by industry using firm-level data from China. Their results indicate that the liquidity index positively impacts the TFP of Chinese firms.

Hanson (2010, p. 5) argued that Mexico failed to provide credit, which restricted the opportunities for productive investments, ultimately affecting productivity growth. The problem with the misallocation of credit is that the financial market is operating with inefficiencies that impede the credit provision to increase the infrastructure and the innovation of production processes. López (2017) built a theoretical model with heterogenous firms' productivities that face credit-constraint. The model was calibrated using data at the establishment level in Mexico. The results indicate a

[42] Asker et al. (2014) argue that high variations (volatility) in the marginal productivity of capital within an industry (economy) suggest the existence of frictions. Asker et al. (2014) found that the high volatility in the marginal productivity of capital is associated with a high dispersion of productivity. Asker et al. (2014) suggest that firms in an environment of high volatility make different decisions than firms in a more stable environment. Those decisions lead to different levels of output, inputs and productivity

[43] According to Levine (1997, p. 692), "Liquidity is the ease and speed with which agents can convert assets into purchasing power".

[44] Chen & Guariglia (2013) measured the liquidity index as the difference between current assets and current liabilities and then normalized by total assets.

10% loss of TFP in Mexico from misallocations due to financial frictions. Lopez-Martin (2017) is another theoretical paper that developed an equilibrium model with firms' entry and exit dynamics. The findings of Lopez-Martin (2017) were that the improvement in access to credit induces investment in 'knowledge-capital' that increases TFP in Mexico.

Iacovone et al. (2022) explained that access to credit improves efficiency in the production process so that firms can access new technology, knowledge or R&D activities. As a result, financial access improve productivity at the firm level. In addition, Iacovone et al. (2022) argue that, according to the literature, financial frictions can generate misallocations and reductions in aggregated productivity. Iacovone et al. (2022) explored the link between financial access and productivity in Mexico. There are three main sources of finance in Mexico: banks, suppliers and informal institutions (i.e. family and friends). Banks are the most important source of finance, while family and friends are an important source of finance for SMEs when neither the banks nor the suppliers satisfy their demand for funding.

Iacovone et al. (2022) found that five factors influence access to credit in Mexico: profitability, tangibility, export, age and size. There is a positive association between profitability and access to finance. In addition, firms with export activities are less financially constrained due to access to foreign credit markets. However, firms with R&D activities are financially constrained in Mexico. Iacovone et al. (2022) argue that firms that promote innovations usually have less tangible assets (measured by the ratio of assets and sales). In addition, small and young firms have constrained access to credit in formal institutions due to the lack of collateral. Then, small and young firms, as well as some firms with R&D activities, have collateral constraints caused by the need for tangible assets (i.e. real estate, machinery and equipment). Iacovone et al. (2022) recommend developing financial products and funding options to overcome the collateral constraint (e.g. improving local development funding, guarantee funds for young and innovative firms, and implementing more innovative types of collateral).

Institutional economics

There is a category of macroeconomic studies that analyse the role of institutions on economic growth and productivity. For instance, Barro (1996) concluded that in a cross-section of 98 countries, GDP growth rates are positively correlated to proxies of political stability and positively related to the share of public investment. North (1991) notes that the achievement of economic development accounts for political and economic institutions that incentive the increase of productivity. Acemoglu et al. (2005) define that institutions matter for economic growth as they induce the incentives of economic actors, economic performance, and the distribution of resources. Economic institutions are also endogenous as they are determined by a social choice or at least part of it. Then, political power shapes economic institutions, structure, and efficiency.

This research accounts that informality is a transmission mechanism that impacts TFP at the establishment level. Informality is classified in Institutional Economics because there is a branch in the literature explaining that informality is caused by institutional rigidities or institutional weakness (Alvarez & Ruane 2019). There is another branch in the literature of Development Economics which explains that informality results from the lack of capital per capita. Ultimately, emergent economies like Mexico are characterised by a large informal sector which is intensive in labour, and most of the informal sector producers have low productivity levels. Overall, the literature points out that informality affects productivity. Informality can be examined in the literature from two perspectives: Development Economics and Institutional Economics.

Informality

The informal sector is usually considered a sector for subsistence. From the view of the classical theories of Development Economics, Lewis (1954) developed a model with a dual economy structure: the capitalist sector and the subsistence sector. The capitalist sector pays higher wages than the subsistence wage. The subsistence sector does not use reproducible capital, and this sector is labour-intensive but with low labour productivity. One of the main arguments in the model of Lewis (1954, p. 419) is that the economic problem of low savings rates in backward economies is not simply explained because those economies are poor; the truthful explanation is that the capitalist nucleus is small. As a result, Lewis (1954) considers the expansion of the capitalist nucleus necessary, which consists of financing the capital stock through different channels such as profits, credit, money supply, and public spending. This perspective considers that the large informal sector in emergent economies is a problem for economic development due to low endowments of capital per worker and insufficient capacity to fund the increase of capital stock.

From an Institutional Economics perspective, the large informal sector results from institutional rigidities or institutional weakness that allows establishments to avoid the law and promotes tax evasion. Alvarez & Ruane (2019) distinguish three categories of informal firms according to their fulfilment of law. The first category consists of productive firms, but they cannot operate in the formal sector due to the high formalisation barriers. The second category considers that there are parasitic informal entrepreneurs that are productive to operate in the formal sector, but they remain in the informal sector to avoid taxes and regulations. The third category includes low-productivity firms that would disappear if the informal sector were eradicated. Then, each type of informal firm reacts differently to policies implemented.

Alvarez & Ruane (2019) reviewed the informality effect on establishments' productivity in Mexico. Alvarez & Ruane (2019) built a structural equilibrium model of heterogenous firms that choose to be formal. Firms face two types of distortions for their incentives of formality: regulatory and idiosyncratic barriers of entry. The distortions to formality incentives lead to the misallocation of resources, higher dispersion of idiosyncratic marginal productivity and lower aggregated productivity.[45] Alvarez & Ruane (2019) found that removing labour costs of employment (e.g. payroll taxes, contribution to social security) reduces the distortions and the margin of informality because formal employees are cheaper to hire, the formal sector grows and the aggregated productivity increases.

Levy-Algazi (2018) argues that productive establishments have exited the Mexican market, and unproductive firms have replaced them. Overall, the problem is that the informal sector in Mexico allows unproductive and small establishments to survive, creating a dysfunctional firm dynamic that contributes negatively to the aggregated TFP.[46] Therefore, Mexico is not having a Schumpeterian process of 'creative destruction' in which the market induces unproductive firms to exit the market and replace unproductive firms with the entrance of productive firms. The failure of public policy in Mexico has influenced inefficient firm selection through disparities in social insurance mechanisms, asymmetries of tax policies and poor contract enforcement. These failures have created an environment where large and formal firms subsidize informal firms and negatively impacted Mexico's aggregated TFP.[47]

2.4.2 Spatial TFP determinants

Spatial Economics

In recent years, Spatial Economics has arisen as a field that comprises all the branches of Economics to provide analysis and explanations of the differentials of regional economic development in the geographic space. Fujita (2010) argues that Spatial Economics seeks to provide a general location theory of the economic activities and the spatial inequalities that comprised from the contributions of Thunen in 1826, which gave foundations to the location theory, to the New Economic Geography initiated by Krugman (1991). According to Fujita (2010), Spatial Economics gathers economic theories that explain the differences in economic activity concentration in space and how this concentration influences regional development and productivity disparity. This research accounts that there are two mechanisms of transmission in Spatial Economics that determine TFP. The first

[45] For simplicity, Alvarez & Ruane (2019, p. 25) assume that aggregated TFP is equivalent to aggregated labour productivity.

[46] Levy-Algazi (2018, p. 95) calculated there were 4.1 million establishments in Mexico in 2013, and 90% were informal, representing around 3.7 million informal establishments. The informal establishments in Mexico have a low size. In fact, 91.58% of the informal establishments in 2013 had between 1 and 5 workers. The informal sector has a significant allocation of resources; 55.67% of the employees in Mexico (9.7 million) work in the informal sector. In addition, informal establishments concentrate 42.69% of the capital (2,560 million of Mexican Pesos in 2013).

[47] In a complementary analysis, Levy-Algazi (2018) examined different characteristics of the TFP distributions at the establishment level. The comparison of the TFP distributions between 1998 and 2013 shows an increase in the top and the bottom tails, but the increase in the bottom tail was more than proportional to the increase in the top tail. As a result, TFP decreased between 1993 and 2018. In addition, Levy-Algazi (2018, p. 121) displays a higher dispersion in the TFP distribution at the establishments-level of the Mexican manufacturing sector compared to the manufacturing of the U.S. which suggests that there are more distortions, more misallocation and lower TFP in Mexico compared to the U.S.

transmission mechanism is externalities which can be divided into three types: MAR, Jacobian and Porter's externalities. The second transmission mechanism is the effects of the place, which accounts for heterogenous spatial characteristics. The literature accounts that spatial characteristics determining TFP are usually associated with demographic characteristics (Tsvetkova et al. 2020).

Externalities

Space influences how the economy works through the allocation of factors of production. The New Economic Geography explains the allocation of economic activity in space through two opposite forces: centripetal and centrifugal forces, the former leads to spatial concentration, and the latter promotes the dispersion of economic activity.[48] Then, TFP has a spatial component through agglomeration economies. Lucas (1988) noted the importance of a city as a collection of factors of production, and he suggested the relevance of examining cities to provide a better understanding of the accumulation of factors of production in urban areas. In particular, the accumulation of human capital in large cities is a crucial factor which leads to technological innovations as an engine of endogenous growth.[49]

Rigg et al. (2009) differentiate localisation and urbanisation externalities. Localisation economies derive from the benefits of the proximity to competitors that allow sharing of market information to negotiate with customers and suppliers. Urbanisation economies arise from locating near facilities provided by diverse economic activities. In summary, there is a difference in externalities that impact productivity. On the one hand, Agglomeration/localisation/MAR externalities are based on specialisation. Diversity/urbanisation/Jacobian are externalities of diversification.

Glaeser et al. (1992) formalised with micro foundations the MAR externalities. However, Glaeser et al. (1992) argued that in large urban areas, diversity helps while competition hurts. According to Glaeser et al. (1992), Jacobian externalities are more important. In addition, Glaeser et al. (1992) recovered the idea of Porter (1990) to propose the concept of Porter's externalities. Similar to MAR externalities, Porter's externalities promote intra-industry specialisation. However, Porter's externalities account for local industry diversity rather than local specialisation. Then Porter's externalities emphasise local competition to increase firms' efficiency.

Diversity, specialisation and local competition are externalities that coexist and interact in a location to determine the efficiency of the geographical context. The empirical research indicates

[48] Agglomeration economies are examples of centripetal forces that promotes concentration of economic activity, such as industrial clusters (Glaeser et al. 1992), while congestions costs are centrifugal forces that leads to population dispersion such as housing and commuting costs, crime, pollution and exposure to disease are dispersion forces (Kim 2008). Duranton & Puga (2004, p. 9) states that "The efficient size of a city is the result of a trade-off between urban agglomeration economies and urban crowding".

[49] For instance, Harris & Moffat (2015*a*) found that spatial externalities associated with city location are not as important as the benefits of being situated in the Southeast region in Great Britain.

different results about the effect of externalities on firms' productivity. Then, the following two parts of this section provide a literature review of the impact of externalities on productivity. The first part reviews the MAR and Jacobian externalities. The second covers Porter's externalities.

MAR and Jacobian externalities

The literature accounts that externalities from the spatial context determine firms' productivity. Harris & Moffat (2015*a*, p. 5) state that "Spatial spillovers or agglomeration externalities are benefits that accrue to plants from being located in the vicinity of large concentrations of other plants". Duranton & Puga (2004) described three mechanisms by which externalities perform: sharing, matching and learning. The first mechanism considers that firms concentrate in cities because they facilitate sharing indivisible public goods, production facilities, and marketplaces; these factors comprise differentiated intermediate inputs, urban infrastructure, urban specialisation and declining transport costs. The matching mechanism refers to the correct match of skill requirements in the labour market; this is related to Alfred Marshall's idea that "a localised industry gains a great advantage from the fact that it offers a constant market for skill" Marshall (1890, p. 271). Learning is the last mechanism of agglomeration externalities. This mechanism considers the acquisition of skills through firms' generation, diffusion, and accumulation of knowledge.

Harris & Moffat (2015*a*) pointed out that externalities result from intra and inter-industry externalities. On the one hand, intra-industry externalities define that the concentration of one industry in a location promotes specialisation, innovation and knowledge spillovers between firms of the same industry that generate a positive impact on TFP. Intra-industry externalities are known as localisation externalities and labelled MAR externalities (Marshall 1890, Arrow 1962, Romer 1986). On the other hand, inter-industry externalities refer to the concept in which a firm learns from firms in different industries. Some studies account that the diversity of economic activities increases TFP. Inter-industry externalities are catalogued as urbanisation externalities or Jacobian externalities (Jacobs 1970, 1986).

In the U.S, Henderson et al. (1995) analysed the effect of externalities on the manufacturing industries in 1970 and 1987. Their findings indicate that capital and goods industries have MAR externalities but not Jacobian externalities. However, high-tech industries have MAR and Jacobian externalities.[50] On the contrary, the service sector is subject to urbanisation externalities in large cities. Henderson (1991) argued that localisation externalities could benefit the manufacturing industries in the U.S. to a larger extent.

In the Japanese manufacturing sector, Nakamura (1985) concluded that light industries receive

[50] A simple way to quantify the degree of geographic specialisation is to measure the percentage composition of employment by regions. Henderson (1991) argue that large cities are more specialised in services (e.g. finance insurance and real estate) and less specialised in manufacturing than medium-sized cities.

more advantages from urbanisation externalities and heavy industries have more benefits of localisation, and there is no empirical evidence that industrial variety -Jacobian externalities- positively impacts heavy industries. Cainelli et al. (2007) investigated the impact of technological spillovers on labour productivity growth at local, national and international levels in nine manufacturing industries located in 89 European regions between 1980 and 1992. Cainelli et al. (2007) concluded that the more specialised the industry is, the higher its labour productivity growth.[51]

Combes (2000) analysed not only the manufacturing sector but also the service sectors in France between 1984 and 1993. Combes (2000) concluded that the effects of local economic structure on local employment differ according to the manufacturing or service sector. On the one hand, urbanisation positively impacted the French service sector but affected the services sector. Presumably, urbanisation externalities increase the cost of local inputs and transportation (i.e., congestion costs). In addition, few localisation economies for manufacturing and services were found, which might be the result of asymmetric effects. According to Combes (2000), localisation enhances local growth in expansion periods, but localisation externalities also favour a deep decline in recession periods.

Baptista & Swann (1999) analysed the manufacturing sector in the U.K. in the period 1975-1985. They concluded that industrial clusters are more likely to innovate in locations with specialisation. However, diversification does not appear significant because congestion costs may outweigh positive economies of agglomeration. Then, manufacturing firms that promote innovation might have incentives to cluster in locations with specialised employment.

Henderson (1986, p. 65) analysed productivity in Brazil and U.S., concluding that "In general, external economies of scale are ones of localisation, not urbanisation. Manufacturing plants benefit from agglomerating but are not more productive in large cities. Localisation economies are strongest for industries in which cities tend to specialise and spread out as the city size increases". Batisse (2002) investigated the dynamic externalities associated with specialisation, competition and diversity in local industrial growth in Chinese provinces. He concludes that diversity and competition have a positive effect while specialisation has a negative impact.

MAR and Jacobian externalities are also key factors of productivity growth in large cities. The literature accounts that large cities are more productive due to the better performance of firms and workers in those locations, cities are more innovative and large urban areas are engines of economic growth in advanced economies (Melo et al. 2009, Puga 2010, Duranton & Puga 2001, Glaeser 2011). Duranton & Puga (2000) provided a stylized fact which supports the argument that larger cities have a higher degree of economic diversification. Some cities in the U.S., despite their size, are specialised. For instance, Los Angeles in entertainment and New York in business services. Then, specialisation in services increases productivity in large urban areas (Overman et al. 2010). Large

[51] Cainelli et al. (2007) argue that international knowledge spillovers have a significant role in the transference of technological knowledge. Then, the national level is intermediate between global technology -fully codified- and local technology -tacit-.

cities also have a high propensity for innovation because they are creativity hubs (Duranton & Puga 2000). According to Puga (2010), evidence supports that big cities are learning places where information flows, knowledge is created, and innovation is facilitated.[52]

Porter's externalities

Porter's externalities refer to the local competition that fosters a faster pace of creation, diffusion and assimilation of knowledge and assimilation across firms. Porter (1990) argued that countries with ruthless competition make firms adopt new technology or exit the market. Then, local competition accelerates the creation and development of innovative industries, thus improving productivity. It is generally argued that large cities are more productive due to agglomeration economies. However, another explanation is that large cities have toughened competition, allowing only productive firms to survive. For that reason, the firm selection is reinforced in large urban locations.

Melitz & Ottaviano (2008) developed a theoretical model with firms' productivity heterogeneity that incorporates endogenous mark-up across firms representing the degree of competition. The results indicate that the market size and the trade affect the toughness of competition. Then, larger and more integrated markets via trade exhibit higher productivity and lower mark-ups. This model supports the idea that competition is more challenging in large cities, and less productive firms exit the market in these urban areas.

Combes et al. (2012) indicated that firm selection could not explain productivity differences across regions of France, while the main benefit of productivity across French places is agglomeration economies. However, a region can experience an adverse selection when firms with low productivity decide to locate within an industrial cluster. Then adverse selection generates a negative effect on productivity to the competition of local firms. Harris & Li (2019) used the proportion of new firms at the sector level variable to account for the effect of firm selection on TFP. Harris & Li (2019) suggested that the proportion of net entry by geographic location can be a proxy variable to account for the impact of Porter's externalities on TFP.

Places effects

Places effects reflect exogenous factors that can provide incentives so that industries or firms locate in a particular place, and these incentives positively affect firms' productivity. Places effects can be catalogued as exogenous characteristics such as natural resources and geographic position, which

[52] Denser areas are characterised by higher wages, higher rents and higher housing prices. These factors can provide evidence of industrial concentration, particularly in services. Services are more concentrated in larger urban areas and larger markets get increasing specialisation from professionals (Puga 2010). Glaeser (1999) developed a model in which young workers migrate to big cities to acquire valuable skills and experienced workers remain in cities to get the rents of the learning process.

have a long tradition in the Ricardian comparative advantages. Furthermore, the role of the institutions and the government intervention to attract firms in a region can be catalogued as another factor of place effects. In empirical studies, Harris (2021) found that the place effects were the major TFP driver of New Zealand firms because Wellington and Auckland had locational advantages. Harris & Moffat (2015*a*) controlled place effects with dummy variables in British firms. Harris & Li (2019) also applied the same dummy treatment for places' effects to account for the impact of Chinese regions on firms' TFP.

The literature points out that the place effects generate a concentration of economic activity and factors of production. For instance, Hanson (1997) argues that if one region has water or minerals, these resources incentive firms to locate in that region. Then the availability of resources works as a place effect. Furthermore, a geographic position can provide access to foreign markets via export, which can be considered a place effect.

Iacovone (2012) argue that more productive locations have qualities that make firms more productive in these areas, reinforcing the high level of productivity in these locations compared to other places. Iacovone (2012) consider spatial advantages that trigger productivity as location premium. Then, Iacovone (2012) conducted an econometric analysis of a cross-section sample in which the dependent variable is the municipality-sector productivity —henceforth municipality productivity premium—.[53] The econometric analysis measures the impact of a set of proxy variables that account for the location effect on municipality productivity premium. However, the collapse of productivity at the municipality level to analyse productivity determinants is a drawback because there is omitted the large productivity heterogeneity across firms, which is crucial to consider in the link between the Industrial Organisation and Spatial Economics (Harris & Moffat 2015*a*, Bartelsman & Wolf 2017, De Loecker & Syverson 2021, Harris 2021).[54]

Iacovone (2012) found that connectivity impact positively municipality productivity premium in Mexico but only in the manufacturing sector located in the North-Centre and Centre, and the services sector located in the North and North-Centre. This result can infer that connectivity is an important determinant for the productivity in the internal market of Mexico. In addition, restrictions to access the international market negatively affect municipality productivity in the manufacturing and services sectors in the North and the services sector in the Central region of Mexico. This result implies that access to foreign markets, particularly the U.S., is a relevant productivity determinant that primarily benefits manufacturing and services in municipalities near the border of Mexico-U.S. Furthermore, urbanisation is a variable with a positive effect on municipality productivity premium in services and manufacturing in most regions, but this variable is

[53] In the online appendix, Iacovone (2012) defined municipality-sector productivity as a variable that is generated from the regression of the TFPR at the firm level with a set of dummy variables that capture the fixed effects of municipality-sector-year.

[54] A proposition to consider the link between the Industrial Organisation and Spatial Economics comprises estimating production functions with data at the establishment and including spatial variables as control variables, as Bartelsman & Wolf (2017) recommend. This thesis follows the previous methodological proposition.

not significant in the manufacturing sector of the South region. Clustering is a variable that positively affects municipality productivity premium in the manufacturing sector across all Mexican regions.[55] Iacovone (2012) found that the number of universities within the municipality is the only robust determinant that increases municipality productivity premium in the manufacturing and services across all Mexican regions. Then, the number of universities increases highly skilled labour and entrepreneurs, generating a productivity spillover within the municipality (i.e., human capital externalities).

Other geographic locations with amenities such as beaches, good weather, and a good location can incentivise firms to cluster in those regions. For instance, Wen (2004) found that resource-based industries are concentrated in coastal locations, while sectors that produce goods face higher costs and geographical dispersion. There can be the case that some firms decide to remain isolated despite the benefits of being located in places with comparative advantages or large urban areas that create agglomeration economies. Puga (2010) points out that a partial answer is that isolated firms do not find incentives to locate in denser urban areas due to the expensive rents and high wages. When a firm decides to locate in urban areas despite the expensive rents and high wages, the firm expects that high productivity will compensate for the expenses in urban areas (Dekle & Eaton 1999).

Tsvetkova et al. (2020) account for demographic profiles as place effects. For instance, workers' age can affect firms' productivity due to the deterioration of health and physical activity, but the accumulated knowledge can counteract this effect (Garibaldi et al. 2010). The spatial component of the demography accounts for differences in age and size composition in space. For instance, Brunow & Hirte (2009) estimated spatial cross-section regressions between average regional productivity and the age structure of human capital in Germany. The results indicate an inverted U-shape relationship between productivity and the age composition of the human capital.

Other empirical studies suggest that population density or population size is another variable of place effects that impacts firms' productivity, but with an unclear direction. For instance, Ding et al. (2016) use dummy variables that account for the top 200 cities with the highest population in China to estimate the effect of population size on the TFP of Chinese firms. The results of Ding et al. (2016) indicate that the population size has a negative spillover in Chinese cities due to congestion costs that affect Chinese firms' productivity.

[55] Connectivity is measured with two variables: the municipal road count and road efficiency. Restriction of access to international markets is measured with: distance and travel time to the U.S. border. Urbanisation is measured with municipal population and population density. Clustering is measured with the clustering index. The observations are disaggregated by municipality-sector-year, in which sector represents the 4-digit of NAICS (See the online Appendix of Iacovone (2012). The variables of clustering and urbanisation can be considered as proxy variables of externalities.

2.5 Contributions of this research to the literature

In conclusion for this Chapter, this research contributes to the literature on productivity analysis in emergent economies by providing TFP estimations at the establishment level in Mexico and examining its determinants. According to this Chapter of the literature review, the contribution of this PhD thesis to the literature can be summarised in the following four contributions:

- **A comparison of parametric methods to estimate production functions**. The literature review in subsection 2.3.2 accounts that parametric methods to estimate production functions can be classified into four categories. Those methods emphasise parametric correction due to simultaneity and selection bias (Van Beveren 2012, Del Gatto et al. 2011). In numerous empirical papers that use microdata to estimate production functions, the researcher's preference usually chooses arbitrarily the parametric method. There is also left aside whether the choice of an alternative parametric method can substantially change the parameters in the production function and the TFP estimates at the firm level. Van Beveren (2012) compares the difference in the parameters of the production function and the TFP estimates across the implementation of various econometric techniques, but this comparison did not include methodologies of S.F. (e.g. Battese & Coelli (1995); Karakaplan & Kutlu (2017)). This PhD thesis aims to update the parametric comparison with recent methodological contributions and to extend the number of econometric techniques included in the methodological comparison (e.g. Wooldridge (2009)). Therefore, this PhD thesis contributes to the literature by providing an updated and extended methodological comparison to estimate production functions. This comparison can guide researchers in choosing a particular econometric technique above the others based on the advantages each methodology delivers in estimating production functions.

- **Incorporation of imperfect competition in the TFP measurement at the establishment level**. This literature review considers the necessity to incorporate imperfect competition in the production function estimation as a relevant characteristic of Industrial Organisation and to overcome the price bias in the TFP estimation (Van Beveren 2012, De Loecker & Syverson 2021). Empirical papers have followed the approach to estimating production functions, including a mark-up correction to incorporate imperfect competition and price bias correction. The inclusion of the mark-up correction follows the approach initially proposed by Klette & Griliches (1996). Some empirical research has estimated the production function with mark-up correction that includes De Loecker (2011), Ehrl (2013) and Harris (2021). Ehrl (2013) estimated production functions with mark-up correction using the OP model while Harris (2021) used the SYS-GMM model. This thesis uses the Wooldridge (2009) model as the preferred method of estimation (particularly preferred due to the microdata structure and the use of instruments, see discussion in subsection 3.3.2). There are two theoretical advantages to using the Wooldridge (2009) model. The first advantage is that this model overcomes the simultaneity and selection bias, and compared to other CFA methods, variables are not dependent in the Wooldridge (2009) model (Ackerberg et al. 2015). As De Loecker & Syverson (2021, p.63) suggest, the second advantage is that the Wooldridge (2009) model is more flexible than SYS-GMM by dealing with the endogeneity process of inputs in the determination of TFP (which is a characteristic defined by construction in the models of CFA). This PhD contributes to the literature by extending the line of research to include mark-up correction in the production function to estimate TFP at the establishment level and estimated with Wooldridge (2009), which has theoretical and empirical advantages above the rest.

- **Evidence of TFP heterogeneity at the establishment level and its determinants across sectors in an emergent economy**. The microdata used in this research is a rich source of information, and this type of longitudinal dataset is rare across emergent economies (Busso, Levy & Torres 2019). Therefore, the availability of this microdata (Economic Census) in Mexico allows a productivity analysis and provides empirical evidence of the productivity determinants and dynamics in an emergent economy. Various empirical papers estimate TFP at the establishment level and analyse its determinants by only including the manufacturing sector and omitting the productivity analysis in the large sample of the service sector (Blyde & Fentanes 2019, Puggioni 2019, Rodríguez-Castelán et al. 2020, López-Noria 2021). Levy-Algazi (2018) used the Economic Census extensively to estimate TFP at the establishment level across sectors using the Hsieh & Klenow (2009) model. However, two limitations can be identified by using this approach. The first limitation is that the TFP measurement can have a price-pass through, and the TFP distribution and dispersion can be partly explained by prices rather than by productivity (Haltiwanger et al. 2018, De Loecker & Syverson 2021). The second limitation is that the underlying causes of TFP heterogeneity cannot be determined beyond the concept of misallocations and distortions in the Hsieh & Klenow (2009) model. The recent study of Iacovone et al. (2022) estimated TFP at the establishment level and its determinants across sectors in Mexico using parametric methods. Two gaps in Iacovone et al. (2022) research allow this PhD thesis to contribute to the literature by measuring TFP and its determinants at the establishment level in Mexico. The first gap is a lack of transparency in estimating the production functions, and there are no parametrical results of the production functions provided by the authors (See the online appendix of Iacovone et al. (2022)). The second gap is that the analysis of the TFP determinants in Iacovone et al. (2022) uses productivity metric at the municipality level, which is defined as fixed effects of productivity aggregated at the municipality-sector-year level (this variable is referred to in Iacovone et al. (2022) as municipality productivity premium). The use of a productivity metric aggregated at the municipality level to examine the TFP determinants omits a large productivity heterogeneity that arises from the Industrial Organisation and defines the structure of the economy (including regional economies).[56] This PhD thesis provides empirical

[56] Misch & Saborowski (2018) also conducted a similar analysis in which aggregated TFP by regions (calculated

evidence of TFP heterogeneity and analyses its determinants (i.e. spatial and non-spatial) at the establishment level across all sectors of the Mexican economy. Therefore, this thesis extends the empirical research of productivity analysis in emergent economies. The examination of spatial TFP determinants (to test the presence of externalities) at the establishment level follows the connection between productivity heterogeneity (present in the Industrial Organisation) and Spatial Economics (Harris & Moffat 2015*a*, Bartelsman & Wolf 2017, Harris 2021, De Loecker & Syverson 2021).

- **TFP analysis at a higher level of aggregation using regions and sectors**. The high granularity of TFP estimates allows to extend the productivity analysis in the TFP aggregation from micro to macro. In particular, the TFP aggregation measures productivity by different geographic and sectoral levels, which has not been deeply explored in the literature to illustrate the large disparities across geographical locations and sectors in emergent economies (Harris & Moffat 2022, Harris 2021, Iacovone et al. 2022). Few papers in the literature calculate TFP growth decomposition in emerging countries to identify whether these economies are affected by misallocations (Levy-Algazi 2018, Iacovone et al. 2022). This research calculated the TFP growth decomposition regarding the contribution of entering, surviving and exiting firms using two complementary approaches using the methods of Haltiwanger (1997) and Melitz & Polanec (2015) as a robustness analysis. Finally, the author is unaware of a paper on convergence analysis of productivity using TFP as the metric across states and municipalities in the Mexican economy (Cabral et al. 2020). Iacovone et al. (2022) provide some arguments about TFP convergence in Mexico, but that study does not present the parametrical results of the convergence model. Therefore, the convergence analysis of this thesis contributes to examine whether geographical locations have caught up in productivity to generate productivity growth that reduces the productivity disparities across locations.

with the Hsieh & Klenow (2009) model) and then examined TFP determinants with econometric methods.

Chapter 3

Data and methodology

3.1 Overview of Chapter 3

This research uses a methodological strategy to estimate TFP at the establishment level in Mexico, divided into two stages. The first stage compares different parametric methodologies using the specification of a log-linear Cobb-Douglas production function. The parametric methods estimated include the FE model, SF models (Battese & Coelli 1995, Karakaplan & Kutlu 2017), CFA models (Levinsohn & Petrin 2003, Wooldridge 2009) and the SYS-GMM model (Blundell & Bond 1998). The first stage has two objectives (i) to analyse whether there is a significant difference in the parametrisation of the production function that leads to different TFP estimates and (ii) to quantify the effect of a larger number of TFP determinants. The first stage includes more TFP determinants in comparison to the second stage. The first stage is useful to define the parametric method that is more appropriate and provides more plausible results in the TFP estimation at the establishment level. The second stage of the methodological strategy estimates a Cobb-Douglas function with a mark-up correction. The Wooldridge model is estimated as the preferred parametric approach above the rest in this stage. The second stage has two objectives (i) to correct the price bias in the production function by economic sector and (ii) to quantify the effect of TFP determinants in all the economic sectors of the Mexican economy.

This research uses microdata at the establishment level of the Economic Census of Mexico from 1993 to 2018 with a 5-years gap (Subsection 3.2.1). The first stage of the methodology strategy uses a subset of the microdata for the parametric comparison (Subsection 3.3.1). This subset considers medium and large establishments in the manufacturing sector. The second stage extensively uses microdata, incorporating all establishments across economic sectors to estimate TFP (Subsection 3.2.2). The microdata used in the second stage allows the parametric estimation of a production function with mark-up correction per economic sector. The outcome of the second stage is the estimation of TFP with mark-up correction at the establishment level in Mexico using parametric methods (Subsection 3.3.2). Table 3.1 displays the strategy of estimation in two stages, including the description of data and methodology for each stage.

Table 3.1: Estimation strategy to measure TFP at the establishment level in Mexico

Stage	Description
First stage	**Data:** Subset of the manufacturing sector. **Methodology:** Comparison of parametric approaches.
Second stage	**Data:** All economic sectors. **Methodology:** Production function with price bias correction

Source: Own elaboration

3.2 Data

The microdata used for this research is the Economic Census of Mexico collected by INEGI from 1993 to 2018 with 5-years intervals. The observation of the microdata is at the establishment level. The variables of production, geographical location and industrial classification have a disaggregation of 6-digit of the NAICS code (i.e. national industry). Table 3.2 displays the microdata structure of the Economic Census with 22 economic sectors at 2-digits of NAICS.[1] The microdata of the Economic Census covers 20.77 million establishments, but 1.9 million establishments do not report production information. Table 3.2 only presents the number of establishments with data on production. The reason for the loss of about 1.9 million observations is that the Economic Census of 1993 only collected production information from establishments in the agriculture, mining, manufacturing, and information sector. Therefore, the number of establishments with information available during 1993 is significantly lower than in subsequent years. For the whole period 1993-2018, the microdata of the Economic Census in Mexico has 18.83 million establishments with information on production available.[2]

[1]Classifications of INEGI usually gathers sectors 31-33 and 48-49.

[2]The microdata of the Economic Census covers 20.77 million of establishments but 1.9 million of establishments do not report production information. Table 3.2 only presents the number of establishments with data on production.

Table 3.2: Number of establishments in the Economic Census of Mexico by economic sector (2-digits of NAICS) and year, 1998-2013.[a/]

NAICS code	Economic Sector	1993	1998	2003	2008	2013	2018	Total
11	Agriculture	258	21,456	21,252	19,443	20,407	24,372	107,188
21	Mining	2,835	2,905	3,075	2,956	3,032	3,123	17,926
22	Utilities	37	2,435	2,433	2,586	2,721	2,961	13,173
23	Construction	-	14,612	13,438	18,637	17,063	19,501	83,251
31	Manufacturing (food, beverage, etc.)	133,914	172,477	170,706	235,362	274,485	342,438	1,329,382
32	Manufacturing (wood, paper, etc.)	42,898	72,423	67,654	84,663	88,360	104,933	460,931
33	Manufacturing (primary metals, machinery, etc.)	76,060	97,705	90,354	116,824	126,685	132,457	640,085
43	Wholesale	-	110,756	86,997	118,027	130,348	155,545	601,673
46	Retail trade	-	1,331,718	1,493,588	1,740,522	1,912,293	2,092,770	8,570,891
48	Transportation	29	37,044	38,048	15,261	16,488	20,489	127,359
49	Postal services and warehose	-	3,670	3,818	2,441	1,501	1,756	13,186
51	Information	11,956	7,164	7,586	11,353	9,338	8,828	56,225
52	Finance and Insurance	-	6,630	10,410	18,706	23,761	26,593	86,100
53	Real estate, rental and leasing	-	36,469	45,577	54,188	62,815	68,010	267,059
54	Professional, scientific, and technical services	-	71,200	68,587	84,695	89,254	100,098	413,834
55	Management of companies and enterprises	-	650	348	204	357	366	1,925
56	Administrative support and waste management.	-	23,558	43,151	80,921	91,611	76,059	315,300
61	Educational services	-	33,493	30,891	43,286	46,882	53,524	208,076
62	Health care and social assistance	-	106,915	102,940	146,532	170,937	196,089	723,413
71	Arts, entertainment, and recreation	-	31,194	31,790	41,821	50,392	51,352	206,549
72	Accommodation and food services	-	246,161	277,435	392,242	501,448	637,124	2,054,410
81	Other services (except public adminsitration)	-	373,993	395,013	493,337	590,567	681,769	2,534,679
	Total	**267,987**	**2,804,628**	**3,005,091**	**3,724,007**	**4,230,745**	**4,800,157**	**18,832,615**

[a/] Observations with gross output values different from zero and null values.
Source: Own elaboration using microdata of the Economic Census of Mexico.

Table 3.3 displays the main production variables in the Economic Census aggregated at the national level. These variables are necessary to estimate the production functions per economic sector. Variables in Table 3.3 include the production of the Mexican establishments (i.e., gross output) and the factors of production (i.e., intermediate inputs, fixed assets and employment). The first three variables in Table 3.3 are in nominal values and presented in Mexican Pesos (MXP) and U.S. Dollars (USD) to have an international reference.[3]

Data in Table 3.3 is consistent with information from other sources in Mexico, such as the System of National Accounts (SNA) and the Survey of Employment (ENOE, in Spanish) collected by INEGI. For instance, the nominal GDP in Mexico in 2018 was 23.52 trillion MXP, while the gross output reported in the microdata of the Economic Census was 22.20 trillion MXP in nominal value. ENOE reported 36.4 million workers in 2018, and the Economic Census reported 36.03 million workers in the same year.[4] Table 3.3 only reports workers that receive remuneration or a wage, with a total of 27.13 million workers in 2018.

[3] Variables used in the parametric estimations are calculated in MXP in real terms.

[4] The information of the Economic Census is complemented with 6.1 million workers employed in religious or public institutions, and these institutions do not have production information

Table 3.3: Main variables of the Economic Census in Mexican Pesos (MXP) and U.S. Dollars (USD) in nominal terms, 1993-2018.[a/]

Variable	**Metric**	**1993**	**1998**	**2003**	**2008**	**2013**	**2018**
Gross output	MXP (Trillion)	0.59	3.71	6.29	10.9	13.9	22.2
	USD (Trillion)	0.19	0.41	0.58	0.95	1.09	1.15
Intermediate inputs	MXP (Trillion)	0.12	2.07	3.08	5.93	7.99	12.2
	USD (Trillion)	0.04	0.23	0.29	0.52	0.63	0.63
Fixed assets	MXP (Trillion)	0.47	0.48	0.49	0.5	0.51	0.52
	USD (Trillion)	0.15	0.05	0.05	0.04	0.04	0.03
Employment	Persons (Million)	9.55	13.82	16.23	20.11	21.58	27.13

[a/] The exchange rate by years was: 3.12 MXP/USD (1993), 9.16 MXP/USD (1998), 10.80 MXP/USD (2003), 11.15 MXP/USD (2008), 12.77 MXP/USD (2013) and 19.24 MXP/USD (2018)
Source: Own elaboration using microdata of the Economic Census of Mexico

Table 3.4 presents the main variables of the Economic Census in real terms. These variables were deflated with the price indices of the KLEMS model estimated by INEGI. The advantage of using the KLEMS price indices is that the information is disaggregated by factors of production and sector at 2-digits of NAICS code.[5] The KLEMS price indices provide better accuracy of real values than the Producer Price Index (PPI), which only includes one price index for the whole economy.[6] In addition, the KLEMS price index has a more extended period of information available (1991-2020) than the PPI (2003-2022). Appendix A presents the price indices by economic sector and year used to deflate the variables of the Economic Census. Table A.1 presents the price index of gross production, Table A.2 displays the price index of intermediate inputs, and Table A.3 shows the price index of investment in fixed assets.[7] Table 3.4 presents the main variables of the Economic Census deflated with the KLEMS price indices.

Table 3.4: Main variables of the Economic Census in Mexico in real terms, 1993-2018

Variable	**Metric**	**1993**	**1998**	**2003**	**2008**	**2013**	**2018**
Gross output	MXP (Trillion)	2.52	7.13	8.55	9.89	10.57	13.71
Intermediate inputs	MXP (Trillion)	0.37	3.92	3.83	5.17	5.52	6.84
Fixed assets	MXP (Trillion)	3.20	3.51	3.46	4.57	6.63	6.90

Source: Own elaboration using microdata of the Economic Census of Mexico

The microdata of the Economic Census was recently linked longitudinally by Busso, Fentanes Téllez & Levy Algazi (2019), which makes it possible to track establishments over time.

[5] There are cases that the disaggregation can be at 4-digits NAICS. However, it is preferred to use the KLEMS price index at 2-digits to keep consistency across sectors.

[6] The variables of production were deflated and divided by 1×10^{12} to keep proportions with the variables measured as percentages.

[7] The price index of investment was used to deflate the fixed asset investment of the Economic Census.

For that reason, the structure of the Economic Census database in Table 3.2 is an unbalanced panel dataset because establishments may enter, remain or exit the economy.

The first stage of the methodology strategy has two objectives (i) to analyse whether there is a significant difference in the parametrisation of the production function that leads to different TFP estimations and (ii) to quantify the effect of a larger number of TFP determinants. The first stage of the methodology strategy selects a sample of medium and large manufacturing establishments from 2003 to 2018 because that sample has more information available. It is therefore possible to estimate the effect of more TFP determinants in the first stage sample.

Table 3.5 shows the TFP determinants available in the first and the second stage of the methodology strategy. Table 3.5 incorporates the classification of TFP determinants according to the economic theory in the literature review (Table 2.3). Columns 5 and 6 in Table 3.5 display the availability of TFP determinants in each stage of the methodology strategy. The TFP determinants that share the first and second stages are the firm's age, HHI, fixed costs index, agglomeration index, diversification index and population density. The first stage provides three additional TFP determinants: export dummies, interest expenses dummies and firms entering the market. These three additional TFP determinants quantify the effect of the transmission mechanisms, including learning by exporting, firms' funding and Porter's externalities (Table 3.5).

Table 3.5: TFP determinants available in the first and second stages of the methodology strategy

Categories of TFP determinants	**Economic theories**	**Mechanism of transmission**	**Proxy variables**	**First stage**	**Second stage**
Non-spatial	Endogenous growth theory	Learning-by-doing	Firm's age	Available	Available
		Learning-by-exporting	Export dummy	Available	-
	Non-competitive markets	Market concentration	HHI	Available	Available
		Managerial capabilities	Fixed costs index	Available	Available
	Institutional economics	Informality	Formality dummy	Available	-
Spatial	Spatial Economics	MAR externalities	Agglomeration index	Available	Available
		Jacobian externalities	Diversity index	Available	Available
		Porter's externalities	Firms entering the market	Available	-
		Demographic	Population density	Available	Available

Source: Own elaboration

The first stage of the methodological strategy uses a sample of 43,952 observations of medium and large manufacturing establishments. The second stage uses the total number of establishments in the Mexican economy, including 18,832,615 observations (Table 3.2). The primary outcome of the first stage is to define whether the selection of a particular parametrical approach leads to different TFP estimations compared to the other methodologies. Then, the first stage aims to determine the preferred parametric approach to be implemented in the second stage. The second stage estimates a production function by sector and then estimates TFP at the establishment level in the Mexican economy. The rest of this section presents the main characteristics of the data used in the first and the second stage of the methodology strategy.

3.2.1 First stage

The first stage of the methodology strategy estimates a production function with different methodologies using the sample of medium and large manufacturing establishments for the period 2003-2018 because there is more information available in this sample of the Economic Census. The parametrical comparison provides evidence to select the methodology with more plausible results.

It is possible to categorise the size of the establishments from the Economic Census according to the number of workers. Micro establishments have between 1 and 10 workers; small establishments have 11 to 50 workers; medium establishments have 51 and 250 workers; and large establishments have more than 251 workers. Table 3.6 presents the number of establishments classified by size and year between non-manufacturing and manufacturing establishments in Mexico. The sample of the first stage comprises the number of medium and large manufacturing establishments for the period 2003-2018. The size of the sample in the first stage is 43,952 observations (total sample in red, Table 3.6).

Table 3.6: Number of establishments (non-manufacturing and manufacturing) classified by size and year, 1993-2018.[a/]

Type of establishment	Size	1993	1998	2003	2008	2013	2018	Total
Non-manufacturing	Micro	2,778	2,366,392	2,554,577	3,132,020	3,577,807	4,012,027	15,645,601
	Small	1,038	78,407	98,315	127,617	133,278	169,176	607,831
	Medium	373	14,671	19,832	23,584	25,903	33,016	117,379
	Large	145	2,553	3,653	3,937	4,227	6,110	20,625
Manufacturing (NAICS 31-33)	Micro	235,190	309,330	298,678	404,156	458,096	543,236	2,248,686
	Small	19,129	22,261	19,752	22,349	20,455	24,247	128,193
	Medium	7,098	8,019	7,234	7,112	7,431	7,808	44,702
	Large	2,236	2,995	3,050	3,232	3,548	4,537	19,598
Total		**267,987**	**2,804,628**	**3,005,091**	**3,724,007**	**4,230,745**	**4,800,157**	**18,832,615**

[a/] Observations in this Table 3.6 are equivalent to the total observations in Table 3.2. Large and medium manufacturing establishments for the period 2003-2018 are 43,952 observations. This is the initial sample for the first stage of the estimation strategy.
Source: Own elaboration using microdata of the Economic Census of Mexico

Table 3.7 describes the variables included to estimate the production function to analyse the methodological comparison from the sample of medium and large manufacturing establishments (Table 3.6). The first variable in Table 3.7 ln gross output is the dependent variable (y_{it}) in the production function of equation 2.1, the variables ln intermediate inputs, ln employment, and ln capital are the factors of production (m_{it},l_{it}, k_{it}).[8] The following variables are proxies for different TFP determinants: ln age, export activity (dummy), ln fixed costs ratio, ln HHI, interest expenses (dummy), formal (dummy), ln population density, ln agglomeration index, ln diversification index, and ln percentage of entering establishments. The time-trend captures exogenous efficiency

[8]By definition, medium establishments have between 51 and 250 workers, and large establishments have more than 251 workers. For that reason, the mean of employment is around 181 employees per establishment.

improvement over time in the production function, which is the Hicks-neutral technical change.

Table 3.7 shows that the variable ln percentage of entering establishments rate has 39,399 observations, the ln investment has 27,493 observations[9], but the other variables have at least 42,000 observations. Therefore, the information available in the variable ln percentage of entering establishments and ln investments reduce the sample of medium and large manufacturing establishments in Table 3.7. Particularly, the variable ln investment is used as an instrument in the model of Karakaplan (2017) to correct endogeneity in the capital factor. The variable ln investment constrains the number of observations in the SF model of Karakaplan (2017). Other TFP determinants were excluded from this analysis but deserve special attention in future research. Those variables include R&D[10], subsidies[11], export rate[12], and Times Interest Earned (TIE).[13] Their exclusion is because those variables have less information available, which reduces the estimation sample in Table 3.7.

The theoretical foundations of the proxy variables as TFP determinants are described in the literature review of Chapter 2 and summarised in Table 3.5.[14] Variables in Table 3.5 can be categorised into Non-Spatial and Spatial TFP determinants. In the Non-Spatial TFP determinants, the variables can be divided into three theories: (i) Endogenous Growth Theory, (ii) Non-Competitive Markets, and (iii) Institutional Economics. The background theory in the Spatial TFP determinants is Spatial Economics. The variables are classified and explained as follows.

Non-Spatial TFP determinants.

(i) Endogenous Growth Theory.

- The variable ln age represents the ability of the establishments to increase TFP over time through the channel of learning-by-doing.

[9] There are 16,459 observations with missing and zero values of investment, and thus these observations are excluded in the estimation sample of the Karakaplan & Kutlu (2017) model.

[10] Dummy variables can be used to identify establishments with R&D. The limitation in the measurement of R&D is the lack of consistent criteria to identify R&D activities over time. For instance, there was information available about investment in R&D during 2003, but this variable was discontinued in subsequent years. In 2008 and subsequent years, R&D can be identified with binary variables whether the establishment had R&D staff, patents, or agreements for R&D activities. A potential solution for exploring the effect of R&D activities on TFP is to use cross-sections to compare the same variable of R&D across establishments in specific years.

[11] There is limited information about establishments' subsidies. There were 3,096 observations of manufacturing establishments with subsidies (1998-2018). This variable severely reduces the sample in the parametric comparison. One option to examine the effect of subsides on TFP is to analyse the agriculture sector (NAICS 11) because this sector has more subsidies in comparison to the rest. It is interesting to analyse the effect of subsidies during the financial crisis of 2008 because subsidies increased significantly in that year.

[12] The variable export rate measures the share of exports in total revenues. However, there were only 12,346 observations with export share of output, and this variable restricts the estimation sample.

[13] The variable Times Interest Earned (TIE) identifies whether a higher capacity of interest repayment (i.e., financial liquidity) has a positive effect on TFP. However, TIE had 32,998 observations for the period 1998-2018 and restricted the sample.

[14] These variables can also be referred as control variables.

Table 3.7: Description of variables used in the methodological comparison (first stage), 2003-2018.[a/]

Variable	Description	N	μ	σ
ln gross output	ln gross production (one hundred million) in real terms (MXP, 2013 prices).	42,845	-2.216	1.585
ln intermediate inputs	ln intermediate inputs (one hundred million) in real terms (MXP, 2013 prices).	43,947	-2.875	1.823
ln employment	ln employed persons.	43,952	5.2	0.969
ln capital	ln real net tangible fixed assets (one hundred million) in real terms (MXP, 2013 prices).	42,571	-3.908	2.133
ln age	ln of firms' age, measured as the number of years in activity.	43,952	2.7	0.929
export activity	Dummy variable. If the establishment has export activities, export_activity=1. Otherwise, export_activity =0	43,952	0.275	0.446
ln fixed costs ratio.	ln % of expenses in marketing, accessories, rent and professional services on total expenses.	43,952	0.431	3.387
ln HHI	HHI is calculated by year and industry group (4 digit of NAICS) and then converted to ln.	43,952	5.059	1.075
interest expenses	Dummy variable. If the establishment had interest expenses, financial_nterest=1. Otherwise, financial_nterest =0	43,952	0.519	0.5
Formal	Dummy variable. If the establishment contributes to payments of social healthcare services, formal=1. Otherwise, formal=0.	43,952	0.831	0.375
ln population density	ln of population density, measured as the ratio of population and km2 at the municipality level.	43,717	6.706	1.947
ln agglomeration index.	ln % of industry group output (4-digit NAICS) by municipality –MAR-spillovers–.	43,817	0.189	1.739
ln diversification index.	ln proportion of 4-digit NAICS industries by year (maximum 275) within the municipality (in total 2,461) –Jacobian spillovers–.	43,952	4.204	0.461
ln percentage of entering establishments	ln % of entering establishments at 4-digit NAICS by municipalities and year.	39,399	3.895	0.416
ln investment.	ln investment in fixed assets.	27,493	-6.082	2.283
time-trend	Linear trend of the year 1993=1, 1998=2, 2003=3, 2008=4, 2013=5, 2018=6	43,952	4.578	1.129

[a/] Population data was collected from the Census of Population and Housing in Mexico. There were calculated average intermediate points for the 5-year gap of this source

Source: Own elaboration using microdata of the Economic Census of Mexico

- The variable export activity examines whether establishments with exports have higher TFP through the channel of learning-by-exporting.

(ii) Non-Competitive markets.

- The variable ln fixed costs ratio can be categorised in the theory of non-competitive market as it represents the managerial capabilities and organisational efforts to reduce fixed costs. It is expected that the lower the ln fixed costs, the higher the TFP at the establishment level is.
- ln HHI intends to test whether lower sectorial competition reduces TFP at the establishment level.
- The variable interest expenses is a dummy variable that tests whether establishments with financial credits have higher TFP than their counterparts.

(iii) Institutional Economics.

- According to institutional economics theory, the variable formal examines whether formal establishments have a higher TFP.

Spatial TFP determinants.

(i) Spatial Economics

- The variable ln population density tests whether locations with high population density are more productive.
- ln agglomeration and ln diversification are proxy variables to the MAR and Jacobian externalities, respectively.
- The variable ln percentage of entering establishments is a proxy for Porter's externalities that promotes local competition.

3.2.2 Second stage

The second stage comprehends the extensive use of microdata at the sectoral level. The extensive use of the Economic Census implies selecting TFP determinants with more information available so that the sample has as many observations as possible. For that reason, the second stage of the methodology strategy has fewer TFP determinants than the first stage, but more observations are available.

Table 3.8 describes the variables included to estimate the production functions with the mark-up correction in the period 1993-2018. The only sector in which TFP can be estimated at the establishment level from 1993 to 2018 is the manufacturing sector (See Table 3.2). Finally, the variable ln industrial gross output is included in the production function to estimate the inverse of the constant elasticity of substitution of the establishment's demand $1/\sigma$ which is a crucial parameter to estimate the mark-up component $(\sigma - 1)/\sigma$ to correct the price bias in the production function.

Table 3.8: Description of variables used to estimate the mark-up model (second stage), 1993-2018.[a/]

Variable	**Description**	N	μ	σ
ln gross output	ln gross production (one hundred million) in real terms (MXP, 2013 prices).	18,361,226	-9.113	1.835
ln intermediate inputs	ln intermediate inputs (one hundred million) in real terms (MXP, 2013 prices).	17,880,079	-10.114	1.978
ln employment	ln employed persons.	18,743,696	0.722	0.87
ln capital	ln real net tangible fixed assets (one hundred million) in real terms (MXP, 2013 prices).	16,910,582	-10.029	2.011
ln age	ln of firms' age, measured as the number of years in activity.	18,816,973	1.69	1.14
ln fixed costs ratio.	ln % of expenses in marketing, accessories, rent and professional services on total expenses.	18,817,508	-3.765	7.882
ln HHI	HHI is calculated by year and industry group (4 digits of NAICS)	18,817,507	1.924	2.049
ln population density	ln of population density, measured as the ratio of population and km2 at municipality level.	18,626,681	6.215	2.092
ln agglomeration index.	ln % of industry group output (4-digit NAICS) by municipality –MAR-spillovers–.	18,795,680	-1.847	2.291
ln diversification index.	ln proportion of 4-digit NAICS industries by year (maximum 275) within the municipality (in total 2,461) –Jacobian spillovers–.	18,817,517	4.34	0.467
Time-trend	Linear trend of the year 1993=1, 1998=2, 2003=3, 2008=4, 2013=5, 2018=6	18,817,517	4.234	1.44
ln industrial gross output.	ln gross production (one hundred million) in real terms aggregated at 4-digits of NAICS (MXP, 2013 prices).	18,817,507	3.811	1.183

[a/] Data on population was collected from the Census of Population and Housing in Mexico. There were calculated average intermediate points for the 5-year gap of this source
Source: Own elaboration using microdata of the Economic Census of Mexico

The variables ln intermediate inputs and ln capital reduce the sample (Table 3.8). Most variables have at least 18,000,000 observations, while ln intermediate inputs and ln capital have 17,880,079 and 16,910,582, respectively. The establishments were sectioned at 2-digit of NAICS code to estimate the production functions with mark-up correction by the economic sector. Then, the Wooldridge (2009) model was estimated for each group of establishments. The TFP determinants are classified into the categories of Non-Spatial and Spatial as follows.

Non-Spatial TFP determinants.

(i) Endogenous Growth Theory.

- ln age.

(ii) Non-Competitive markets.

- ln fixed costs.
- ln HHI.

Spatial TFP determinants.

(i) Spatial Economics

- ln population density.
- ln agglomeration index.
- ln diversification index.

The production function estimation with the mark-up correction includes three TFP determinants classified as Non-Spatial and three Spatial determinants. The inclusion of Non-Spatial TFP determinants reflects the self-determination of each establishment to adopt and adapt better production practices that incentivise higher efficiency. On the other hand, the inclusion of Spatial TFP determinants intends to represent the non-neutrality of the geographical location in determining efficiency at the establishment level. Then, the hypothesis to test with the spatial determinants is whether the geographical location matters in determining productivity through the channel of externalities.

3.3 Methodology

3.3.1 First stage

Specification of the production function

This section presents the production function specification and the parametric comparison of the methodologies in the sample of medium and large manufacturing establishments from 2003 to 2018.

The specification of the production function is a log-linear Cobb-Douglas function applied to a Panel Data of dimension NT with establishments $i = 1, 2, \ldots, N$ in the period $t = 1, 2, \ldots, T$.

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t + \varepsilon_{it} \tag{3.1}$$

In equation 3.1, the variables y, m, l, k refer to the real gross output, intermediate inputs, employment and capital stock, respectively (all variables in ln). This production function has an output orientation as y depends on three factors of production.[15] The TFP calculation, which represents technical efficiency change or technological change in the production process, is specified in equation 3.2 as the part of the production function not attributed to the factors of production.

$$\ln(TFP_{it}) = y_{it} - (\beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it}) = \beta_0 + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t + \varepsilon_{it} \tag{3.2}$$

In equation 3.2, TFP is explained with the constant term β_0, variables in x' (i.e., TFP determinants), the neutral technical efficiency change over time t, and the random shocks ε_{it}. The significance and effect of the TFP determinants are defined with the variables from the vector β_{x}.

Models to estimate

The literature accounts for different econometric/parametric approaches to estimate unbiased parameters in the production function to overcome estimation issues. In particular, endogeneity bias and selection bias (Del Gatto et al. 2011, Van Beveren 2012). Figure 2.1 in Chapter 2 points out that the parametric approaches can be classified into four categories: (i) the FE model, (ii) SF models, (iii) CFA models and (iv) Dynamic Panel Data models with Instrumental Variables. The objective of the first stage of the methodology strategy is to analyse whether the sign and statistical significance of the elasticities (β_m, β_l, and β_k), the vector of TFP determinants parameters β_{x} and the parameter of Hicks-neutral technical change β_T are susceptible to changes according to the parametric approach estimated.

There were selected models of each parametric approach to compare the parameters across models. In category (i) it was selected the FE model, for category (ii) there were selected the SF models of Battese & Coelli (1995) (BC95 hereafter) and Karakaplan & Kutlu (2017) (KK17 hereafter) for category (iii) there were estimated the CFA models of LP and Wooldridge model; and finally, for the category (iv) it was selected the SYS-GMM model. The routine of Belotti et al. (2013) was implemented to estimate the SF model of BC95, and the command of Karakaplan (2017) was applied to estimate the KK17 model. In addition, the LP and the Wooldridge model were estimated with the command of Mollisi & Rovigatti (2017). Finally, the command of Roodman

[15] The production function can also have a value-added orientation in which the value-added is the dependent variable of two factors of production: employment and capital.

(2009) was implemented to estimate the SYS-GMM model.[16]

The specification of the log-linear Cobb-Douglas function using the models FE, BC95, KK17, LP, Wooldridge, and SYS-GMM are presented in the equations 2.5, 2.6, 2.7, 2.8 and 2.9 in Chapter 2, respectively. Table 3.9 presents the methodological categories to measure TFP and the selected models to estimate in each category. The rest of this section shows the parametric comparison across the models evaluated.

Table 3.9: Parametric methodologies classification and selected models to estimate the log-linear Cobb-Douglas function [a/]

Category	**Models to estimate**	**Estimator**
FE model		WE
SF models	BC95	ML
	KK17	ML
CFA model	LP	FS: OLS. SS: GMM
	Wooldridge	GMM
Dynamic Panel Data Models and IV.	SYS-GMM	GMM

[a/] Abbreviation of the estimators. Within Estimator (WE). Maximum Likelihood (ML). First Stage (FS): Ordinary Least Squares (OLS). Second Stage (SS): Generalised Method of Moments (GMM)
Source: Own elaboration

Although the sample of medium and large manufacturing establishments has 43,952 observations (Table 3.6), there is a loss of observations in the estimation sample depending on the model estimated. Table 3.10 displays the sample in each model. Column (1) of Table 3.10 shows the number of medium and large establishments in the manufacturing sector. Column (2) of Table 3.10 shows the loss of observations due to variables with null values. For instance, the KK17 model is the parametric approach with the largest loss of observations because the instrument (ln investment) and the variable ln percentage of entering establishments have many observations with null values. The models FE, BC95, LP and SYS-GMM have the same loss of observations due to null values that come from the variable ln percentage of entering establishments. The Wooldridge model has a loss of 5,407 observations from the variable ln percentage of entering establishments. In addition, the Wooldridge model has a loss of observations due to restricted dynamic instruments (Column 3, Table 3.10). Chapter 4 explains the feature of the loss of observations due to dynamic instruments in the Wooldridge model. Finally, Column (5) of Table 3.10 displays the sample in each model estimated for the parametrical comparison.

[16] For the different parametric methods estimated, only the FE model and the SYS-GMM account for individual specific effects.

Table 3.10: Sample in each model of the first stage of the estimation strategy [a/]

Model	(1) Medium and large manufacturing establishments	(2) Loss of observations due to null values	(3) Loss of observations due to dynamic instruments	(4)=(1)-(2)-(3) Sample
FE	43,952	6,736	0	37,216
BC95	43,952	6,736	0	37,216
KK17	43,952	19,922	0	24,030
LP	43,952	6,736	0	37,216
Wooldridge	43,952	5,407	23,016	15,529
SYS-GMM	43,952	6,736	0	37,216

[a/] Observations in Column 1 comes from Table 3.6. Sample of large and medium establishments in the manufacturing sector from 2003 to 2018. (obs 43,952).

Source: Own elaboration using microdata of the Economic Census of Mexico

Parametric comparison

Table 3.11 shows extended results in estimating the log-linear Cobb-Douglas function specified in equation 3.1 by implementing six Panel Data Models from Table 3.9. Table 3.11 displays the estimated elasticities in the factors of production β_m, β_l, and β_k, the effect and statistical significance of the TFP determinants in the vector β_{x}, as well as additional parameters of specification in the SF models.

Table 3.11 shows a difference in observations across models. The observations represent the dimension NT of the unbalanced panel data that includes N establishments in T years. The difference in the sample across models is explained in Table 3.10. The SF model of BC95 and KK17 include additional parameters for the specification of the composite error. The model BC95 consists of the vector of parameters $\phi_{BC95} = (\beta, \delta, \gamma, \vartheta)$ and the model KK17 includes the vector of parameters $\phi_{KK17} = (\beta, \eta, \rho, \sigma_w)$. Appendix B includes the specification in the parametrization of the BC95 model and KK17 model. Additionally, Table 3.11 includes some tests of the correct specification estimated for the FE, KK17 and SYS-GMM models. The Hausman test for the FE model was estimated under the null hypothesis of no difference between the WE and the Random Effects (RE) estimator. According to the Hausman test, the null hypothesis was rejected. Thus, the FE model is preferred over the RE model. Additionally, applying the FE model is appropriate as it overcomes the endogeneity of inputs.

Table 3.11: Production function of medium and large establishments in the manufacturing sector (NAICS 31-33) estimated with different Panel Data Models, 2003-2018 [a/]

		FE	BC95	KK17	LP	Wooldridge	SYS-GMM
Parameter	**Dependent variable**	**ln gross output**	**ln gross output**	**ln gross output**	**ln gross output**	**ln gross output**	**ln gross output**
β_m	ln intermediate inputs	0.647***	0.722***	0.739***	0.707***	0.658***	0.638***
		(0.004)	(0.004)	(0.002)	(0.002)	(0.008)	(0.012)
β_l	ln employment	0.243***	0.312***	0.278***	0.282***	0.283***	0.296***
		(0.006)	(0.004)	(0.003)	(0.003)	(0.005)	(0.015)
β_k	ln capital	0.031***	0.039***	0.066***	0.028***	0.040***	0.027***
		(0.002)	(0.002)	(0.003)	(0.007)	(0.003)	(0.005)
β_x	ln age	0.014***	0.015***	0.014***	0.047***	0.006*	0.043***
		(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
	export activity	-0.010	-0.035***	-0.047***	-0.003	-0.059***	0.054***
		(0.008)	(0.005)	(0.006)	(0.003)	(0.005)	(0.011)
	ln fixed costs ratio	0.001	0.003***	0.006***	0.005***	0.007***	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	ln HHI	-0.011*	0.020***	0.019***	0.053***	0.017***	0.036***
		(0.006)	(0.002)	(0.002)	(0.001)	(0.003)	(0.004)
	interest expenses	-0.025***	-0.102***	-0.095***	-0.097***	-0.108***	-0.053***
		(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)
	formal	0.133***	0.104***	0.109***	0.139***	0.143***	0.051***
		(0.010)	(0.007)	(0.007)	(0.003)	(0.008)	(0.011)
	ln population density	-0.027**	-0.026***	-0.024***	-0.015***	-0.025***	-0.028***
		(0.012)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)
	ln agglomeration index	0.095***	-0.004	0.023***	0.085***	0.016***	0.052***
		(0.004)	(0.005)	(0.002)	(0.011)	(0.002)	(0.003)
	ln diversification index	0.072***	-0.013*	-0.009	0.022***	0.017	-0.039***
		(0.023)	(0.007)	(0.007)	(0.002)	(0.011)	(0.009)
	ln percentage entering establishments	0.004	-0.031***	-0.029***	-0.019***	-0.062***	-0.021***
		(0.007)	(0.006)	(0.006)	(0.004)	(0.008)	(0.006)
β_T	time-trend	-0.010***	-0.007***	-0.005**	0.013***	-0.008**	0.002
		(0.003)	(0.002)	(0.002)	(0.001)	(0.004)	(0.002)
δ	μ_{1it}(ln agglomeration index)		-0.060***				
			(0.012)				
γ	σ^2_{1it},σ^2_{4it}(constant)		-4.696***	-3.114***			
			(0.848)	(0.071)			
ϑ	σ^2_{2it} (constant)		-1.886***				
			(0.019)				
η	ε_{it}(ln capital)			-0.027***			
				(0.002)			
ρ	k_{it}(ln investment)			0.577***			
				(0.004)			
ρ_0	k_{it}(constant)			-0.086***			
				(0.027)			
τ	σ_{5it} (constant)			-2.241***			
				(0.012)			
β_0	Constant	-1.751***	-1.354***	-1.007***			-1.771***
		(0.117)	(0.062)	(0.048)			(0.141)
	Observations	37,216	37,216	24,030	37,216	15,529	37,216

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a/] Test for FE model. Hausman test: 162.8. p-value: 0.00. Test for KK17 model (SF): Endogeneity test: 123.1. p-value: 0.00. Tests for SYS-GMM model. AR(1): -14.85. p-value: 0.00. AR(2) -1.154. p-value 0.248. Hansen test: 7.636. p-value: 0.0542. Sargan test: 27.01. p-value: 5.85e-06

Source: Own elaboration using microdata of the Economic Census of Mexico

The KK17 model was tested with the eta endogeneity test. The eta test evaluated endogeneity under the null hypothesis that states "Correction for endogeneity is not necessary." The alternative hypothesis is "There is endogeneity in the model and correction is needed." (Karakaplan 2017, p. 47). The p-value indicates the rejection of the null hypothesis. As a result, the endogeneity of the capital in the SF model was not corrected. The KK17 model used the investment i_{it} as the instrument to correct the capital factor k_{it} in the auxiliary regression (Appendix B). The choice of the investment as an instrument is because this variable can correct the capital endogeneity, as Olley & Pakes (1996) proposed. Although the parameters of the investment and the constant term (ρ,ρ_0) in the auxiliary regression were statistically significant; the eta test indicates endogeneity in the SF. The persistence of endogeneity in the KK17 model is the result of simultaneous endogeneity in the rest inputs of the production function (i.e. intermediate inputs and employment). For that reason, the correction of endogeneity in only one input with the KK17 model is limited to consider the instrumental approach as valid.

The SYS-GMM model was tested for autocorrelation in the residuals in the first differences. The null hypothesis is no autocorrelation. AR(1) is the autocorrelation of the first order. This test usually rejects the null hypothesis, and the residual in the first differences are autocorrelated because Δv_{it} and $\Delta v_{i,t-1}$ share $v_{i,t-1}$. As expected, AR(1) is autocorrelated because the null hypothesis of no autocorrelation is rejected. The test of interest is the autocorrelation of second-order AR(2). The AR(2) test accepts the null hypothesis of no autocorrelation. Thus, the SYS-GMM model does not present second-order autocorrelation.[17] The validity of the instruments used in the SYS-GMM model was tested using the Hansen and Sargan tests. The crucial assumption in the SYS-GMM model is that the instruments are exogenous. The null hypothesis in the Hansen/Sargan tests is no-overidentification, which measures the joint validity of the instruments (i.e., no correlation between the instruments and the random error).[18] In the Hansen test, the null hypothesis is not rejected; as a result, the instruments used are statistically valid.

Table 3.12 is a summary that displays the estimated elasticities of the factors of production and the parameter of Hicks-neutral technical change in the log-linear Cobb-Douglas function. Across models, the estimation of the elasticities in the production function of medium and large manufacturing establishments indicates that the elasticity of intermediate inputs β_m is in a range of 0.638-0.739, the elasticity of the employment β_l is in the range of 0.243-0.312. and the elasticity of the capital factor β_k is in a range of 0.027-0.066. Overall, the results indicate that the estimated elasticities in the factors of production were positive and statistically significant. The parametric comparison suggests that the magnitudes of the elasticities differ across Panel Data Models. The

[17] The Arellano-Bond test for autocorrelation is based under the null hypothesis of zero order correlation of errors in time (no autocorrelation) assuming that errors are sufficiently uncorrelated across individuals (Roodman 2009, p. 120). Then, the lower AR(1) and AR(2) values are in absolute terms, the more evidence of no-autocorrelation.

[18] Roodman (2009) states that the SYS-GMM model has to be overidentified instead of just identified to detect the invalid instruments. In other words, if the instruments are valid, they do not have explanatory power to the residuals estimated in the SYS-GMM. Then Hansen/Sargan tests are based under the null hypothesis that the correlation between instruments and errors is zero.

more significant difference is in the elasticity of capital because this elasticity is more than double from the lowest magnitude of 0.027 (SYS-GMM) to the highest magnitude of 0.066 (KK17).

The parameter of Hicks-neutral technical change β_T in Table 3.12 shows a negative magnitude in most of the models estimated. Then, the results indicate a negative disembodied technical change over 2003-2018 on 'average' in medium and large manufacturing establishments. This result is plausible and related to the evidence which measures a negative TFP growth with a declining trend in the manufacturing sector over the last 20 years (Figure 1.4). However, the negative disembodied technical change is an 'average', which means that not all the medium and large manufacturing establishments have had a negative technical change, but most deteriorated their technical change during 2003-2018. The only exception is the LP model, which shows a positive technical change β_T. The reason for different results in the parameter β_T with the LP model is the use of instruments in the polynomial function.

Table 3.12: Elasticities of the factors of production and parameter of Hicks-neutral technical change of medium and large establishments in the manufacturing sector (NAICS 31-33), 2003-2018

	Model	**FE**	**BC95**	**KK17**	**LP**	**Wooldridge**	**SYS-GMM**
Parameter	**Dependent variable**	**ln gross output**	**ln gross output**	**ln gross output**	**ln gross output**	**ln gross output**	**ln gross output**
β_m	ln intermediate inputs	0.647***	0.722***	0.739***	0.707***	0.658***	0.638***
β_l	ln employment	0.243***	0.312***	0.278***	0.282***	0.283***	0.296***
β_k	ln capital	0.031***	0.039***	0.066***	0.028***	0.040***	0.027***
β_T	time-trend	-0.010***	-0.007***	-0.005**	0.013***	-0.008**	0.002

*** p<0.01, ** p<0.05, * p<0.1

Source: Own estimation using microdata of the Economic Census of Mexico

Table 3.13 summarises the effect of the factors of production and the TFP determinants on TFP divided into three categories according to the values of the parametric estimation: statistically significant and not significant.[19] Column (1) in Table 3.13 represents the number of models in which the variable was statistically significant; the significance is divided according to the sign of the parameter, whether the parameter is positive or negative. Cells in green of Column (1) display if the TFP determinant was positive or negative in at least three of the six models estimated. This means that the TFP determinants represent at least 50% of the models estimated. Cells in green provide evidence about the parametric dominance according to the sign (positive or negative) and the statistical significance of the TFP determinants across models. Cells in red in Column (1) do not provide conclusive evidence. Column (2) includes the number of models in which the variables were not statistically significant. Column (3) is the total number of models estimated.

[19]TFP determinants can also be defined as control variables in the production function to overcome the issue of omitted variable bias; when the control variables are statistically significant, there is evidence that these variables are an appropriate proxy to the TFP determinants.

Table 3.13: Classification of the elasticities and TFP determinants by the parameter's sign and statistical significance in medium and large manufacturing establishments, 2003-2018 [a/]

	Parameters	Column (1) Statistically significant Positive	Column (1) Statistically significant Negative	Column (2) Not significant	Column (3) Total
	β_m	6	0	0	6
	β_l	6	0	0	6
	β_k	6	0	0	6
β_x	ln age	5	0	1	6
β_x	export activity	1	3	2	6
β_x	ln fixed costs ratio	4	0	2	6
β_x	ln HHI	5	0	1	6
β_x	interest expenses	0	6	0	6
β_x	formal	6	0	0	6
β_x	ln population density	0	6	0	6
β_x	ln agglomeration index	5	0	1	6
β_x	ln diversification index	2	1	3	6
β_x	ln percentage entering establishments	0	5	1	6
	β_T	1	4	1	6

[a/] In green, there is evidence of parametric consistency due to the statistical significance of parameters with positive or negative in at least three of the six models estimated, representing at least 50% of the models estimated in each manufacturing industry. In red, there are cells without conclusive evidence. The first two columns report $p<0.05$

Source: Own elaboration using microdata of the Economic Census of Mexico

The results can be divided according to the classification of the TFP determinants (See Table 2.3 in Chapter 2):

Non-Spatial TFP determinants.

1. Endogenous Growth Theory.

    - The variable ln age tested the ability of the establishments to increase TFP over time through the channel of learning by doing. Table 3.13 shows that age positively impacts TFP. Then, the production processes of medium and large manufacturing establishments increase their efficiency over time due to endogenous improvements in technical change, which indicate an effect of learning-by-doing. Then, the variable ln age can reflect the increasing knowledge applied to production. In addition, the variable ln age can be associated with the internal and external creation of knowledge that allows medium and large manufacturing establishments in Mexico to increase their intangible capabilities and competitiveness.

- The variable export activity tested whether establishments with exports have higher TFP through the channel of learning-by-exporting. Contrary to the hypothesis, the variable export activity negatively affected TFP, indicating that Mexican medium and large manufacturing establishments with exports have lower TFP in 3 of 6 models estimated. This variable can be limited because it is not distinguished between non-processing/trade exporters and assembly exporters. Dai et al. (2016) recommend that it is necessary to distinguish between processing/assembly exporters and non-processing/trade exporters because in countries focused on assembly processes like Mexico, the assembly exporters have a low value-added, which might be reflected in a lower TFP. Empirical research in other countries shows the results of an inconclusive effect of export activity on TFP. For instance, Ding et al. (2016) found limited evidence to support the hypothesis that exporter Chinese firms have higher TFP. In Mexico, López-Noria (2021) found a positive association between trade liberalisation and TFP in medium-size manufacturing establishments but not for small and large establishments. Then, the negative effect of export activity on TFP in the first stage can result from including medium and large manufacturing establishments in the same sample, similar to the findings of López-Noria (2021). A plausible explanation for the negative relationship between export activity and TFP is the effect of international (external) competition. The reason is that international competition negatively affected the export activity of medium and large manufacturing establishments in Mexico from 2003 to 2018. Therefore, the variable of export activity captures the negative shock that gets reflected in a negative effect on TFP at the establishment level. For instance, Blyde & Fentanes (2019) found an overall negative productivity shock to the Mexican manufacturing establishments from Chinese competition, but with a heterogeneous effect. Therefore, it can be concluded that export activity does not increase TFP in medium and large manufacturing establishments in Mexico. Instead, export activity negatively affects TFP, which can result from a negative shock of international competition to Mexican manufacturing establishments (medium and large) and affecting TFP negatively. This section followed the approach of TFP measurement using the framework of Harris & Moffat (2015*a*) and included proxies of export activity in the production function. However, future research can apply the two approaches to measure learning by exporting, according to De Loecker (2013), to provide more evidence about the effect of export on TFP in Mexican establishments (See literature review for the description of De Loecker (2013)).

2. Non-Competitive markets.

   - The variable ln fixed costs ratio tested whether the managerial capabilities and efforts to reduce fixed costs lead to higher TFP. Contrary to the hypothesis, four models show that the variable ln fixed costs ratio positively impacts TFP. As a result, lower costs do not necessarily lead to higher TFP. This result indicates that the efficiency of medium and large manufacturing establishments does not come from reducing costs but from other sources. In addition, a higher proportion of fixed costs on revenues can indicate better quality of expenses reflected in more efficient processes.

- The variable ln HHI tested whether lower sectorial competition reduces TFP at the establishment level. The results indicate that the ln HHI positively impacted TFP in five models estimated. The conclusion of the Schumpeterian and endogenous growth theory models can explain this result. These models account for a negative relation between the level of competition and TFP. This theory argues that granting innovator monopoly rights incentivises investment in R&D and innovation through a patent system, which increases productivity. For that reason, high levels of competition do not necessarily reflect high TFP levels.

- The variable interest expenses tested the role of financial access on establishments' TFP to analyse whether medium and large manufacturing establishments with financial credits have higher TFP. The justification for using interest expenses is that this variable represents credit access, and those establishments are less likely to have financial constraints from financial institutions (e.g. banks). [20] Other variables like cash flows can be proxies for financial constraints. This variable measures profitability but does not represent credit access per se. [21] The results indicate that the variable interest expenses had a negative and statistically significant effect in all estimated models. As a result, medium and large manufacturing establishments with interest expenses have lower TFP than their counterparts. This evidence can indicate two possible explanations. The first explanation is that there is a reversal causality in which establishments with low TFP (and probably low profits) demand financial credit to survive in the market. This idea is consistent with the pecking order theory, which explains that firms with financial success have funding from their profits. Therefore, the first explanation is that financial access not necessarily reflects investment in productive capacity and higher TFP. Instead, financial access could reflect financial failure and a condition of survival due to the low TFP levels. The second explanation is that many of those establishments in the sample could have high debt ratios, which reflect indebtedness that reduce TFP. The idea is that a high proportion of debt generates financial distress, and the ability of debt repayment reduces productive capacity and ultimately decreases TFP. This result is in line with the works of Blažková & Dvouletỳ (2018) and Dvouletỳ & Blažková (2021), that found a negative relationship between debt and productivity in Czech firms. In addition, Coricelli et al. (2012) found that the increase in debt had a positive effect on TFP growth until a critical level; beyond that level, debt negatively impacted TFP growth. Therefore, the second explanation indicates that interest expenses can reflect indebtedness

[20] Those establishments had credit at some point during their economic activities because they were profitable, had collateral, and/or had a good credit record.

[21] Cash flow can measure profitability, and this is positively correlated with credit access, as Iacovone et al. (2022) pointed out.

and financial distress that affect productive capacity and ultimately decreases TFP at the firm level in Mexico.

3. Institutional Economics.

   - According to institutional and development economics theory, the variable formal examines whether formal establishments have a higher TFP. The results indicate that in all models estimated, large and medium formal establishments in the manufacturing sector have higher TFP than their counterparts. This result is explained because formal establishments are out of the subsistence sector, which provides the incentives to accumulate capital and better technology to survive in the market and to increase efficiency. Levy-Algazi (2018) argues that one of the main problems of the Mexican economy is the large informal sector, which allows unproductive and small establishments to enter and survive in the economy. The survival of unproductive establishments creates a dysfunctional firm selection that contributes negatively to the aggregated TFP.

Spatial TFP determinants.

1. Spatial Economics

   - The variable ln population density tests whether highly populated locations are more productive. Table 3.13 indicates that population density was statistically significant and affected TFP in all models estimated. Then, the evidence supports the argument that municipalities with more population density reduce TFP of medium and large manufacturing establishments in Mexico due to congestion costs.
   - The variables ln agglomeration is a proxy variable to the MAR externalities. Table 3.13 shows that the agglomeration index was positive and statistically significant in five Panel Data Models estimated. This result indicates that a high output agglomeration of manufacturing industries (4-digit NAICS code) in a Mexican municipality influences TFP positively in medium and large manufacturing establishments. For that reason, the manufacturing sector generates positive agglomeration externalities due to MAR spillovers. For instance, Baptista & Swann (1999) found that manufacturing firms that promote innovation have incentives to cluster in locations with specialised employment. Then, there are incentives generated by agglomeration economies so that manufacturing establishments are clustered in particular areas. Clusters created by MAR externalities allow Mexican manufacturing establishments (medium and large) to promote localisation advantages (related to employment, human capital, infrastructure and materials) to minimise costs and maximise output (Glaeser et al. 1992, Duranton & Puga 2004, Harris & Moffat 2015*a*).
   - The ln diversification is a proxy variable to the Jacobian externalities. The effect of the ln diversification index on TFP is not statistically significant in three of the models

estimated. Other studies like Nakamura (1985) found that Jacobian externalities do not positively impact TFP in heavy industries in Japan. For that reason, the evidence in the first stage indicates that high diversification of economic activities (i.e. Jacobian externalities) does not necessarily benefit productivity of medium and large manufacturing establishments. Instead, Jacobian externalities generate congestion cost and thus a negative effect on TFP.

- The variable ln percentage of entering establishments is a proxy of Porter's externalities that promotes local competition. The results indicate that Porter's externalities are statistically significant, with a negative effect on TFP in four models estimated. Therefore, local competition reduces TFP of Mexican medium and large manufacturing establishments. This result is consistent with the variables ln HHI, which shows that market concentration benefits TFP (Table 3.13). In the literature, Glaeser et al. (1992) argue that in large urban areas, competition can affect productivity.

Additionally, the time trend was negative and significant in most estimated models. Therefore, there is evidence of TFP decrease due to the exogenous and disembodied efficiency deterioration over time, reflecting a negative Hicks-neutral technical efficiency. However, the average effect of a negative technical change can only reflect the downward trend of decreasing TFP during 1998-2018 in Mexico. The evidence in Figure 1.4 indicates that the secondary sector (including manufacturing) has had a negative TFP growth, which implies a downward trend of TFP between 1991 and 2020.

Figure 3.1 shows the empirical cumulative distributions of the ln TFP estimated from equation 3.2 with the results of the parametric approaches presented in Table 3.13. Figure 3.1 displays similar patterns across ln TFP distributions. This appreciation can be confirmed by Table 3.14, which shows a correlation matrix of the ln TFP distributions. According to Table 3.14, the ln TFP distributions have a high correlation among them. Therefore, the ln TFP estimations did not significantly differ between different parametric approaches (Figure 3.1, Table 3.14).

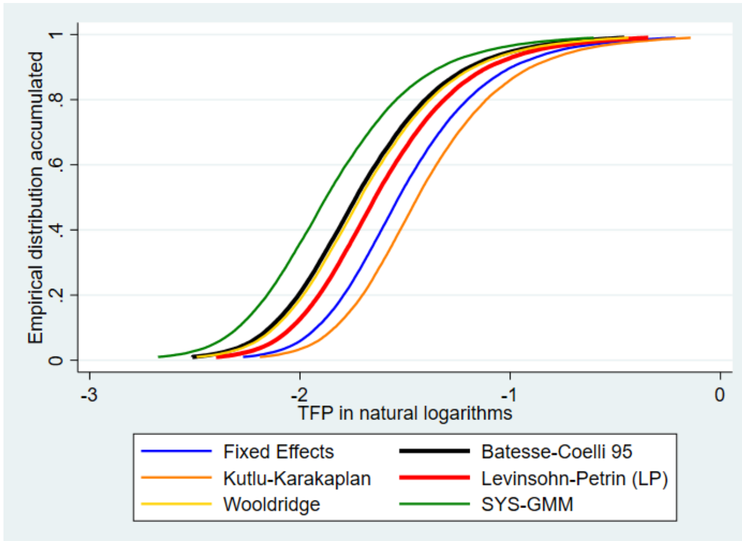
Table 3.14: Correlation matrix of ln TFP in medium and large manufacturing establishments (NAICS 31-33) estimated with different parametric approaches, 2003-2018

Model	**FE**	**BC95**	**KK17**	**LP**	**Wooldridge**	**SYS-GMM**
FE	1					
BC95	0.995	1				
KK17	0.995	0.991	1			
LP	0.999	0.998	0.992	1		
Wooldridge	0.995	0.999	0.993	0.998	1	
SYS-GMM	0.989	0.998	0.982	0.994	0.998	1

Source: Own elaboration

In summary, the evidence of the ln TFP distribution shows that the magnitudes of the ln

Figure 3.1: Empirical cumulative distribution of ln TFP in medium and large manufacturing establishments (NAICS 31-33) estimated with different parametric approaches, 2003-2018.[a/]



[a] Distribution with 99% of the interval
Source: Own estimation using microdata of the Economic Census of Mexico

TFP can vary across models, but they are highly correlated. Even though there are parametrical differences, the TFP estimations across models do not produce TFP results with large differences. Therefore, the decision to use a specific parametrical approach above the rest does not generate a bias in the TFP estimation due to the approach selection. In the end, the different parametrical approaches lead to similar TFP estimations.

Van Beveren (2012) had similar results by estimating TFP in Belgium's Food and Beverages Industry with different parametric methods. The findings are that TFP estimates are highly correlated and yield no different implications when simple policy questions are concerned about productivity. However, Van Beveren (2012) did not include SF models in the analysis of parametric comparison. Van Beveren (2012) argues that the result of similar TFP estimations responds to the fact that the methodological literature has focused mostly on selection and simultaneity bias at the expense of other potential biases, such as the omitted price and the level of analysis (i.e., firm-level versus plant-level versus product level). The conclusion of the first stage in the strategy of estimation is that the estimation of ln TFP at the establishment level is not susceptible to considerable changes according to the parametric approach estimated. However, the author considers the Wooldridge and the SYS-GMM models are the most efficient approaches to solving the endogeneity bias. The reason is that both methodologies tackle the simultaneity bias with a simultaneous approach using a system of equations estimated with GMM.

3.3.2 Second stage

Specification of the production function with mark-up correction

The estimation of TFP at the firm level can lead to potential bias. For instance, it is well known that the parametric estimation of the production function using OLS lead to endogeneity bias, which means that the stochastic errors are correlated with the regressors (i.e., factors of production, TFP determinants). Then, the endogeneity issue causes parametric bias in the production function, leading to inaccurate TFP estimations.

An additional TFP estimation issue is the omitted price bias. The origin of this issue is that most firms' production databases are not disaggregated in prices and quantities, and the production information is presented in monetary values. The information in monetary values is deflated using a price index by sector. However, information on production in real terms does not reflect the real production at the establishment level. Usually, the price index at the sectoral level p_{st} is different to the price at the establishment level p_{it}. In the case of perfect competition, the price index at the sectoral level and the price index at the establishment level would not be different. However, in an imperfect competition market, the difference $p_{st} - p_{it} \neq 0$ is the omitted price bias that leads to an inaccurate TFP estimation. The correction of the omitted price bias implies the specification of a production function that infers the price at the establishment level by including a mark-up over the marginal cost for every economic sector (2-digits of NAICS code). The mark-up model considers a monopolistic demand system with a Constant Elasticity Substitution (CES) into the production framework.

The second stage of the methodology strategy overcomes two estimation biases in the literature: (i) endogeneity of inputs and (ii) price bias. This section explains the most relevant equation to estimate the production function with the mark-up correction, initially derived by Klette & Griliches (1996). The mark-up correction was applied by De Loecker (2011) to analyse the effect of trade liberalisation on TFP, and Ehrl (2013) and Harris (2021) applied the mark-up correction in the regional analysis. Ehrl (2013) estimated TFP with the OP model and using microdata from Germany, and Harris (2021) estimated TFP with the SYS-GMM model and microdata from New Zealand.

Equation 3.3 is the production function with the mark-up correction, which is the central equation to estimate TFP at the establishment level in Mexico.

$$\tilde{r}_{it} \equiv p_{it}+q_{it}-p_{st} = \left(\frac{\sigma-1}{\sigma}\right)\left(\alpha_i + \alpha_m m_{it} + \alpha_l l_{it} + \alpha_k k_{it} + \mathrm{x}_{it}'\alpha_{\mathrm{x}} + \alpha_T t\right)+\frac{1}{\sigma}\left(r_{st}-p_{st}\right)+u_{it} \quad (3.3)$$

In equation 3.3, $\tilde{r}_{it}$ is the real revenue in ln of the establishment i in year t. The ln real revenue $\tilde{r}_{it}$ is equivalent to the price p_{it} plus the quantity output q_{it} minus the price index at the sector level

p_{st}, all variables in ln. Therefore, the real revenue is equivalent to $\ln\left(\tilde{R}_{it}\right) \equiv \ln\left(P_{it}Q_{it}/P_{st}\right)$.

The right-hand part of equation 3.3 comprises three components. The first component is a log-linear Cobb-Douglas production function $q_{it} = (\alpha_i + \alpha_m m_{it} + \alpha_l l_{it} + \alpha_k k_{it} + \mathrm{x}'\alpha_{\mathrm{x}} + \alpha_T t)$ multiplied by the mark-up factor $((\sigma-1)/\sigma)$. The second component is the output at the sector level in ln represented as $q_{st} = (r_{st} - p_{st})$ multiplied by the inverse of the constant elasticity of substitution of the firm's demand $1/\sigma$. The third component is the stochastic shocks of supply and demand u_{it}. Appendix C describes in detail the derivation of the mark-up model in equation 3.3.

In the log Cobb-Douglas function in equation 3.3, the factors of production in ln are the intermediate inputs m_{it}, the employment l_{it} and the capital k_{it}; while α_m, α_l and α_k are the elasticities of the factors of production. In addition, x'_{it} is a transposed vector with a dimension of $1 \times c$, where c is the number of exogenous regressors or TFP determinants that comprises the X-efficiency attributes, α_{x} is the vector of parameters that measures the effect of TFP determinants. Finally, t is the time-trend and α_T is the parameter that accounts for exogenous increasing technical change over time, known as the Hicks' effect.

The estimation of TFP is specified in equation 3.4. This equation measures TFP as part of the real revenue $\tilde{r}_{it}$ not explained by the production factors or the output's correction component at the industry group level (4-digit NAICS code).

$$\ln\left(TFP_{it}\right) = \tilde{r}_{it} - \left(\frac{\sigma-1}{\sigma}\right)\left(\alpha_m m_{it} + \alpha_l l_{it} + \alpha_k k_{it}\right) - \frac{1}{\sigma}\left(r_{st} - p_{st}\right) = \left(\frac{\sigma-1}{\sigma}\right)\left(\alpha_i + \mathrm{x}'_{it}\alpha_{\mathrm{x}} + \alpha_T t\right) + u_{it} \tag{3.4}$$

The following section describes the selection process of the parametric approach to estimate the production function with the mark-up correction of equation 3.4.

The selection process of the parametric approach to estimate the production function with mark-up correction

The main conclusion in the first stage of the estimation strategy is that the parametric approaches to estimate a production function do not provide results with significant differences on the TFP estimations. Then, it is inferred that one parametric approach does not differ largely in the TFP estimations in relation to other approaches when the mark-up model is estimated. The Wooldridge and the SYS-GMM model are the most plausible approaches to estimate the production function with mark-up correction. The rest of the models in the parametrical comparison present the following disadvantages.

- Even though the FE model accounts for individual-specific effects in u_i that comprises the composite error term; it is implausible to assume that the idiosyncratic term of efficiency is time-invariant.

- The SF model BC95 can present problems of endogeneity. In addition, the estimation of the endogenous SF of KK17 did not overcome the endogeneity bias. The reason is that the KK17 model did not correct the endogeneity of inputs because only one factor of production was instrumented.

- The issue with the LP model is the dependence on the free variable due to the estimation in two stages (Ackerberg et al. 2015).[22] This issue can be solved with the ACF model. However, the ACF model can only be estimated in a production function with a value-added orientation, and the value-added production function differs from the output-oriented function of the estimation strategy in equation 3.3.

Appendix D reports the estimation of the production function with the mark-up correction using the SYS-GMM model, but only seven production functions were estimated with that approach.[23] The reason is that only seven sectors provided appropriate dynamic instruments for a plausible parameterisation and correct specification of the SYS-GMM production function with the mark-up correction.[24] For that reason, using the SYS-GMM to estimate the mark-up model is not appropriate due to weak instruments in most economic sectors. The weak instruments are caused by the limited dynamic structure of the microdata. There are two main reasons for weak instruments using the microdata of the Economic Census of Mexico (1993-2018).

- Weak instruments in the SYS-GMM model due to many observations with zero values. Chapter 2 reviews the theoretical features of the SYS-GMM model, and it was specified that the equation in differences has a matrix of instruments that includes exogenous and endogenous instruments $\mathrm{z}_{1it} = (\Delta \mathrm{x}_{it}, m_{i,t-1}, l_{i,t-1}, k_{i,t-1}, \ldots, m_{i,t-T}, l_{i,t-T}, k_{i,t-T})$. The command of Roodman (2009) allows an extensive estimation coverage of the database when the SYS-GMM is estimated. The reason is that the routine of Roodman (2009) replaces null values for zeros in the matrix of instruments. As a result, if it is specified two lags in the endogenous instruments, establishments that remained in the market only for one period will have instruments in the first lag replaced with zeros $m_{i,t-1} = 0, l_{i,t-1} = 0, k_{i,t-1} = 0$ and similarly for the second lag. In addition, the replacement with zero values also applies to instruments in the equations of differences or levels. The instruments can be biased in a dataset with many entering and exiting establishments because many instruments have null values. Therefore, replacing zero in observations with null values generates information that does not exist. The inaccuracy of instruments with zero values can generate a bias in the parametric estimation

[22] The OP algorithm also has dependence of free variables.

[23] Those seven sectors estimated with the SYS-GMM approach in the Appendix D represent 12.73% of the microdata (2,400,567 observations).

[24] The correct specification of the SYS-GMM overcomes autocorrelation of second-order and overidentification of instruments

due to weak instruments. In the case of the microdata of Mexico, 67% of observations are entering establishments and survivors in the market for only one period. For that reason, the SYS-GMM model generated instruments that do not exist in a large percentage (67%) of the microdata. This issue leads to an inaccurate estimation of the production function parameters due to weak instruments with many zero values.

- Weak instruments in the SYS-GMM model due to a large gap between years. Chapter 2 reviewed this feature of the SYS-GMM model, and it was specified that the matrix of instruments in the equation in levels is $\mathrm{z}_{2it} = (\mathrm{x}_{it}, t, \Delta m, \Delta l, \Delta k)$. The use of the Economic Census of Mexico implies that the factors of production are differenced in a 5-years gap: Δm,Δl,Δk. For instance, the difference in the capital factor Δk between 2003 and 1998 is the instrument to explain the output in levels in 2003. There is a large gap between 2003 and 1998. This time gap can generate weak instruments. As a result, the estimation of the SYS-GMM model generated overidentification and autocorrelation of the second order in most sectors estimated (Appendix D).

The estimation of the Wooldridge model provides better results because this model estimates plausible magnitudes in the parametric estimation. In addition, the estimation of the Wooldridge model using the command of Mollisi & Rovigatti (2017) becomes an easier implementation in the microdata because this routine uses a set of instruments simpler to compute in comparison to the SYS-GMM model (See subsection of CFA model in Chapter 2). In conclusion, the Wooldridge model is the preferred approach to estimate the production function with mark-up correction by economic sectors in the microdata of the Economic Census of Mexico (1993-2018). The next Chapter analyses the parametric results in the second stage of the methodology strategy using the Wooldridge model. In addition, the next Chapter 4 presents the parametric results of the TFP determinants, estimates the ln TFP at the establishment level and analyses insights into the ln TFP distribution.

Chapter 4

Analysis of results 1: TFP determinants

4.1 Overview of Chapter 4

This chapter analyses TFP at the establishment level in Mexico. The results are obtained from the estimations of the production function with the mark-up correction using data from the Economic Census in Mexico (1993-2018). In particular, Chapter 4 covers the second stage of the estimation strategy by applying the Wooldridge model in all the economic sectors of Mexico. This chapter is divided into two sections. Section 4.2 analyses the parametric results of the production functions by economic sector estimated with the Wooldridge model. Section 4.2 also analyses the main features in the implementation of the Wooldridge model, including (i) the analysis of the magnitudes of the elasticities across economic sectors and (ii) the effect and significance of the variables that determine TFP in Mexican establishments. Section 4.3 estimates the ln TFP at the establishment level.

4.2 Production functions with the mark-up correction

The previous Chapter 3 selected the Wooldridge model as the preferred parametric approach to estimate the production function with the mark-up correction. The main advantage is that the Wooldridge model with the mark-up correction overcomes the endogeneity bias and the omitted price bias in the production function. For this estimation, the microdata of the Economic Census of Mexico was used extensively for the period 1993-2018 (Table 3.2). In the microdata, the manufacturing sectors with NAICS codes 31, 32 and 33 are the only sectors that cover the parametric estimation for the period 1993-2018. The other sectors cover the period 1998-2018.

Two economic sectors were excluded from the parametric estimation: the sector of Utilities and the sector of Management of Companies and Enterprises with NAICS code 22 and 55, respectively (Table 3.2). Sectors 22 and 55 were excluded from the sample due to potential output mismeasurement, leading to lower data quality than the other sectors. For instance, headquarter establishments in these sectors can report the aggregated production of their subsidiaries (i.e., multi-plant establishments) instead of the output of the headquarters. The inaccurate output report generates output mismeasurement.

As the literature review accounts, the initial debate about the Theory of Production in the 1970s was that using a single production function could oversimplify the production process. Johansen (1972) formalised the mathematical existence of an aggregated production function at the industry level, which can be estimated to measure TFP. This initial concept was the point of departure for estimating some statistics in the growth accounting, such as the KLEMS model that measures TFP by sectors in different countries (Jorgenson et al. 2000). This thesis uses the concept of the existence of an aggregated production function by sector in which establishments have a common technology with shared elasticities that lead to estimate TFP heterogeneity across establishments (Bartelsman & Wolf 2017, Harris 2021).

According to Bartelsman & Wolf (2017), the frontier production approach considers that establishments in the same industry can reach a "possibility of production frontier". As a result, productivity measures the distance between the output at the establishment level and the "possibility of production frontier", which refers to the industry's most efficient output possible. Following the frontier production approach (and narrative), the production function $f()$ represents a common function across establishments that transform inputs into output, which Bartelsman & Wolf (2017) labelled as an input aggregator. Estimating a common "possibility of production frontier" across establishments in a delimited industry creates differentials in the distance between the establishments' output, ultimately leading to TFP dispersion (i.e. heterogeneity) across producers.

Bartelsman & Wolf (2017) argue that production functions are estimated at a different level of industrial aggregation. Thus TFP dispersion is usually presented at the country level but arises from different industrial levels. For instance, Bartelsman & Wolf (2017) mention that in the U.S economy, production functions are estimated at 4-digits of NAICS (i.e. industry), while in Europe, particularly in smaller countries, the production functions are estimated at 2-digits of SIC (i.e. sector) because sample size at the sector level can be more appropriate to estimate the production function in economies with particular characteristics The decision to estimate production functions at 4-digits or 2-digits is a matter of empirical research. It relies on the author's decision and preference, considering the level of disaggregation that provides a better longitudinal sample size (Bartelsman & Wolf 2017). Harris (2021) followed the recommendation of Bartelsman & Wolf (2017) and estimated production functions at a 3-digit industry level in New Zealand. Subsequently, the production functions were aggregated under the assumption of a common (average across industries) technology in the economy. This research follows the recent literature approach and estimates production functions at 2-digits of NAICS in Mexico because this disaggregation provides a better longitudinal sample size. Subsequently, the production functions are averaged, considering a common technology across sectors in the Mexican economy (Bartelsman & Wolf 2017, Harris 2021).

4.2.1 Application of the Wooldridge model

A particular characteristic in the estimation of the Wooldridge model is that this approach only considers the number of establishments with more than one period in the sample. This feature comes from the specification of instruments with lags using the GMM framework. Chapter 2 presented the estimation of the idiosyncratic productivity in the system of equations of the Wooldridge model that accounts for lags in the control and proxy variables. The lags of these variables are included in the function of the polynomial $f^{-1}(k_{i,t-1}, m_{i,t-1})$ and the function over the polynomial $h\left(f^{-1}(k_{i,t-1}, m_{i,t-1})\right)$ (See Literature review of Chapter 2). For that reason, the specification of the Wooldridge model drops establishments in the sample with less than two periods with operations in the market because observations of those establishments cannot be instrumented using lags in the control and proxy variables.

Table 4.1 displays the sample of the Wooldridge model applied to the microdata of the Economic Census. Columns (1) and (2) of Table 4.1 classify the number of establishments by periods in the market. Microdata of the Economic Census comprises 18,832,615 observations (Table 3.2). There were excluded 15,098 observations because sectors 22 and 55 did not provide an appropriate parametrization with the Wooldridge model (Column 3). Column (4) shows the initial database to estimate the model that comprises 18,817,517 observations. Column (5) describes the loss of observations due to the dynamic instruments in the Wooldridge model. Establishments that survive in the market for one period are excluded from the estimation of the Wooldridge model because there are no dynamic instruments available in the function of the polynomial $f^{-1}(k_{i,t-1}, m_{i,t-1})$ and the function over the polynomial $h\left(f^{-1}(k_{i,t-1}, m_{i,t-1})\right)$.[1] Subsequently, establishments that survived in the market for more than one period, exclude one lagged period in the sample of the Wooldridge model due to the loss of dynamic instruments (Mollisi & Rovigatti 2017). Column (6) displays the number of establishments with a loss of observations due to variables with null values mainly coming from the variable of ln capital and ln intermediate inputs (Table 3.8). Finally, Column (7) shows the sample in the second stage of the methodology strategy. Therefore, the sample to estimate the Wooldridge model considers a sample of 6,007,240 observations (Table 4.1).

[1] In particular, the last row of Column (5) accounts for the total number of establishments (10,942,369) in the Economic Census with production data available during the period 1993-2018.

Table 4.1: Sample in the Wooldridge model.[a/]

(1) Periods in the market	(2) Number of observations	(3) Observations of sectors dropped (NAICS 22 and 55)	(4)=(2)-(3) Initial database (number of observations)	(5)=(4)/(1) Loss of observations due to dynamic instruments	(6) Loss of observations due to null values	(7)=(4)-(5)-(6) Second stage: sample
1	6,657,566	1,604	6,655,962	6,655,962	0	0
2	4,473,800	1,568	4,472,232	2,236,108	600,610	1,635,514
3	3,214,191	1,378	3,212,813	1,070,938	540,657	1,601,218
4	1,805,192	1,284	1,803,908	450,967	307,060	1,045,881
5	2,498,560	9,264	2,489,296	497,843	372,463	1,618,990
6	183,306	0	183,306	30,551	47,118	105,637
Total	**18,832,615**	**15,098**	**18,817,517**	**10,942,369**	**1,867,908**	**6,007,240**

[a/] Total number of observations in Column 2 is equivalent to total observations in Table 3.2.
Source: Own elaboration using microdata of the Economic Census of Mexico.

The estimation sample in the Wooldridge model is representative as there are only excluded observations without dynamic instruments and information unavailable of capital and intermediate inputs at the establishment level. The exclusion of the observations in the Wooldridge model overcomes the simultaneity bias because TFP and factors of production are determined simultaneously over time. Then, observations without a dynamic framework do not add relevant information for estimating the elasticities in the production function.

Table 4.2 displays the microdata coverage of the Economic Census with the estimation of the Wooldridge model by economic sector (2-digits of NAICS). Column (4) of Table 4.2 shows that there were considered 4,210,245 establishments (N) to estimate the Wooldridge model. Column (5) displays that there were6,007,240 observations in the dimension of the unbalanced Panel Data (NT) in the Wooldridge model. These observations can be instrumented with lags in the control and proxy variables. Column (6) shows that there are 18,817,517 observations in the microdata of the Economic Census in Mexico for the period 1993-2018. Then, the Wooldridge model covered 32% of the microdata (Column (7)). The percentage of microdata coverage using the Wooldridge model varies per economic sector. The highest coverage is the agriculture sector, with 42%, while the lowest coverage is the information sector, with 17%.

There were estimated 20 production functions with a mark-up correction using the Wooldridge model. One production function per economic sector (2-digits NAICS) using the sample presented in Table 4.2. The parametric estimation of the Wooldridge model allows estimating the inverse of the demand function $1/\sigma$ and with this parameter, it is possible to calculate the factor of mark-up correction $\sigma/(\sigma-1)$. The product of the mark-up correction $\sigma/(\sigma-1)$ and the production function is expressed as $((\sigma-1)/\sigma)\left(\alpha_m m_{it}+\alpha_l l_{it}+\alpha_k k_{it}+\mathrm{x}_{it}'\alpha_{\mathrm{x}}+\alpha_T t\right)$. The estimation of the parameter $1/\sigma$ allows separating the mark-up factor from the elasticities in the production function.[2]

[2]The constant term in the production function using the Wooldridge model is omitted as the routine of Mollisi & Rovigatti (2017) specifies. The relevant parameters are the elasticities as well as the effect and significance of the TFP determinants.

Table 4.2: Microdata coverage of the Economic Census with the estimation of the production function with the mark-up correction using the Wooldridge model, 1993-2018 [a/]

(1) Sector	(2) NAICS code	(3) Economic sector	(4) Establishments (N) in the sample	(5) Observations (NT) in the sample of estimation	(6) Total observations	(7)=(5)/(6) Percentage of coverage
1	11	Agriculture	26,437	45,240	107,188	42%
2	21	Mining	4,134	5,823	17,926	32%
3	23	Construction	16,331	25,862	83,251	31%
4	31	Manufacturing (food, beverage, etc.)	290,029	407,690	1,329,382	31%
5	32	Manufacturing (wood, paper, etc.)	98,835	137,558	460,931	30%
6	33	Manufacturing (primary metals, machinery, etc.)	137,763	212,018	640,085	33%
7	43	Wholesale	124,001	160,460	601,673	27%
8	46	Retail trade	2,004,000	2,788,694	8,570,891	33%
9	48	Transportation	23,841	34,850	127,359	27%
10	49	Postal services and warehouse	2,304	2,287	13,186	17%
11	51	Information	7,251	8,349	56,225	15%
12	52	Finance and Insurance	18,239	22,250	86,100	26%
13	53	Real estate, rental and leasing	55,779	68,692	267,059	26%
14	54	Professional, scientific, and technical services	83,137	133,909	413,834	32%
15	56	Administrative support and waste management.	63,847	80,738	315,300	26%
16	61	Educational services	44,885	72,797	208,076	35%
17	62	Health care and social assistance	167,151	271,786	723,413	38%
18	71	Arts, entertainment, and recreation	39,059	48,894	206,549	24%
19	72	Accommodation and food services	430,679	562,602	2,054,410	27%
20	81	Other services (except public administration)	572,543	916,741	2,534,679	36%
		Total	4,210,245	6,007,240	18,817,517	32%

[a/] Total number of observations in Column 6 is equivalent to total observations in Column 4 of Table 4.1

Source: Own elaboration using microdata of the Economic Census of Mexico.

The extended results on the parametric estimation of the production function with mark-up correction are in Tables 4.3, 4.4, 4.5 and 4.6.

Table 4.3: Parameters estimated in the production function with mark-up correction using the Wooldridge model by economic sector (NAICS, 2 digits) in Mexico, 1993-2018. Economic sectors (11-32).[a/]

Parameter	NAICS (2 digits) Dependent: ln gross output	11 Agriculture	21 Mining	23 Construction	31 Manufacturing (food, beverage, tobacco, etc.)	32 Manufacturing (wood, paper, printing, etc.)
α_m	ln intermediate inputs	0.586***	0.898***	0.789***	0.807***	0.851***
		(0.009)	(0.032)	(0.004)	(0.001)	(0.002)
α_l	ln employment	0.263***	0.504***	0.168***	0.193***	0.172***
		(0.005)	(0.026)	(0.003)	(0.001)	(0.002)
α_k	ln capital	0.084***	0.128***	0.027***	0.034***	0.028***
		(0.005)	(0.013)	(0.002)	(0.001)	(0.001)
α_x	ln age	0.012**	-0.009	0.003	0.015***	0.007***
		(0.006)	(0.019)	(0.004)	(0.001)	(0.002)
	ln fixed costs ratio	0.001***	-0.011***	0.001**	0.000	-0.001***
		(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
	ln HHI	0.115***	0.043	0.001	-0.015***	0.008***
		(0.007)	(0.034)	(0.003)	(0.002)	(0.002)
	ln population density	-0.025***	0.058***	-0.005***	0.002***	-0.012***
		(0.003)	(0.009)	(0.002)	(0.001)	(0.001)
	ln agglomeration index	0.057***	0.122***	0.014***	0.012***	0.006***
		(0.003)	(0.009)	(0.002)	(0.001)	(0.001)
	ln diversification index	-0.007	-0.042	-0.025***	0.001	0.044***
		(0.009)	(0.041)	(0.008)	(0.003)	(0.003)
α_T	time-trend	-0.185***	-0.105***	-0.009***	0.008***	0.000
		(0.005)	(0.012)	(0.003)	(0.001)	(0.001)
$1/\sigma$	Inverse of the elasticity of demand	0.058***	0.363***	-0.020***	-0.001	0.004***
		(0.014)	(0.019)	(0.003)	(0.002)	(0.002)
$\sigma/(\sigma$-1)	Mark-up correction	1.062***	1.570***	0.980***	0.998***	1.005***
		(0.015)	(0.044)	(0.002)	(0.001)	(0.001)
N	Observations	45,240	5,823	25,862	407,690	137,558

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a/] Sample per sector is presented in Column 5 of Table 4.2
Source: Own estimations using the Economic Census of Mexico collected by INEGI

Table 4.4: Parameters estimated in the production function with mark-up correction using the Wooldridge model by economic sector (NAICS, 2 digits) in Mexico, 1993-2018. Economic sectors (33-49).[a/]

Parameter	NAICS (2 digits) Dependent: ln gross output	33 Manufacturing (machinery, computers, electronics, etc.)	43 Wholesale	46 Retail trade	48 Transport	49 Postal service and warehousing
α_m	ln intermediate inputs	0.872***	0.513***	0.579***	0.733***	0.615***
		(0.002)	(0.003)	(0.001)	(0.005)	(0.021)
α_l	ln employment	0.241***	0.460***	0.458***	0.309***	0.317***
		(0.001)	(0.004)	(0.001)	(0.005)	(0.018)
α_k	ln capital	0.011***	0.080***	0.065***	0.062***	0.035***
		(0.001)	(0.002)	(0.001)	(0.004)	(0.011)
α_x	ln age	0.009***	0.012***	0.073***	-0.000	0.104***
		(0.001)	(0.004)	(0.001)	(0.005)	(0.017)
	ln fixed costs ratio	-0.002***	-0.033***	-0.014***	0.003***	0.015***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
	ln HHI	0.016***	0.054***	0.117***	0.117***	-0.113***
		(0.002)	(0.003)	(0.001)	(0.004)	(0.012)
	ln population density	-0.007***	-0.021***	0.015***	-0.014***	-0.007
		(0.001)	(0.002)	(0.001)	(0.002)	(0.008)
	ln agglomeration index	0.014***	0.073***	0.051***	0.068***	0.063***
		(0.001)	(0.002)	(0.001)	(0.003)	(0.009)
	ln diversification index	0.001	-0.106***	-0.124***	-0.020***	-0.032
		(0.002)	(0.009)	(0.006)	(0.007)	(0.035)
α_T	time-trend	0.009***	-0.008***	-0.063***	-0.009***	-0.047***
		(0.001)	(0.003)	(0.001)	(0.003)	(0.012)
$1/\sigma$	Inverse of the elasticity of demand	-0.007***	0.043***	0.150***	0.102***	0.022
		(0.003)	(0.003)	(0.001)	(0.003)	(0.019)
$\sigma/(\sigma$-1)	Mark-up correction	0.993***	1.045***	1.176***	1.113***	1.023***
		(0.001)	(0.002)	(0.001)	(0.003)	(0.019)
N	Observations	212,018	160,460	2,788,694	34,850	2,287

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a/] Sample per sector is presented in Column 5 of Table 4.2

Source: Own estimations using the Economic Census of Mexico collected by INEGI

Table 4.5: Parameters estimated in the production function with mark-up correction using the Wooldridge model by economic sector (NAICS, 2 digits) in Mexico, 1993-2018. Economic sectors (51-56).[a/]

Parameter	NAICS (2 digits) Dependent: ln gross output	51 Information	52 Finance and Insurance	53 Real Estate and Rental and Leasing	54 Professional, Scientific, and Technical Services	56 Administrative Support and Waste Management
α_m	ln intermediate inputs	0.728***	0.731***	0.808***	0.804***	0.914***
		(0.013)	(0.008)	(0.005)	(0.005)	(0.008)
α_l	ln employment	0.274***	0.390***	0.253***	0.537***	0.525***
		(0.012)	(0.010)	(0.005)	(0.004)	(0.005)
α_k	ln capital	0.045***	0.059***	0.046***	0.090***	0.031***
		(0.006)	(0.004)	(0.002)	(0.002)	(0.003)
α_x	ln age	0.078***	0.051***	0.066***	0.079***	0.083***
		(0.009)	(0.009)	(0.005)	(0.003)	(0.004)
	ln fixed costs ratio	0.000	0.012***	-0.000	-0.001***	-0.005***
		(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
	ln HHI	0.007	-0.073***	0.087***	-0.024***	0.169***
		(0.006)	(0.006)	(0.003)	(0.003)	(0.009)
	ln population density	-0.037***	-0.018***	-0.003*	-0.021***	-0.009***
		(0.005)	(0.004)	(0.002)	(0.002)	(0.002)
	ln agglomeration index	0.103***	0.060***	0.055***	0.062***	0.033***
		(0.007)	(0.004)	(0.003)	(0.002)	(0.003)
	ln diversification index	-0.142***	-0.197***	-0.064***	-0.054***	-0.007
		(0.021)	(0.019)	(0.012)	(0.011)	(0.006)
α_T	time-trend	0.196***	0.053***	-0.030***	-0.018***	-0.021***
		(0.008)	(0.007)	(0.004)	(0.003)	(0.005)
$1/\sigma$	Inverse of the elasticity of demand	0.079***	0.108***	0.120***	0.221***	0.208***
		(0.009)	(0.008)	(0.004)	(0.005)	(0.007)
$\sigma/(\sigma$-1)	Mark-up correction	1.087***	1.120***	1.136***	1.284***	1.263***
		(0.009)	(0.009)	(0.004)	(0.006)	(0.009)
N	Observations	8,349	22,250	68,692	133,909	80,738

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a/] Sample per sector is presented in Column 5 of Table 4.2

Source: Own estimations using the Economic Census of Mexico collected by INEGI

Table 4.6: Parameters estimated in the production function with mark-up correction using the Wooldridge model by economic sector (NAICS, 2 digits) in Mexico, 1993-2018. Economic sectors (61-81).[a/]

Parameter	NAICS (2 digits) Dependent: ln gross output	61 Educational Services	62 Health Care and Social Assistance	71 Arts, Entertainment, and Recreation	72 Accommodation and Food Services	81 Other Services (except Public Administration
α_m	ln intermediate inputs	0.443***	0.823***	0.679***	0.821***	0.732***
		(0.004)	(0.003)	(0.005)	(0.001)	(0.001)
α_l	ln employment	0.651***	0.397***	0.300***	0.254***	0.357***
		(0.004)	(0.003)	(0.006)	(0.001)	(0.001)
α_k	ln capital	0.067***	0.067***	0.047***	0.019***	0.042***
		(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
α_x	ln age	0.083***	0.059***	0.057***	0.026***	0.060***
		(0.004)	(0.002)	(0.004)	(0.001)	(0.001)
	ln fixed costs ratio	-0.000	-0.008***	-0.000	0.001***	-0.002***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	ln HHI	0.015***	0.038***	-0.004*	0.031***	0.013***
		(0.004)	(0.002)	(0.003)	(0.001)	(0.001)
	ln population density	-0.004***	-0.015***	0.000	-0.002***	-0.005***
		(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
	ln agglomeration index	0.052***	0.077***	0.055***	0.021***	0.027***
		(0.003)	(0.002)	(0.003)	(0.001)	(0.001)
	ln diversification index	-0.174***	-0.177***	-0.065***	-0.008**	-0.026***
		(0.013)	(0.009)	(0.012)	(0.004)	(0.006)
α_T	time-trend	-0.085***	-0.096***	-0.088***	0.021***	-0.027***
		(0.003)	(0.002)	(0.004)	(0.001)	(0.001)
$1/\sigma$	Inverse of the elasticity of demand	0.065***	0.197***	0.047***	0.020***	0.049***
		(0.004)	(0.003)	(0.005)	(0.002)	(0.001)
$\sigma/(\sigma\text{-}1)$	Mark-up correction	1.070***	1.245***	1.050***	1.021***	1.052***
		(0.003)	(0.004)	(0.004)	(0.001)	(0.001)
N	Observations	72,797	271,786	48,894	562,602	916,741

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a/] Sample per sector is presented in Column 5 of Table 4.2

Source: Own estimations using the Economic Census of Mexico collected by INEGI

In particular, the Wooldridge model applied to medium and large manufacturing establishments in the first stage (Table 3.11) can be applied to the dataset of the second stage that comprises all establishments in the manufacturing sector by 2-digits of NAICS (Tables 4.3-4.4) as well as the rest of sectors. This argument is plausible because a similar parametrical method can be applied to different subsamples to evaluate disaggregated effects across selected (disaggregated) samples. According to the literature, Konings & Vanormelingen (2015) evaluated the effect of training on productivity in different subsamples to provide evidence of the measurement of production functions with disaggregated samples. The general estimation of the effect of training on productivity accounts for the estimation of a production function in two large sectors, including manufacturing and non-manufacturing in a firm-level dataset of Belgium. Subsequently, Konings & Vanormelingen (2015) disaggregated the large sample into subsamples of 2-digit sectors and estimated production functions by sectors, including the variable of training.

The objective of the first stage was the parametrical comparison, which is usually possible by selecting a subsample. For instance, Van Beveren (2012) selected the industry of Food and Beverages in Belgium to compare different parametric (econometric) methods (but it was omitted the SF models). Although TFP estimates do not lead to large differences across parametric methods (Figure 3.1 and Table 3.11), the parametrical results can have variations in magnitude, direction and significance. For instance, the elasticities in the sample of large and medium establishments have larger elasticities of capital and employment but are lower in intermediate inputs compared to the total sample of establishments in the manufacturing sector (Table 3.11 and Tables 4.3-4.4). This result implies that large and medium establishments are more intensive in capital and employment than their counterparts. Including micro, small, medium and large manufacturing establishments into a single production function accounts for a common technology (and thus common elasticities), but the differences in efficiency are measured by the heterogeneity of TFP across establishments.

The recent paper of Iacovone et al. (2022) divided TFP determinants at the firm level in Mexico into two categories: firm premium and location premium. On the one hand, firm premium refers to the firms' variables that capture more efficient production processes. These variables include (i) credit access, (ii) contractual enforcement, (iii) Global Value Chain (GVC), and (iv) management quality and innovation. On the other hand, the location premium refers to the place that allows firms and workers to be more productive. Iacovone et al. (2022) argue that the drivers of local productivity in Mexico are (i) urbanisation, (ii) access to markets and connectivity, (iii) human capital externalities and universities, and (iv) specialisation and clustering. Iacovone et al. (2022) explored the TFP determinants using different specifications in the models and various datasets (See online appendix in Iacovone et al. (2022)). For that reason, there are different sets of TFP determinants in this thesis and Iacovone et al. (2022) because this PhD thesis uses the Economic Census in Mexico as a unique source of information to cover the statistical universe of establishments in Mexico extensively over the period 1993-2018 and to provide a granular analysis of the TFP determinants at the establishment level. The extensive use of the Economic Census in the TFP analysis is the main difference between this study and Iacovone et al. (2022). The positive effect of externalities (agglomeration) is the TFP determinant in which this thesis and Iacovone et al. (2022) provide similar arguments. Future research can combine the Economic Census with other sources of information to explore other TFP determinants, particularly Spatial TFP determinants (e.g. public infrastructure, and institutions).

4.2.2 Elasticities and mark-up by economic sectors

The extended results of the parametric estimation in Tables 4.3-4.6 are analysed in two parts. The first part of the analysis is presented in Table 4.7, which shows the elasticities in the factors of production (α_m, α_l, α_k), the inverse of the demand CES function $1/\sigma$ and the mark-up correction in the production function $\sigma/(\sigma-1)$ per economic sector. This analysis focuses on comparing the magnitudes of the elasticities, the parameter $1/\sigma$ and the mark-up correction component $\sigma/(\sigma-1)$. The second part analyses the sign of the effect (positive or negative) in the parameters of the production function with particular attention to the analysis of the parameters included in the vector of TFP determinants α_{x} as well as the parameter describing the Hicks-neutral technical change α_T. The second part of the parametric analysis is presented in Table 4.8.

The estimated elasticities across economic sectors are positive and statistically significant. The results of the elasticities, the inverse of the demand function and the mark-up correction factor are summarised as follows:

- The magnitude in the elasticity of the intermediate inputs is in the range of $0.513 < \alpha_m < 0.914$, and it was statistically significant across sectors. The meaning about the magnitude of these elasticities is that if the intermediate inputs of the Mexican establishments m_{it} increases by 1%, the real revenue of the establishments $\tilde{r}_{it}$ will increase between 0.513% and 0.914%, depending on the economic sector.[3]
- As expected, the elasticity of the intermediate inputs α_m is the highest in most of the economic sectors. The only sector in which α_l is higher than α_m is the educational services. There is inferred that employment is more important in the education sector due to a large proportion of education staff (e.g., professors, teachers, researchers) compared to the infrastructure. The educational sector can be better described as intensive in using human capital instead of describing this sector as labour-intensive per se.
- In all sectors, the employment elasticity α_l has a higher magnitude than the elasticity of capital α_k. This estimation means that the establishments of the Mexican economy are more intensive in employment l_{it} than in capital k_{it}. The elasticity of employment α_l is in the range of $0.168 < \alpha_l < 0.651$, it was statistically significant in all the production functions. Then, the increase of 1% in employment l_{it} causes the real revenue of the establishments $\tilde{r}_{it}$ increases between 0.168% and 0.651%, depending on the economic sector.
- The elasticity of capital is in the range of $0.0196 < \alpha_k < 0.128$, it was statistically significant in all the production functions estimated across sectors. However, the magnitude of the elasticity of capital is low as $\alpha_k < 0.1$ in 19 of 20 economic sectors. The only exception is the mining sector. The low magnitude of the elasticity α_k means that if the capital stock of the

[3] However, the elasticity has to be multiplied by the mark-up $\sigma/(\sigma-1)$

Table 4.7: Summary of the main parameters estimated in the production function with mark-up correction using the Wooldridge model by economic sector (2 digits of NAICS) in Mexico, 1993-2018.[a/]

NAICS code	**11**	**21**	**23**	**31**
Parameters	**Agriculture**	**Mining**	**Construction**	**Manufacturing (food, beverage, tobacco, etc.)**
α_m	0.586***	0.898***	0.789***	0.807***
α_l	0.263***	0.504***	0.168***	0.193***
α_k	0.084***	0.128***	0.027***	0.034***
$1/\sigma$	0.058***	0.363***	-0.020***	-0.001
$\sigma/(\sigma$-1)	1.062***	1.570***	0.980***	0.998***
NAICS code	**32**	**33**	**43**	**46**
Parameters	**Manufacturing (wood, paper, printing, etc)**	**Manufacturing (machinery, computers, electronics, etc.)**	**Wholesale**	**Retail trade**
α_m	0.851***	0.872***	0.513***	0.579***
α_l	0.172***	0.241***	0.460***	0.458***
α_k	0.028***	0.011***	0.080***	0.065***
$1/\sigma$	0.004***	-0.007***	0.043***	0.150***
$\sigma/(\sigma$-1)	1.005***	0.993***	1.045***	1.176***
NAICS code	**48**	**49**	**51**	**52**
Parameters	**Transport**	**Postal service and warehousing**	**Information**	**Finance and Insurance**
α_m	0.733***	0.615***	0.728***	0.731***
α_l	0.309***	0.317***	0.274***	0.390***
α_k	0.062***	0.035***	0.045***	0.059***
$1/\sigma$	0.102***	0.022	0.079***	0.108***
$\sigma/(\sigma$-1)	1.113***	1.023***	1.087***	1.120***
NAICS code	**53**	**54**	**56**	**61**
Parameters	**Real Estate and Rental and Leasing**	**Professional, Scientific, and Technical Services.**	**Administrative Support and Waste Management**	**Educational Services**
α_m	0.808***	0.804***	0.914***	0.443***
α_l	0.253***	0.537***	0.525***	0.651***
α_k	0.046***	0.090***	0.031***	0.067***
$1/\sigma$	0.120***	0.221***	0.208***	0.065***
$\sigma/(\sigma$-1)	1.136***	1.284***	1.263***	1.070***
NAICS code	**62**	**71**	**72**	**81**
Parameters	**Health Care and Social Assistance**	**Arts, Entertainment, and Recreation**	**Accommodation and Food Services**	**Other Services (except Public Administration**
α_m	0.823***	0.679***	0.821***	0.732***
α_l	0.397***	0.300***	0.254***	0.357***
α_k	0.067***	0.047***	0.019***	0.042***
$1/\sigma$	0.197***	0.047***	0.020***	0.049***
$\sigma/(\sigma$-1)	1.245***	1.050***	1.021***	1.052***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a/] Main parameters of Table 4.3, 4.4, 4.5 and 4.6.

Source: Own estimation using microdata of the Economic Census of Mexico

Mexican establishments k_{it} increases by 1%, the real revenue of the establishments $\tilde{r}_{it}$ will increase lower than 0.1% in 19 of 20 economic sectors. In the mining sector, the increase of 1% in capital k_{it} causes that $\tilde{r}_{it}$ increases by 0.128%. This estimation describes low returns of capital in the Mexican economy.

- The negative parameter $-\sigma$ represents the negative relationship between output and price in the CES demand function of the mark-up model, described in Appendix C. Table 4.7 presents the estimation of the inverse elasticity in the CES demand function $1/\sigma$. The magnitude of this parameter must be in an appropriate range to estimate plausible magnitudes in the mark-up correction $\sigma/(\sigma-1)$. In this case, the parameter $(1/\sigma)$ was in the range of $-0.002<(1/\sigma)<0.363$. In two economic sectors, this parameter was not statistically significant, but the parameter of relevance is that the mark-up factor of correction $\sigma/(\sigma-1)$ was statistically significant in all sectors.

- The parameter that estimates the mark-up correction $\sigma/(\sigma-1)$ is in the range of $0.98<\sigma/(\sigma-1)<1.57$. Therefore, the omitted price bias is corrected in the production function with the mark-up factor. In addition, the magnitude of the mark-up factor across economic sectors measures the price over the marginal cost, reflecting the extent to which the establishment exploits its market power (Klette & Griliches 1996). The results in Table 4.7 indicate that the parameter $\sigma/(\sigma-1)<1$ in 3 economic sectors. As a result, three sectors present a mark-down correction factor while 17 sectors present a mark-up. The highest magnitude of the mark-up correction is in the mining sector, equivalent to $\sigma/(\sigma-1)=1.57$. This fact is explained because the parameter $1/\sigma$ estimated is high, mainly caused by a high output concentration in this sector. Harris (2021) estimated the production function with mark-up correction using the microdata of New Zealand. The magnitudes of the mark-up (and mark-down) are in the range of $0.895<\sigma/(\sigma-1)<1.252$.

4.2.3 TFP determinants at the establishment level in Mexico

Table 4.8 replicates the analysis in Chapter 3 about the categorisation of the parameters in the production function by their statistical significance and effect. Table 4.8 summarises the factors of production, TFP determinants, the inverse of demand and the mark-up factor of correction divided into three categories according to values of the parametric estimation: statistically significant and not significant.

In Table 4.8, Column (1) represents the number of production functions in Tables 4.3-4.6, where the variable was statistically significant. The significance of a variable is divided according to the sign of the parameter: positive or negative. Column (1) of green cells displays the highest number of sectors estimated in each TFP determinant (i.e. largest frequency). This effect means the highest number of production functions with a particular effect per variable (in a row). Then, cells in green provide evidence of the TFP determinants with large frequency and significance across economic sectors to identify the impact of the TFP determinant (positive or negative). On the contrary, the cells in red in Column (1) do not provide evidence of large frequency. Column (2) includes the number of production functions in which the variables were not statistically significant. Column (3) is the total number of production functions (economic sectors) estimated.

Table 4.8: Parameters estimated in the production functions with mark-up correction using the Wooldridge model classified by the sign of the parameter and statistical significance [a/]

Variables		Column (1) Statistically significant		Column (2)	Column (3)
		Positive	Negative	Not significant	Total
	α_m	20	0	0	20
	α_l	20	0	0	20
	α_k	20	0	0	20
α_{x}	ln age	17	0	3	20
α_{x}	ln fixed costs ratio	6	9	5	20
α_{x}	ln HHI	12	4	4	20
α_{x}	ln population density	3	14	3	20
α_{x}	ln agglomeration index	20	0	0	20
α_{x}	ln diversification index	1	13	6	20
	α_T	5	14	1	20
	$1/\sigma$	16	2	2	20
	$\sigma/(\sigma\text{-}1)$	20	0	0	20

[a/] Cells in green display the highest number of sectors in each row (i.e. large frequency). Most of the TFP determinants were statistically significant ($p<0.05$) in more than 50% of the sectors estimated (>10). The only exception is the ln fixed cost ratio, which was significant in 9 sectors (45% of the total sectors estimated).
Source: Own estimation using microdata of the Economic Census of Mexico

Table 4.8 reports that the elasticities in the factors of production (α_m, α_l, α_k) are positive and statistically significant in all economic sectors. The most relevant analysis of Table 4.8 is the examination of the effect (positive/negative) and the significance of the TFP determinants according to the parameters in the vector α_{x}. The TFP determinants can be categorised into Non-Spatial and Spatial. The main parametric results of the TFP determinants are the following:

Non-Spatial TFP determinants.

1. Endogenous Growth Theory.

   - The variable ln age tested the ability of the establishments to increase TFP over time through the learning channel, which encourages an endogenous growth of the efficiency in the establishment. Table 4.8 shows that the variable ln age was positive and statistically significant in 17 economic sectors. Therefore, establishments in the Mexican economy improve their efficiency with better production processes over time. There is conclusive evidence to define age as a determinant with positive effects on TFP at the establishment level in Mexico. This result is related to the finding of the life cycle and TFP that positively associates TFP and age in Hsieh & Klenow (2014). Harris & Moffat (2015*a*) and Ding et al. (2016) found that firm age negatively affected TFP at the plant level in Great Britain and China, respectively. Those studies conclude that a firm's age has a vintage effect on TFP due to the deterioration of the capital factor instead of the learning-by-doing effect. The relationship between age and TFP can depend on the magnitude of the elasticity of the capital factor. The magnitudes in the elasticities of capital across sectors reflect the extent to which an economy's production relies on capital. For instance, Harris & Moffat (2015*a*) and Ding et al. (2016) estimated larger elasticities of capital across sectors in Great Britain and China than the elasticities of capital in the Mexican economy (Table 4.7). Then, the British and Chinese economies are more intensive in capital. The deterioration of capital over time causes a decrease in efficiency, affecting Great Britain and China to a larger extent. On the contrary, the Mexican economy relies to a larger extent on the employment factor; as a result, the process of learning by doing is more evident in the production process as a worker with more experience develops more capabilities that get reflected in a better efficiency on the production process. This result is relevant because emergent economies are more intensive in employment, and thus the development of technical capabilities and specialisation generate more experience to reach higher efficiency. Future research can provide more evidence of whether the relationship between age and TFP at the establishment level tends to be positive in emergent economies intensive in employment.

2. Non-Competitive markets.

   - The variable ln fixed costs ratio tested whether managerial efforts and capabilities that reduce fixed costs lead to higher TFP. It was estimated that in 9 of 20 production functions (45% in the total sectors), which is a significant effect across sectors. The relation between ln fixed cost ratio and ln TFP at the establishment level had a negative and significant effect. This negative relationship means that high fixed costs decrease TFP. For that reason, the managerial and organisational efforts or capabilities to reduce costs in the production process increase efficiency. Ding et al. (2016) and Harris & Li (2019) also found a negative effect of fixed costs on TFP in China. In addition, Bloom et al. (2022) found that better managerial practices can create a better allocation of resources and thus higher efficiency. Policies of zero waste or reduction of costs, such as the process implemented by Just In Time (JIT) manufacturing, improve efficiency in manufacturing or the services sector. The results in Tables 4.3-4.6 show that the fixed cost reduction increases TFP in three manufacturing economic sectors and six economic sectors of services at 2-digits of NAICS.

- The ln HHI tested whether low or high sectorial competition reduces TFP at the establishment level. The results indicate that high levels of ln HHI positively impacted ln TFP in 12 of 20 economic sectors. Thus, in most economic sectors, low competition increases efficiency at the establishment level in Mexico. The conclusions of the Schumpeterian models can be a framework to explain this result. These models account for the fact that in industries with low levels of competition, the innovator monopoly rights are granted to incentive investment in R&D and innovation through a patent system. Ultimately, Schumpeterian models predict firms with high concentration generate higher R&D, increasing efficiency in particular industries. For that reason, high levels of competition are not necessarily reflected in high levels of productivity. In addition, under some conditions, high competition can lower the expected income of managers, and managers' efforts can be reflected in reductions in productivity levels (Aghion et al. 2001, Aghion & Howitt 1990, Grossman & Helpman 1991). The positive relationship between ln HHI and ln TFP in most Mexican economic sectors is explained because establishments that concentrate a large share of the output within the industry group (4-digits of NAICS) also have high levels of efficiency. The results provide evidence that establishments with high output concentration might have better technology and technical efficiency in their production process, increasing TFP. Aghion et al. (2005) argue that there is an inverted-U shape between competition and productivity growth. A future line of research can investigate whether there is a potential non-linear effect from the HHI to TFP at the establishment level.
- However, Table 4.3 indicates that HHI negatively affects TFP in the manufacturing sector that produces food, beverages, etc. (NAICS code 31). This result is similar to the paper of Rodríguez-Castelán et al. (2020), which reports a negative effect of HHI on TFP at the establishment level in the Mexican manufacturing sector. Rodríguez-Castelán et al. (2020) applied the pooled model, FE model and OP model to calculate TFP, and they regressed TFP with industrial concentration and trade exposure variables. Rodríguez-Castelán et al. (2020) concluded that there is a negative and statistically significant impact of the HHI on TFP in 10 of 20 subsectors of the manufacturing sector. However, the parametric results of Rodríguez-Castelán et al. (2020) can have a bias caused by the dependence on the input elasticities estimated with the OP model (Ackerberg et al. 2015). The negative relationship between HHI and TFP in the manufacturing sector dedicated to producing food, beverages, etc. (NAICS 31) is relevant for the productivity analysis because this sector is the fourth sector with more observations in the sample (Table 4.2). However, the negative effect of the HHI in the manufacturing sector is not representative of the whole Mexican economy because sector 31 only represents 6.7% of the sample used to estimate the Wooldridge model (Table 4.2).

Spatial TFP determinants.

1. Spatial Economics

    - The literature points out that space is not neutral in the determination of productivity, and there are "place effects" that generate the concentration of resources due to their natural advantages, considered Ricardian comparative advantages. The concentration of resources can generate higher efficiency. For that reason, the variable ln population density was included as a TFP determinant in the production function to test whether locations with high population concentration generate higher levels of TFP at the establishment level. Table 4.8 indicates that this variable had a negative effect and was statistically significant in 9 production functions estimated across 20 economic sectors. Then, there is no evidence to support the hypothesis that municipalities with more population increase TFP at the establishment level in 9 of 20 economic sectors of Mexico. For that reason, a high population density does not necessarily create a context to increase efficiency at the establishment level. Therefore, in 9 economic sectors, there is evidence that ln population density negatively affects TFP at the establishment level. For instance, Ding et al. (2016) indicated that the population size has a negative spillover in Chinese cities due to congestion costs that affect Chinese firms' productivity. However, it is relevant that population density positively impacts TFP in the retail trade sector (Table 4.4). For that reason, an association indicates that largely populated municipalities have a positive effect on the TFP of the retail sector. The retail trade sector (NAICS 46) is particularly important because it is the largest sector in the Mexican economy, concentrating 41.6% of the establishments in 2018. Then large cities (with high population concentration) benefit from TFP of the retail sector. The reason is that Mexican municipalities with high population concentration also generate positive localisation externalities in the retail sector due to proximity to large markets (with high populations). In addition, largely populated municipalities can also minimise costs in the retail sector, which gets reflected in the negative parameter of the variable ln fixed costs in Table 4.4.
    - The variables ln agglomeration is a proxy variable to the MAR externalities. Table 4.8 shows that the agglomeration index was positive and statistically significant in all the economic sectors of Mexico. This result indicates that a high agglomeration of the output of the same industry group (4-digit NAICS code) in a Mexican municipality has a positive effect on TFP at the establishment level across all economic sectors. Therefore, there are positive agglomeration externalities due to the MAR spillovers in the Mexican economy. This result indicates that geographical specialisation generates a positive effect on TFP. MAR externalities result from a large concentration of establishments in the same industry in a geographical vicinity, also labelled intra-industrial externalities. Establishments of the same industry in the same Mexican municipality can generate

higher efficiency by sharing resources and infrastructure, matching workers' skills with the skills that the establishments need, and there is a learning process through the generation, diffusion, and accumulation of knowledge between establishments (Harris & Moffat 2015*a*). The positive relationship between MAR externalities and TFP is also identified by Henderson et al. (1995). In that work, Henderson et al. (1995) found that MAR externalities have a positive impact on the efficiency of the manufacturing sector in the U.S., but Jacobian externalities have no effect on productivity. The results in Tables 4.3-4.6 indicate that the elasticity of the ln agglomeration index is higher in sectors characterised by a higher specialisation, such as the mining and the information sector. This result indicates that MAR externalities are a spatial channel that positively determines TFP of Mexican establishments.

- Literature accounts that a wide variety of industries in the same geographical vicinity can generate positive effects on establishment productivity, known as Jacobian externalities. However, there can be cases in which the diversity of industries causes inefficiencies due to congestion costs. For that reason, Jacobian externalities are considered the result of inter-industrial interactions that generate a positive or negative effect on productivity, depending on the sector. Including the ln diversification index in the production function is a proxy variable to Jacobian externalities. Table 4.8 indicates that the diversification index presents a negative and statistically significant effect on TFP at the establishment level in 13 economic sectors. For that reason, a high diversification of economic activities affects productivity. This result reflects that diversification spillovers may generate congestion costs that negatively affect TFP at the establishment level. It is generally recognised that urban areas are characterised to have a wider diversity of industries. The negative effect of Jacobian externalities can be related to the effect of 'isolated firms' that do not find incentives to locate in denser urban areas due to the expensive rents and high wages (Puga 2010). Therefore, negative Jacobian externalities are the result of urbanisation costs. These results indicate that wide diversity in urban areas cause congestion effects, which is reflected in lower efficiency at the establishment level.

In addition, the time trend in the production function with mark-up correction was negative and significant in 14 production functions. Therefore, there is evidence to accept the hypothesis that there is a decrease in TFP in most economic sectors due to the exogenous and disembodied efficiency deterioration over time. This result reflects a negative Hicks-neutral technical change.[4] It is difficult to assume that a negative technical change affects all establishments in Mexico. Instead, the time trend could reflect an 'average' effect across establishments where TFP decreased from 1993 to 2018. This result is consistent with the evidence in Figure 1.4, which displays the growth accounting estimated by INEGI. In Figure 1.4, TFP growth is negative, which implies that TFP

[4]Hicks-neutral technological change improves efficiency to the factors of production in the same extent. In contrary, Harrod-neutral technological change is labour augmenting and Solow-neutral technological change is capital augmenting (Chen 1997).

has followed an 'average' downward trend from 1991 to 2018 in Mexico. Finally, the inverse of the CES demand $1/\sigma$ was positive and statistically significant in 16 economic sectors, and the factor of mark-up (mark-down) correction was positive and statistically significant in all economic sectors. The following section describes the estimation of TFP at the establishment level using the parametric estimation of the production functions by economic sector in Tables 4.3-4.6.

4.3 Estimation of TFP at the establishment level

The calculation of TFP at the establishment level follows the approach of Harris (2021). According to that approach, it is necessary to calculate common output elasticities (average across industries) that account for common technology rather than individual elasticities at the economic sector level. Harris (2021) pointed out that using common elasticities is necessary due to the need for a multilateral index of TFP to make comparisons across industries using a reference technology. Then, the parameters estimated in the production functions by the economic sector are weighted and aggregated in a single production function. The elasticities of the production functions with the mark-up correction presented in Table 4.7 were weighted with the output share of the sector e (2-digits of NAICS code) in the Mexican economy for the period 1998-2018. Output weights at the sectoral level are calculated in equation 4.1.

$$\theta_e = \frac{\sum Y_{it}^e}{\sum Y_{it}} \tag{4.1}$$

The elasticities of Table 4.7 are weighted and aggregated across sectors $e = 1, 2, \ldots, 20$ as follows:

$$\dot{\alpha}_m = \sum_{e=1}^{E} \theta_e \alpha_{m,e}; \quad \dot{\alpha}_l = \sum_{e=1}^{E} \theta_e \alpha_{l,e}; \quad \dot{\alpha}_k = \sum_{e=1}^{E} \theta_e \alpha_{k,e} \tag{4.2}$$

In addition, the inverse of the demand function and the mark-up factor presented in Table 4.7 are also weighted and aggregated to measure TFP with common output elasticates:

$$\frac{1}{\dot{\sigma}} = \sum_{e=1}^{E} \theta_e \frac{1}{\sigma_e}; \quad \frac{\dot{\sigma} - 1}{\dot{\sigma}} = \sum_{e=1}^{E} \theta_e \frac{\sigma_e - 1}{\sigma_e} \tag{4.3}$$

Table 4.9 presents the results of the common output elasticities, the inverse of demand and the mark-up factor aggregated in equations 4.2 and 4.3.

Table 4.9: Common output elasticities, the inverse of demand and mark-up factor in Mexico, 1993-2018 [a/] [b/]

(1) Sectors	(2) 2-digit NAICS code	(3) Economic sector	(4) Output weights	(5) Intermediate inputs elasticity (α_m)	(6) Employment elasticity (α_l)	(7) Capital elasticity (α_k)	(8) Returns to Scale (RTS)	(9) Inverse of demand elasticity ($1/\sigma$)	(10) Mark-up factor ($\sigma/(\sigma$-1))
1	11	Agriculture, Forestry, Fishing and Hunting	0.01	0.59	0.26	0.08	0.93	0.06	1.06
2	21	Mining, Quarrying, and Oil and Gas Extraction	0.09	0.9	0.5	0.13	1.53	0.36	1.57
3	23	Construction	0.03	0.79	0.17	0.03	0.98	-0.01	0.98
4	31	Manufacturing (food, beverage etc.)	0.12	0.81	0.19	0.03	1.03	-0.002	0.998
5	32	Manufacturing (wood, paper, etc.)	0.17	0.85	0.17	0.03	1.05	0.005	1.005
6	33	Manufacturing (primary metals, machinery, etc.)	0.21	0.87	0.24	0.01	1.12	-0.008	0.993
7	43	Wholesale	0.05	0.51	0.46	0.08	1.05	0.045	1.045
8	46	Retail trade	0.07	0.58	0.46	0.07	1.1	0.15	1.18
9	48	Transport	0.04	0.73	0.31	0.06	1.1	0.1	1.13
10	49	Postal service and warehousing	0	0.62	0.32	0.04	0.97	0.02	1.02
11	51	Information	0.04	0.73	0.27	0.05	1.05	0.08	1.09
12	52	Finance and Insurance	0.05	0.73	0.39	0.06	1.18	0.11	1.13
13	53	Real Estate and Rental and Leasing	0.01	0.81	0.25	0.05	1.11	0.12	1.13
14	54	Professional, Scientific, and Technical Services	0.02	0.8	0.54	0.09	1.43	0.22	1.28
15	56	Administrative and Support and Waste Management	0.02	0.91	0.53	0.03	1.47	0.21	1.25
16	61	Educational Services	0.01	0.44	0.65	0.07	1.16	0.07	1.07
17	62	Health Care and Social Assistance	0.01	0.82	0.4	0.07	1.29	0.2	1.24
18	71	Arts, Entertainment, and Recreation	0	0.68	0.3	0.05	1.03	0.05	1.05
19	72	Accommodation and Food Services	0.03	0.82	0.25	0.02	1.09	0.02	1.02
20	81	Other Services (except Public Administration)	0.01	0.73	0.36	0.04	1.13	0.05	1.05
		Aggregated parameters	**1**	**0.79**	**0.3**	**0.05**	**1.14**	**0.07**	**1.08**

[a/] Most of the parametric values are rounded to two decimals
[b/] Parameters of Columns 5,6,7, 9 and 10 come from Tables 4.3, 4.4, 4.5, and 4.6
Source: Own estimation using microdata of the Economic Census of Mexico

Column (4) in Table 4.9 presented the output weights specified in equation 4.1. Columns (5)-(7) are the elasticities of factors of production presented in Table 4.7, and Column (8) displays the sum of the elasticities that represent the Return to Scale (RTS) by economic sector. Columns (9) and (10) show the inverse of the demand and the mark-up factor correction, also presented in Table 4.7. The calculation of the common output parameters implies the multiplication of the output weights in Column (4) by each Column (5)-(10) and then its aggregation. The last row shows the results in calculating the common output elasticities, the inverse of demand, and the mark-up specified in equations 4.2 and 4.3. The common output elasticities had a value $\dot{\alpha}_m = 0.79$, $\dot{\alpha}_l = 0.30$, $\dot{\alpha}_k = 0.05$, and the common output inverse of demand and the mark-up factor of correction was $\frac{1}{\dot{\sigma}} = 0.07$ and $\frac{\dot{\sigma}}{\dot{\sigma}-1} = 1.08$, the inverse of the latter parameter indicates that $\frac{\dot{\sigma}-1}{\dot{\sigma}} = 0.925$.

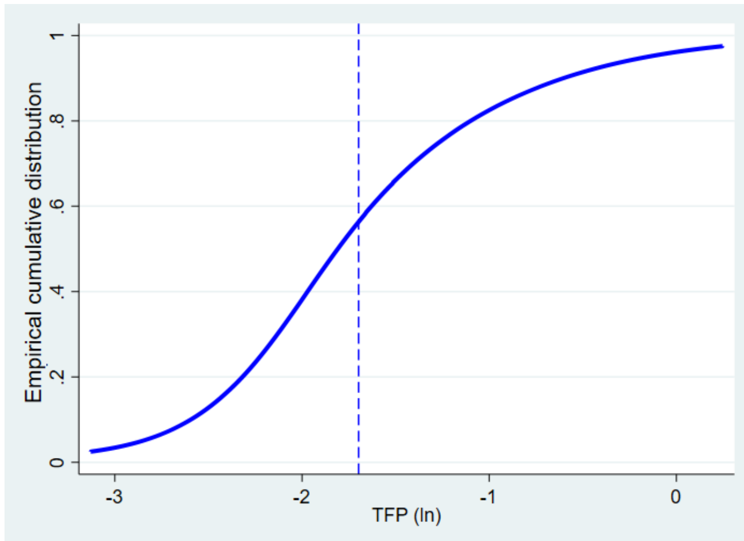
The common output parameters were applied to the microdata to calculate TFP at the establishment level in Mexico for 1993-2018. Common output elasticities were also applied to calculate TFP in the observations not included in the Wooldridge model's estimation sample. The assumption to include all observations for the TFP estimation is that establishments share a common technology of reference (Harris 2021). Then TFP is calculated, including 18,817,517 observations (Column 6, Table 4.2), and ln TFP is calculated as the part of the output not explained neither by the inputs nor by the price bias correction with common output parameters as equation 4.4 describes.

$$\ln\left(\widehat{TFP}_{it}\right) = \tilde{r}_{it} - \left(\frac{\dot{\sigma}-1}{\dot{\sigma}}\right)\left(\dot{\alpha}_m m_{it} + \dot{\alpha}_l e_{it} + \dot{\alpha}_k k_{it}\right) - \frac{1}{\dot{\sigma}}\left(r_{st} - p_{st}\right) \tag{4.4}$$

Figure 4.1 displays the distribution of the ln TFP at the establishment level in Mexico during

1993-2018. The following section analyses insights into the distribution of ln TFP, particularly examining the ln TFP dispersion.

Figure 4.1: Distribution of ln TFP at establishment level in Mexico, 1993-2018.[a/]



[a/] The dashed line is the mean of the TFP index (ln) distribution, equal to -1.7.
Source: Own estimation using microdata of the Economic Census of Mexico

The ln TFP distribution in Figure 4.1 shows a degree of dispersion in which some establishments are more productive than others. Section 4.2 examined that TFP heterogeneity results from the TFP determinants, which are firm-specific or context attributes that determine the efficiency of Mexican establishments. For that reason, the TFP dispersion reflects productivity heterogeneity. Two approaches to TFP estimation account for productivity heterogeneity: parametric and calibrated models (Bartelsman & Wolf 2017).

Calibrated models claim that distortions are responsible for productivity heterogeneity.[5] Hopenhayn (2014) states that efficient allocation equates to marginal products across firms in a perfect neoclassical world. However, firms face idiosyncratic distortions that generate variations in the marginal productivity of the factors of production across firms. Therefore, idiosyncratic distortions cause misallocations[6], and misallocations impede firms from reaching the optimum efficiency level to maximise benefits and TFP.

Restuccia & Rogerson (2013, 2017) indicate that two calibrated theoretical models measure the effect of misallocations on TFP. The first type of calibrated model is the direct approach model, which attempts to explain the source of distortions that affect TFP (e.g. regulations, discretionary

[5]For instance, calibrated models account for heterogeneity of firms that maximise profits and minimizes inputs cost (first-order condition in the producer decision problem). Then, the elasticities are estimated as the share of the inputs costs in the total costs. It is considered that producers face frictions and thus there are imposed common elasticities across production units in the same industry.

[6]Misallocations refer to the situation in which firms have an inefficient amount of factors of production.

provisions made by institutions and market imperfections). Overall, the direct approach models consider that institutions and policies are the main cause of distortions that generate misallocations. The indirect approach model is the second calibrated model that measures TFP, and probably the model of Hsieh & Klenow (2009) is the most influential approach in this category. Hsieh & Klenow (2009) assume that idiosyncratic distortions affect output, factors of production and firm's benefit. Therefore, idiosyncratic distortions deviate the marginal revenue products of capital and labour from their optimal level and generate misallocations of resources. For that reason, larger distortions cause higher misallocations and more dispersion in the TFP distribution. The higher TFP dispersion reflects a lower aggregated TFP in the economy.[7]

The parametric approach accounts for X-efficiency factors as responsible for productivity heterogeneity. This research adopts the parametric approach. For that reason, TFP heterogeneity results from Non-Spatial (i.e. supply-side attributes) and Spatial variables (i.e. externalities and places effects), which are defined as the X-efficiency factors (Tsvetkova et al. 2020). The estimation of the production functions with the mark-up correction accounts for the factors of X-efficiency as TFP determinants (Tables 4.3- 4.6). Then, TFP heterogeneity reflects that some establishments reach higher TFP than others because they adopted better practices of production explained by the TFP determinants. Figure 4.1 indicates that TFP heterogeneity across establishments in Mexico results from TFP determinants. Therefore, there are establishments with better supply-side attributes accompanied by positive externalities that make those establishments reach higher TFP than their counterparts.

[7]Hsieh & Klenow (2009) concluded that more dispersion in the TFP distribution in India and China represents more distortions and misallocations of resources, which lead to a lower aggregated TFP compared to the U.S. Hsieh & Klenow (2009) determined that without distortions, China would have TFP gains of 30-50% and 40-60% in India. Therefore, a better allocation of resources in China and India might equalize their aggregated TFP to the TFP observed in the U.S.

Chapter 5

Analysis of results 2: TFP decomposition

5.1 Overview of Chapter 5

Chapter 5 analyses the decomposition of aggregated TFP. Table 5.1 describes the measurement of TFP decomposition divided into two categories: TFP in levels and TFP growth. Section 5.2 decomposes the aggregated TFP in levels by incorporating the geographical and sectoral dimensions of TFP in Mexico. On the one hand, the geographical dimension of TFP measures the contribution of states and municipalities to aggregated TFP at the national level (Subsection 5.2.1). On the other hand, the sectoral dimension of TFP measures the contribution of economic sectors and the main subsectors on aggregated TFP in Mexico (Subsection 5.2.2). Section 5.3 analyses TFP growth in Mexico regarding the contribution of firm selection. In particular, TFP growth is decomposed by the contribution of establishments that enter, survive and exit the Mexican market. TFP growth decomposition is disaggregated at national, state and sectoral levels. TFP growth decomposition is estimated using the methodologies of Haltiwanger and Melitz-Polanec (Haltiwanger 1997, Melitz & Polanec 2015).

Table 5.1: Measurement of TFP decomposition

TFP decomposition	Description
Decomposition of TFP in levels.	Geographical contribution. Sectoral contribution.
Decomposition of TFP growth	Haltiwanger decomposition. Melitz-Polanec decomposition.

Source: Own elaboration

5.2 The geographical and sectoral dimension of TFP in Mexico

TFP is estimated at the establishment level, and it is possible to aggregate TFP at different dimensions: geographical (e.g., country, state, municipality) and sectoral (e.g., sector, subsector, industry). This section analyses TFP in Mexico, proceeding from the particular to the general and considering the geographical and sectoral dimensions of TFP in Mexico. TFP variation across industries and geographic locations is crucial evidence to target selective interventions in strategic locations and industries to improve the whole TFP in Mexico.

The literature accounts that weights can be used to aggregate TFP metrics at the establishment level to derive productivity measurements from micro to macro. There can be two options for aggregation: average and weighted average TFP. The average TFP implies that establishments have the same relative importance in the TFP aggregation.[1] The weighted average considers imperfect competition as an establishment has a higher relative importance over its counterparts (i.e. market power). These weights are also considered "shares" (Schreyer & Pilat 2001).

There can be two types of weights to measure weighted average TFP. The first type of weight has a sum of one across establishments in the same year, and the second type is the "Domar" weight. The first type of weight is usually used in the literature that analyses TFP growth decomposition. This literature uses weights by measuring the share of each firm in the aggregated gross output. (Foster et al. 2001).[2] The second type of weights is also labelled as the revenue-based Domar weights, which are usually used in the TFP aggregation using the KLEMS model (Schreyer & Pilat 2001). These weights measure the relative importance of the establishment's sale on the total added value. The sum of the Domar weights across establishments over a year is larger than one (Baqaee & Farhi 2019, p. 5).

This research uses weights as a firm's gross output shares to aggregate TFP at the national level to account for the relative importance of each firm in the aggregated gross output. The justification for including weights as a firm's gross output shares is in line with the large literature that analyses TFP from the micro to the macro using methodologies of decomposition (Haltiwanger 1997, Foster et al. 2001, Melitz & Polanec 2015, Dias & Robalo 2021).[3]

[1] In the average TFP, it is considered that weight=$1/N$ across establishments, where N is the total number of establishments.

[2] Foster et al. (2001) accounts that there can also be considered weights of employment by measuring the share of the firm's employment or man-hours. Foster et al. (2001) provided evidence that the differences between weights of gross output and employment lead to different results but not by large. The use of weights of employment and man-hours leads to similar results. However, the weights using added-value have not been deeply explored in the literature. One potential reason is that weights of added-value have many observations with low added-value, almost close to zero. As a result, the aggregation of the weighted-average TFP can overestimate the contribution of establishments of high added-value at the expense of the omission of a large number of establishments with low added-value.

[3] According to this research, the use of gross output as weights can have representative output importance at the establishment level. The weights θ_{it} are measured in real terms.

The departure of analysis is the estimation of the weighted average TFP aggregated with firms' gross output shares in the Mexican economy in equation 5.1:

$$\widetilde{TFP}_t = \sum_{i=1}^{N_t} \theta_{it} \widehat{TFP}_{it} \tag{5.1}$$

According to Melitz & Polanec (2015), equation 5.1 describes the share-weighted average of establishments' TFP, where $\theta_{it} > 0$ and $\sum_{i=1}^{N_t} \theta_{it} = 1$. [4]

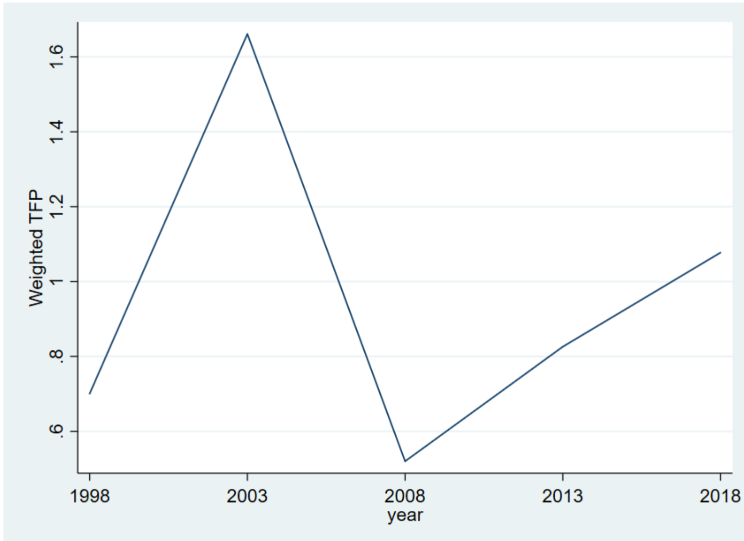
This research suggests that weighted average TFP in levels is more appropriate than weighted average TFP in ln, particularly to measure the geographical dimension of TFP. Weighted average TFP in ln can be a problematic metric in practice to compare productivity across Mexican regions due to the characteristics of the logarithmic distributions of TFP. For instance, regions with high inequality are characterised by many establishments with low TFP, which usually have negative values measured with ln TFP. For example, areas like Mexico City have long tails of negative ln TFP, and aggregating weighted average ln TFP in Mexico City leads to negative or low weighted average ln TFP, which responds to an arithmetical effect rather than a correct representation of the productivity across geographical locations and sectors.

Figure 5.1 displays the time-series of the weighted average TFP —henceforth weighted TFP— in Mexico from 1998 to 2018 with a 5-year interval. The weighted TFP in 1998 was low because the Mexican economy was recovering from the "Mexican Peso crisis" of 1994. In 2003, TFP in Mexico increased to its maximum level. In subsequent years, TFP in Mexico dropped to its minimum level during the global financial crisis in 2008. From 2008 to 2018, TFP in Mexico had a positive trend recovering from the negative impact of the 2008 crisis. Overall, the weighted TFP in Mexico drops during a crisis period, and in subsequent periods, TFP recovers. However, the weighted TFP has not yet reached the levels observed before the crisis in 2003. This result shows that TFP cyclicality influences the phases of recession and expansion in the economic cycle (Kydland & Prescott 1982). It is expected that the microdata collection of the Economic Census of 2023 displays a dropped in TFP due to the Covid-19 crisis affecting the productivity of Mexican establishments.

The literature has different approaches to TFP aggregation, and there is not a clear consensus on the definition of a particular metric of aggregation as the best approach above the rest. For instance, Haltiwanger (1997) and Melitz & Polanec (2015) use output weights for the TFP aggregation. On the contrary, Harris (2021) and Harris & Moffat (2022) use the average TFP in ln, which is proportional to the geometric average of TFP. The measurement of TFP from micro to macro is an ongoing and growing field in productivity analysis. For that reason, the examination of different metrics of TFP aggregation can be complementary to provide a deeper productivity analysis when TFP is examined in the measurement from micro to macro. This document provides evidence of TFP aggregation in Mexico on its geographical and sectoral dimensions using complementary

[4] The weights measure the establishment's output relative importance in the sample, measured in real terms.

Figure 5.1: Time-series of weighted average TFP in Mexico, 1998-2018



Source: Own estimation using microdata of the Economic Census of Mexico

measurements of weighted (average) TFP (Chapter 5) and average TFP (Appendix E) across states, municipalities, sectors and subsectors.

Appendix E proposes alternative metrics of TFP aggregations using average TFP in levels and ln. [5]. The results in Appendix E indicate that average TFP in levels compared to average TFP in ln is a more plausible approach to TFP aggregation because average TFP is higher correlated with labour productivity in different subsamples, as Table E.1 displays.

The objective of Appendix E is to extend the evidence of the empirical measurement of TFP from micro to macro and the different dimensions of productivity in Mexico. The graph in Figure E.1 illustrates the average TFP in Mexico between 1998 and 2018. The average TFP shows a similar pattern over time to the TFP aggregation depicted in Figure 5.1. The evolution of weighted and average TFP confirms the procyclical pattern of productivity in Mexico at the macroeconomic level (Kydland & Prescott 1982).

Estimating the geographical and sectoral dimension of TFP in this Chapter consists of calculating weighted TFP in different subsamples by geographical locations (i.e. states and municipalities) and by sectors at 2-digits and 3-digits of NAICS code (i.e. sector, subsector). The following section uses weighted TFP in ln for approximating TFP growth. Using weighted TFP in ln provides more plausible results for the analysis of TFP growth decomposition. The use of weighted TFP and weighted TFP in ln are not interchangeable because both metrics produce different results (Dias & Robalo 2021). The author is aware of these differences, which are explained in the last section

[5] In particular, the average TFP in ln is the metric of TFP aggregation in Harris (2021) and Harris & Moffat (2022) to measure the productivity difference across geographical locations in New Zealand and Great Britain, respectively

of this Chapter. The choice to use different aggregations of weighted TFP in each section is based on the decision to present a metric that represents the Mexican economy appropriately according to the research objectives.

The following subsections show the geographical and sectoral dimensions of TFP in Mexico. Weighted TFP can be aggregated at different delimitations as equation 5.2 specifies:

$$\widetilde{TFP}_{jt} = \sum_{i=1}^{N_t^j} \theta_{it}^j \widehat{TFP}_{it} \tag{5.2}$$

In equation 5.2, $\widetilde{TFP}_{jt}$ is the weighted (average) TFP in the aggregation j in the year t. The subscript j can represent states, municipalities, sectors, subsectors, etc., depending on the delimitation of aggregation. TFP at the establishment level $\widehat{TFP}_{it}$ is weighted with θ_{it}^j and then aggregated from $i = 1, 2, \ldots, N_t^j$ where N_t^j is the total establishments N in j during the year t. In particular, the sum of the weights $\sum_{i=1}^{N_t^j} \theta_{it}^j = \sum_{i=1}^{N_t^j} Y_{it}/Y_t^j = 1$, which means that the weights are normalised in the subsample j (e.g. states, municipalities, sectors, subsectors), and this characteristic of the weights allows the comparison of TFP aggregation across geographical locations or sectors j and over time t.

The aggregation of weighted TFP using equation 5.2 is based on incorporating imperfect competition in the sum of TFP within the delimitation j. This TFP aggregation means that each firm has a weight, which describes the difference of relative importance of output in the sector/geographic location, and this variable is an approximation to capture the imperfect competition across establishments. The survey of De Loecker & Syverson (2021) argues that one of the empirical relationships in the literature is the positive correlation between size and productivity at the firm level. Therefore, there are reasons to assume that there are establishments in Mexico with a positive correlation between their TFP and weight. A large magnitude of TFP and weight can simultaneously determine a high-weighted TFP at the sectoral or geographical level. Then, the particularity of high levels of weighted TFP is to be driven greatly by a large output concentration of highly productive establishment(s).

Furthermore, large weighted TFP of particular regions or sectors can be explained by the effect of the weights in the aggregation j. For that reason, Appendix E delivers an extension of the analysis of the TFP aggregation by using equal weights. The methods of TFP aggregation in Appendix E use average TFP and average TFP in ln; the latter metric is a transformation of geometric average TFP. Appendix E aims to extend the discussion of the sectoral and geographical dimensions of TFP in Mexico without the effect of output concentration in the delimitation within sectors or geographical locations. The results of Appendix E display alternative metrics of TFP aggregation to compare the spatial distribution of TFP and the TFP differences across sectors/subsectors.

5.2.1 The geographical dimension of TFP

The TFP spatial distribution is an analysis that provides an understanding of the geographical dimension of productivity. Not only does the TFP capacity explain the differences in economic performance at the macroeconomic or microeconomic level, but the evidence has shown that TFP has a geographical dimension that explains the regional productivity heterogeneity within and between regions.

This subsection measures weighted TFP across states and municipalities in Mexico. The most relevant result of the weighted TFP at the state level in 2018 indicates that there are three clusters of states with high levels of weighted TFP that include: (i) three northern Mexican states that share a border with the U.S. and some states in the vicinity, (ii) highly populated states including Mexico City and Jalisco as well some contiguous states of highly populated states, and (iii) states in the Southeast of Mexico with intensive activities of oil extraction. The results also indicate a significant number of municipalities with low levels of weighted TFP in the South of Mexico. In particular, the state of Oaxaca concentrated most of the municipalities with the lowest levels of weighted TFP, and the state of Oaxaca is also characterised to have areas with high levels of poverty (Figure 1.7). There can be an inference of causality between low living standards and Oaxaca's low productivity levels.

Appendix E extended the empirical measurement of the geographical dimension of TFP using the average TFP as the analysis metric. The results in Figure E.2 display a clearer picture of the three clusters of high TFP in the North, Center and Southeast of Mexico. The results in Appendix E confirm the evidence that the three clusters of high TFP in Mexico can be influenced by the proximity with the U.S. (North of Mexico), economies of agglomeration (Center of Mexico) and oil extraction activities (Southeast of Mexico). In particular, average TFP shows evidence that states like Oaxaca, Guerrero, and Veracruz have lower productivity than the weighted TFP results. The difference between weighted and average TFP is the influence of weights in the TFP aggregation (See Appendix E for the explanation). Furthermore, the results of average TFP at the municipality level in Figure E.3 depict a high concentration of municipalities with low average TFP in the states of Oaxaca and Guerrero.

According to Brulhart (1998), three dominant economic theories explain the spatial allocation of factors of production and the geographic concentration of economic activity. These theories are (i) the Neoclassical Theory (NCT), (ii) New Trade Theory (NTT) and (iii) the New Economic Geography (NEG). Overall, the NCT, NTT and NEG are theories that explain the mechanism and the optimal decisions of firms to cluster in a particular location, which are reflected in the high TFP geographical cluster. [6] The explanations of the TFP disparities across geographical locations

[6] Although the geographical or spatial factors are determinants of productivity that induce the economic geographical concentration, firm-specific factors reinforce the economic, geographical concentration.

are enumerated as follows::

- According to NCT, there are comparative advantages in locations with higher weighted TFP. For instance, the Heckscher-Ohlin model accounts that advantages mainly come from the different levels of endowments in the production process. Thus, NCT can explain that locations intensive in capital increase efficiency and are more productive than locations with intensive employment use.
- According to NTT, some regions produce with increasing RTS, mainly in the manufacturing sector (Krugman 1979). This theory argues that some regions concentrate a higher share of manufacturing production; as a result, these regions produce with increasing RTS, which makes them more productive than their counterparts.
- According to NEG, there are geographical locations that are more efficient not only for the increasing RTS but also for the minimisation of costs. Then, these locations are more productive and agglomerate the economic activity in those areas to spontaneously shape the geographic pattern of core-periphery between locations with high and low productivity levels. NEG argues that the concentration of economic activity is driven by productivity (Krugman 1991). Therefore, there is a link between productivity, firms' geographic concentration, and economic activity.

An alternative explanation about TFP disparities across states and municipalities can be related to institutions and initial conditions. In the Mexican case, the institutions promoted the current urban disparities, which rely on a historic process triggered by the unequal land distribution during Spanish colonialism. Thus, regional inequalities persisted because of historic inertia driven by a heritage of extractive institutions (Acemoglu et al. 2002, Frankema 2010). For instance, Ezcurra & Rodríguez-Pose (2014) found a negative relationship between government quality and spatial inequality in forty-six countries. Mexico was placed as the fifth most unequal country.

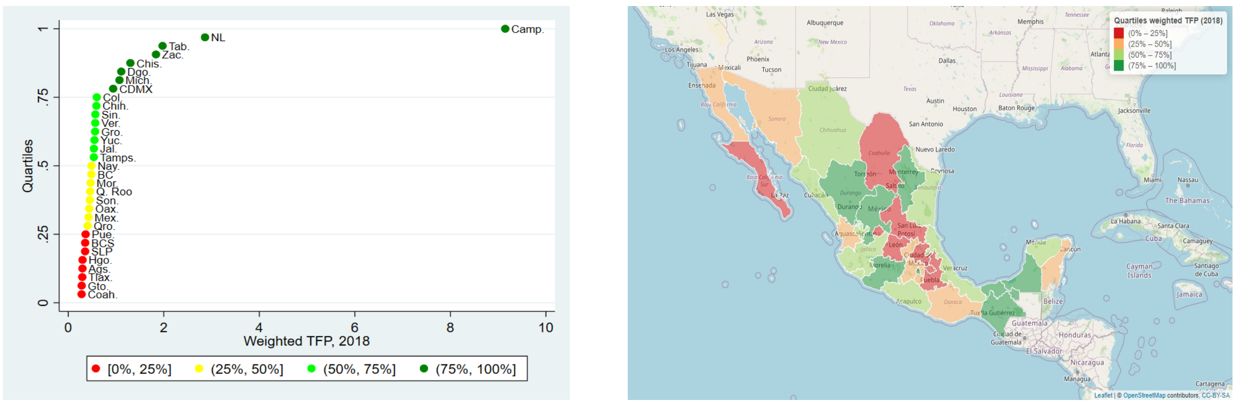
According to this research, an additional explanation is that geographical locations with higher weighted TFP concentrate establishments with better supply-side attributes. Better attributes are the TFP determinants that positively impact TFP at the establishment level and get reflected in higher weighted TFP in a geographical dimension (Table 4.8). In addition, highly productive locations create conditions via externalities so that establishments cluster in those locations and become more efficient in their production process. The rest of this section presents the calculation of the weighted TFP at the state and municipality levels alongside the main results.

State level

Figure 5.2 presents the calculation of the weighted TFP at the state level with equation 5.2 during 2018 and the spatial distribution. Figure 5.2a shows the weighted TFP by states during 2018, categorised by quartiles.[7]. Figure 5.2b displays the spatial distribution of weighted TFP at the state level categorised by quartiles. Figure 5.2 shows the wide TFP disparities within Mexico due to states with higher weighted TFP than their counterparts.

Figure 5.2: Weighted TFP at state-level (a) by quartiles and (b) its spatial distribution, 2018.[a/b/]

(a) (b)



[a/] Names of the Mexican states in alphabetical order (abbreviation of the name in parenthesis): Aguascalientes (Ags.) — Baja California (BC) — Baja California Sur (BCS) — Campeche (Camp.) — Chiapas (Chis.) — Chihuahua (Chih.) — Coahuila De Zaragoza (Coah.) — Colima (Col.) — Durango (Dgo.) — Guanajuato (Gto.) — Guerrero (Gro.) — Hidalgo (Hgo.) — Jalisco (Jal.) — Mexico City (CDMX) — Michoacan De Ocampo (Mich.) — Morelos (Mor.) — Nayarit (Nay) — Nuevo Leon (NL) — Oaxaca (Oax.) — Puebla (Pue.) — Queretaro (Qro.) — Quintana Roo (Q. Roo) — San Luis Potosi (SLP) — Sinaloa (Sin.) — Sonora (Son.) — State of Mexico (Mex.) — Tabasco (Tab.) — Tamaulipas (Tamps.) — Tlaxcala (Tlax) — Veracruz De Ignacio De La Llave (Ver.) — Yucatan (Yuc.) — Zacatecas (Zac.).
[b/] Link to the interactive map 5.2b

Source: Own estimation using microdata of the Economic Census of Mexico.

In Figure 5.2, the results of states with high weighted TFP can be summarised in three clusters of states: (i) three northern Mexican states that share a border with the U.S. (i.e. Nuevo Leon, Tamaulipas and Chihuahua) and states in the vicinity of those northern states (i.e. Sinaloa, Durango, Zacatecas), (ii) highly populated states in the central part of Mexico (i.e., Mexico City, and Jalisco) as well as some neighbour states of highly populated areas (e.g. Michoacan, Colima), and (iii) in the Southeast of Mexico, including the states of Tabasco and Campeche, have intensive activities of oil extraction that reflects a high weighted TFP. The results in Figure 5.2 can be explained according to economic theory as follows:

[7]The total number of states is $R = 32$

(i) The economic theory can explain the high levels of TFP in the north of Mexico with two theories. Firstly, NCT can explain that the north of Mexico has comparative advantages due to its proximity to the U.S. Secondly, NEG can explain that the north of Mexico is an agglomeration economy that incentive manufacturing establishments to cluster in that location. For instance, Borrayo & Quintana (2018) found that technical efficiency is higher in the north of Mexico due to its proximity to the U.S., which increases its exporting capacity. Bloom et al. (2022) provided evidence that proximity to profitable markets influences resource allocation decisions across geographical locations. For that reason, the proximity to the profitable American market can incentive the reallocation of resources to the northern states of Mexico. Consequently, there are higher levels of TFP in the northern region of Mexico.

(ii) The NEG can explain that largely populated locations have agglomeration economies in the services sectors, and some services sectors have increasing RTS, as the NTT predicts. High levels of TFP in large economies of agglomeration such as Mexico City, Jalisco and Nuevo Leon confirm that large urban areas are more productive because firms and workers are more efficient in urban environments (Puga 2010). Therefore, largely populated locations can generate agglomeration externalities, particularly in services sectors. According to the evidence in Table 4.4, population density has a positive effect on the TFP of the Retail Trade sector (NAICS code 46), which is related to the positive impact of MAR externalities in the same sector.

(iii) Furthermore, largely populated locations are prone to concentrate services activities. Table 4.9 displays that several services sectors have increasing RTS, such as Finance and Insurance (NAICS code 52), Real Estate and Rental and Leasing (NAICS code 53), Professional, Scientific, and Technical Services (NAICS code 54), Administrative and Support and Waste Management (NAICS code 56), Educational Services (NAICS code 61) and Health Care and Social Assistance (NAICS code 62). For instance, Borrayo & Quintana (2018) identified Mexico City as a high-productive metropolitan area due to its large market, which can be associated with the large services sectors.

(iv) High levels of weighted TFP in Campeche and Tabasco are due to a natural comparative advantage. This geographical location has desirable natural resources: oil reserves. Establishments dedicated to oil extraction located in Campeche and Tabasco can also have a production process characterised by increasing RTS. Table 4.9 displays that the Mining, Quarrying, and Oil and Gas Extraction (sector 21 NAICS code) have an RTS equivalent of 1.53. Therefore, the NCT can explain that Campeche has a natural comparative advantage, and the NTT can explain that establishments dedicated to oil extraction operate with increasing RTS in Campeche and Tabasco.

Figure 5.2 displays that Guerrero state has a high weighted TFP when that state has low labour productivity. On the contrary, the state of Coahuila has a low weighted TFP when this state has a high labour productivity (Figure 1.5). The aggregation of weighted TFP has the particularity that the use of weights influences to a low or a high degree the TFP aggregation on the different subsamples. Then, using weights cause influence in the aggregation of the TFP distribution using the weighted TFP (See the discussion in Appendix E). For that reason, Appendix E extends the examination of TFP aggregation by states using average TFP as an alternative analysis metric of aggregation without the influence of differneces in weights. Figure E.2 illustrates the three clusters of high productivity in Mexico at the state level, and this result is in line with Iacovone et al. (2022) (i.e. North, Centre and Southeast). In particular, Figure E.2 shows a low TFP in Southern states such as Veracruz, Guerrero and Oaxaca when the average TFP is analysed. This result contrasts with the evidence of weighted TFP because this metric lead to a higher weighted TFP in Oaxaca and Guerrero due to the influence of weights (See discussion in Appendix E).

Municipality level

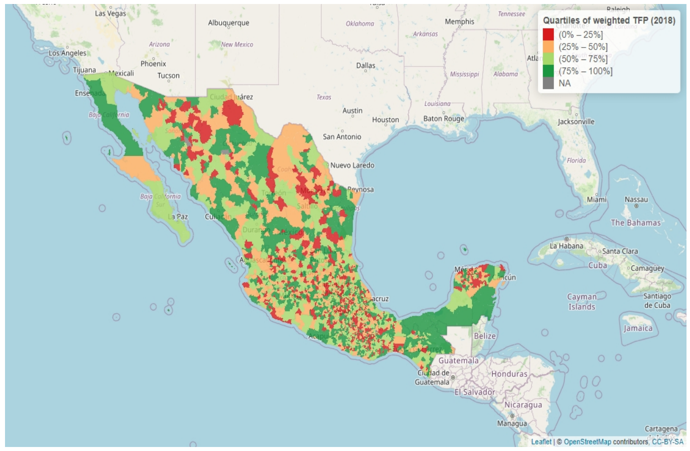
The weighted TFP at the municipality level was calculated using equation 5.2.[8] Then, the weighted average TFP at the municipality level measures each municipality's contribution to the average TFP annually in Mexico.

Figure 5.3 shows the spatial distribution of the weighted TFP at the municipality level categorised by quartiles during 2018. Figure 5.3 shows a significant number of Southern municipalities in the bottom quartiles of weighted TFP located in Campeche and Tabasco (intensive in the oil extraction). At the same time, municipalities in the bottom quartiles of weighted TFP are located in the northern part of Mexico, close to the border with the U.S. The results in Figure 5.3 indicate a significant proportion of municipalities at the bottom of the productivity distribution in Oaxaca. The state of Oaxaca is also characterised by its high poverty levels (See Figure 1.6). Then, industrial strategies with specific geographical targets can be oriented towards increasing TFP in the Oaxaca municipalities. Productivity variables are associated with variables of social equity. Thus, public policy encouraging increasing establishments' productivity and Local Economic Development (LED) in deprived areas can stimulate an economic rebalance across Mexican regions.

Figures 5.2 and 5.3 are not fully comparable between them. For instance, Baja California has a low weighted TFP in Figure 5.2, while in Figure 5.3, the municipalities that comprise Baja California (i.e. Tijuana, Mexicali and Ensenada) are in the top quartile of TFP levels. The contrast (and lack of consistency) in the picture that depicts the geographical dimension of TFP in Mexico is due to the high proportion difference between the geographical delimitation at the state and municipality levels. The number of Mexican states is 32, while the number of municipalities is 2,454. In particular, Oaxaca has 570 municipalities, and a significant proportion have low TFP

[8] The total number of municipalities in Mexico is 2,454.

Figure 5.3: Spatial distribution of the weighted TFP at the municipality level classified by quartiles, 2018.[a/]



[a/] Link to the interactive map 5.3
Source: Own estimation using microdata of the Economic Census of Mexico.

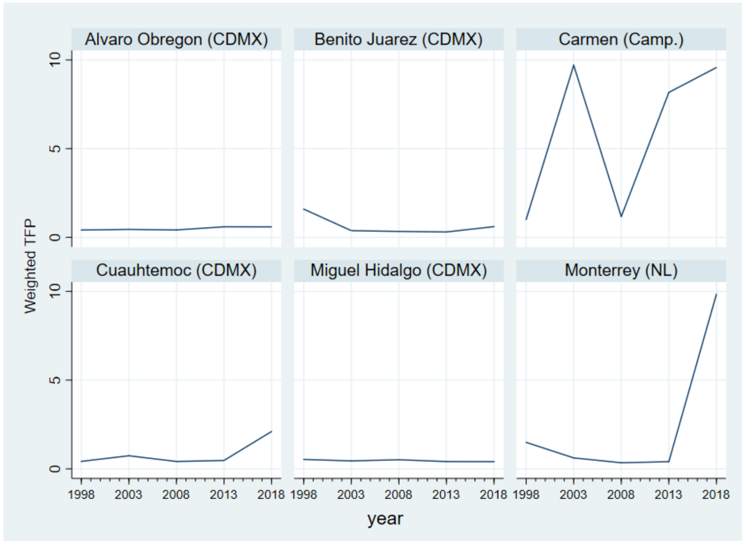
levels. Therefore, the difference in the number of municipalities within states changes the TFP distribution at the municipality level compared to the state level (and the picture of the geographical dimension of TFP in Mexico). Figure E.3d in Appendix E illustrates the spatial distribution of productivity using average TFP at the municipality level. The evidence in Figure E.3d indicates a large proportion of municipalities with low average TFP concentrated in Oaxaca and Guerrero.

Figure 5.4 presents the time-series of weighted TFP in the municipalities with the highest production levels in Mexico. The reason for selecting municipalities in Figure 5.4 is because the productivity of municipalities with the highest production levels is relevant for the public interest as they concentrate a significant proportion of output and inputs in Mexico (i.e. labour, capital and intermediate inputs). The results in Figure 5.4 indicate that weighted TFP is by large higher in Campeche than their counterparts. Particularly, the evolution of weighted TFP follows a similar pattern than the weighted TFP at the national level in Figure 5.1.

Figure E.4 in Appendix E measured the average TFP across the same sample of municipalities in Figure 5.4. The differences in magnitudes across municipalities using average TFP are lower in Figure E.4. For that reason, the large differences in magnitudes of weighted TFP across municipalities are the result of using weights. Furthermore, Figure E.4 clearly shows the procyclicality of average TFP. Then, the use of weights at the municipality level can hide the procyclical pattern of TFP across municipalities in Mexico when weighted TFP is analysed.

The measurement of the weighted TFP by the metropolitan areas in Mexico can be part of the future research agenda. The geographical delimitation of metropolitan areas is relevant due to their differences from other delimitations. Political boundaries delimit states and municipalities, while urban agglomerations define metropolitan areas comprising a group of municipalities with a

Figure 5.4: Time-series of weighted TFP in selected municipalities, 1998-2018



Source: Own estimation using microdata of the Economic Census of Mexico.

core-periphery structure.[9]

Results at the state and municipality levels in Figures 5.2, 5.3, and 5.4 show that Campeche state and the municipality Carmen in Campeche have high levels of TFP. Campeche is a geographical location characterised by a large oil extraction industry which is a natural comparative advantage as the primary source of the significant TFP levels in that location. In addition, states with high output agglomeration, such as Mexico City, Nuevo Leon and Jalisco, have high TFP levels (Figure 5.2). This result indicates that MAR externalities generate localisation economies of scale that create increasing TFP effects of establishments located in those areas because establishments can reduce transportation times, reduce raw materials costs and maximise human capital. The agglomeration index was a positive TFP determinant as a proxy variable of MAR externalities (Table 4.8).

Previous studies that analysed value-added per worker have similar conclusions concerning the factors that explain productivity heterogeneity across Mexican locations. Garduño Rivera (2014) and Díaz-Dapena et al. (2019) also used data from the Economic Census at the municipality level. Both studies concluded that municipalities near the border between Mexico-U.S increased their productivity significantly more than other regions. For that reason, the distance to the border between Mexico-U.S has an important role in determining geographical productivity. In addition, Garduño Rivera (2014) reports that municipalities dedicated to oil and petrol production had higher levels of value-added per worker over 1998-2003.

[9] A metropolitan area comprises multiple municipalities that interact between them due to their demographic and economic activities. Usually, there is a dominant municipality with a higher population, economic activity agglomeration, and surrounding municipalities. Then, metropolitan areas define the structures of municipalities in core-periphery (INEGI 2018).

The space is not neutral in the determination of productivity across geographical locations. This subsection measured TFP disparities across states and municipalities in Mexico. TFP disparity is a type of inequality, and economic inequalities are often associated with political conflicts that might lead to political instability (Kanbur & Zhang 2005). Therefore, the economic policy should include in the agenda to close the productivity gap across regions to provide more equality across Mexican regions. Chapter 7 derives policy recommendations to close the TFP gaps across Mexican regions.

5.2.2 The sectoral dimension of TFP

According to the literature review, the inter-industry and intra-industry are two perspectives that explain why some sectors are more productive than others. The inter-industry perspective accounts for the fact that the manufacturing sector is usually more productive than its counterparts due to its increasing RTS. Evidence suggests that the manufacturing sector has a high level of weighted TFP. On the other hand, the intra-industry explanation accounts for the fact that highly productive sectors have a higher share of highly productive establishments. The intra-industry perspective can be a plausible explanation for the productivity differentials across sectors and subsectors. This perspective has a more empirical view and explains that within highly productive sectors, there is a larger share of establishments with determinants that positively impact TFP.

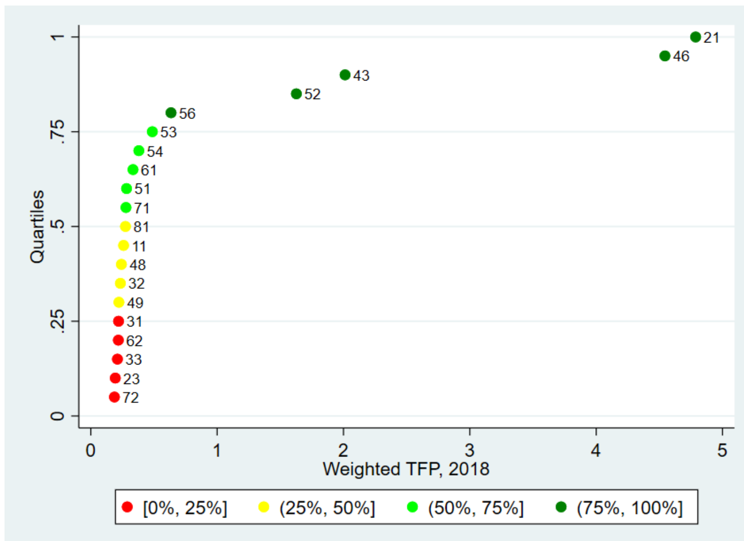
This subsection calculates the weighted TFP by sectors and subsectors. The weighted TFP measures the contribution of sectors and subsectors to the weighted average TFP in Mexico. Figure 5.5 presents the weighted TFP differentials across sectors, while Figure 5.6 presents the subsectors with the highest weighted TFP. The sectoral dimension of weighted TFP accounts for three sectors with high weighted TFP: (i) mining, quarrying, and oil and gas extraction (NAICS 21), (ii) wholesale and retail trade (NAICS 43 and 46, respectively), and (iii) finance and insurance (NAICS 52). Overall, oil extraction and services had a high TFP during 2018 while manufacturing activities had a low TFP performance. The results at the subsector level indicate that the subsector of oil extraction and the wholesale and retail trade had the highest weighted TFP during 2003 when the Mexican economy reached its highest weighted TFP.

Sector level

The weighted average TFP at the national level can also be disaggregated at a different level of the NAICS classification, as equation 5.2 specifies. Figure 5.5 presents the weighted TFP at the sector level during 2018, categorised by quartiles. The economic sectors of mining, quarrying, and oil and gas extraction (NAICS 21), wholesale and retail trade (NAICS 43 and 46, respectively), finance and insurance (NAICS 52) and services of support to management and remediation services

(NAICS 56) were categorised in the top quartile of high weighted TFP. These results can be related to the geographical dimension of TFP because highly populated areas with high TFP have a large share of services, particularly trade, in their economies. MAR externalities (i.e., agglomeration index) and population density have a high positive and significant effect on the TFP of the retail trade sector that gets reflected in a high level of weighted TFP (Table 4.4). In addition, states and municipalities oriented to oil and gas extraction are also characterised by high levels of TFP (Figures 5.2 and 5.3. However, the weighted TFP in the activities of the manufacturing sector (NAICS 31-33) had the lowest weighted TFP.

Figure 5.5: Weighted TFP at sector level by quartiles, 2018.



Source: Own estimation using microdata of the Economic Census of Mexico.

TFP at the sector and subsector levels generates relevant economic policy implications in three industries: manufacturing, trade, and oil extraction. The following outcomes describe the economic policy implications in each of these industries.

- In the trade sector, the high level of weighted average TFP hides the high TFP dispersion across wholesale and retail trade establishments. The high TFP disparity in the trade industry could be more evident in highly populated states such as Mexico City. The comparison across trade establishments implies examining the difference between TFP in Walmart of Mexico City (assuming a high TFP) versus TFP in a little informal shop of groceries in the periphery of Mexico City (with low TFP). Therefore, the challenge for the economic policy is to design industrial strategies for levelling-up (i.e. compensating for) establishments in the trade sector with low TFP. In particular, the trade sector has to be a target of industrial strategies due to its large size (Table 3.2). Dias et al. (2020) also found a larger TFP dispersion in the services sector compared to the TFP dispersion in the manufacturing sector. Dias et al. (2020) measured TFP at the establishment level in Portugal with the Hsieh & Klenow (2009) model. Therefore, Dias et al. (2020) conclude that there is more misallocation in the services sector. This research supports the idea that there is room for productivity improvements in laggard firms in the services sector (Monahan & Balawejder 2020, Dias et al. 2020).

- Tables 5.12 and 5.16 show that TFP growth in the Mexican manufacturing sector decreased over 25 years from 1993 to 2018 (NAICS 31-33). In Figure 5.5, the weighted TFP in the manufacturing sector was in the bottom quartile of the TFP distribution across sectors. The evidence can support the argument of Loría et al. (2019) that low economic growth in Mexico results from stagnation in the manufacturing sector. In addition, there has been a structural change in favour of the services alongside low productivity in the manufacturing sector (Padilla-Perez & Villarreal 2017). The low performance of the manufacturing sector indicates that there is room for TFP improvements in this sector by applying industrial strategies. The manufacturing sector in the north of Mexico has had TFP benefits due to spillovers with the U.S. economy that can reflect supply-side and demand-side linkages between the south of the U.S. and the north of Mexico because both geographical locations share a border. However, the South of Mexico's manufacturing sector has not benefited significantly from TFP gains. It is relevant to generating economic linkages in other Mexican regions to improve the productivity of the manufacturing sector, particularly in the South of Mexico. More transport infrastructure oriented to reduce cost and increase absorptive capacity in the Southern Mexican regions can generate spillovers and TFP increases in the manufacturing sector of the South of Mexico.

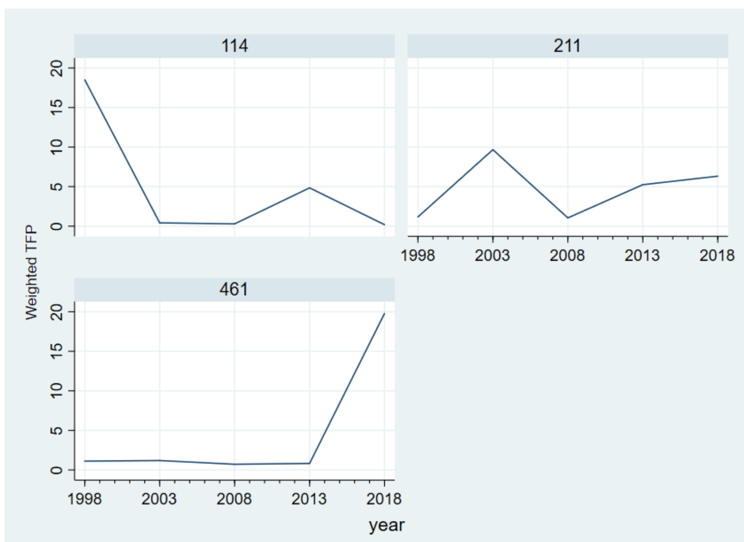
- The decisions to increase production in the oil sector are mainly decided by the state-owned company PEMEX. The reason is that PEMEX is a dominant competitor in the oil extraction industry, which used to be a government monopoly. Then, the production decisions in PEMEX are closely related to the Mexican government, politics and public finances (Romo 2015). TFP increase during 2003 in the oil extraction industry is assumed as a government decision. PEMEX deliberately increased the oil extraction with nitrogen injections in 2003 in the Cantarell oilfield due to the high prices in the international market, as Romo (2015) argues (Figure G.1). Due to emerging technologies, the oil industry is expected to be less dominant in the energy sector in the coming years. Therefore, there will be less room for arbitrary decisions to increase (or reduce) oil extraction deliberately, as PEMEX used to take when it was granted the government monopoly. Therefore, Mexico's oil extraction industry can lose dominance as a driver sector of TFP growth. The Mexican government must initiate a route for the energy transition so that TFP growth does not primarily depend on oil extraction but also on emerging technologies.

Appendix E calculated the average TFP at the sector level in Mexico during 2018, presented in Figure E.5. The main difference between weighted and average TFP from Figure 5.5 and E.5 is the sector of mining, quarrying, and oil and gas extraction (NAICS 21). This sector has the highest weighted TFP, while in the average TFP, this sector is in the third quartile of the TFP distribution. Therefore, using weights leads to higher productivity in the weighted TFP aggregation of the sector NAICS 22 in 2018. However, the subsector of oil and gas extraction (NAICS 211) is characterised by having high TFP levels, according to the results in the following subsection and Appendix E (Figures 5.6 and E.6.

Subsector level

The weighted (average) TFP at the subsector level is calculated with equation 5.2.[10] The average of the weighted TFP at the subsector level was calculated for the period 1998-2018 to identify the subsectors with the highest weighted TFP. Figure 5.6 presents the three most productive subsectors in the Mexican economy using the weighted TFP from 1998 to 2018. These subsectors are identified with the NAICS code 114 (Fishing, Hunting and Trapping), the subsector 211 (Oil and Gas Extraction), and 461 (Retail trade of groceries, food, drinks, ice and tobacco).

Figure 5.6: Selected subsectors with the highest average weighted TFP, 1998-2018.



Source: Own estimation using microdata of the Economic Census of Mexico.

The high-weighted TFP in subsector 114 (Fishing, Hunting and Trapping) describes the importance of primary activities in Mexico during the 1990s. Since 1998, the weighted TFP in subsector 114 has decreased. The wholesale and retail trade of groceries, food, beverages, etc. (NAICS 461) denotes the importance of trade as an economic activity with high productivity, which can be associated with the structural change that the Mexican economy has had over the recent years in favour of services (Padilla-Perez & Villarreal 2017). One of the relevant results in Figure 5.6 is a substantial increase in the weighted TFP of subsector 461 in 2013. Then, this subsector could be

[10]The total number of economic subsectors in Mexico is 89.

one of the economic activities leading the recovery of the weighted TFP at the national level after the global financial crisis in 2008.

The weighted TFP of the oil and gas extraction subsector in Figure 5.6 highly correlates with the weighted average TFP in Mexico (Figure 5.1. The evolution of the weighted TFP of the subsector of oil and gas extraction (NAICS 211) is consistent with the evolution of oil production in Mexico, particularly during 2003. In 2003, the state-owned petroleum company PEMEX had one of its highest oil production levels in the world due to higher extraction in the oil field Cantarell. Therefore, the large increase in the weighted average TFP in Mexico during 2003 was caused by the subsector of oil and gas extraction via PEMEX production and ultimately due to the rise of oil extraction in Cantarell.[11] Figure G.1 in Appendix G provides evidence reinforcing the weighted TFP results in the oil and gas extraction subsector according to the significant increase in PEMEX's production during 2003. Appendix E concluded that the subsector of oil and gas extraction (NAICS 211) had the highest average TFP from 1998 to 2018 (Figure E.6). Weighted and average TFP followed the same pattern of evolution over time, and they are complementary metrics that found the high TFP of oil and gas extraction in Mexico from 1998 to 2018.

5.3 TFP growth decomposition

The literature accounts that there is an effect of firm selection on TFP growth. Firm selection is a dynamic process in which firms enter, remain and exit the market. Then, the firm selection determines changes in the TFP distribution through the reallocation of resources between entering, continuing and exiting firms in the market. The firm selection process can be considered a Schumpeterian process of 'creative destruction' because there is evidence that entering firms contribute to a larger extent to TFP growth (Haltiwanger 1997, Foster et al. 2008). Haltiwanger (1997) points out that microheterogeneity of productivity, associated with firm selection, explains the aggregated fluctuations of TFP. Changes in TFP at the firm level cause variations in the aggregated TFP growth.

The TFP growth decomposition of Haltiwanger (1997) has a strong connection with the theoretical selection models of Hopenhayn (1992) and Jovanovic (1982). Those models were precursors to include firm-specific productivity shocks, and the selection process leads to an equilibrium framework. The theoretical selection models contribute to the interplay between firms' dynamics and productivity. This argument is present in numerous empirical methodologies that measure TFP. Hopenhayn (1992) associated the probability of exit with productivity shocks. This contribution

[11] Romo (2015) argued that Cantarell was the second largest oil field in the world in 2003, just behind the Arab oil field, Ghawar. In that year, Cantarell supplied 2.3% of the world's oil production. The significant increase in oil extraction was due to the application of nitrogen injections, which was a controversial decision of the PEMEX's directors because this decision caused declining oil reserves.

gave theoretical foundations to the parametric CFA models that focus on particular specifications to overcome selection bias.

The relevant point of the TFP growth decomposition with the Haltiwanger (1997) approach —Haltiwanger decomposition henceforth— is to understand the aggregated TFP fluctuations by tracking the evolution of TFP microeconomic changes. The Haltiwanger decomposition was applied to microdata of the manufacturing sector in the U.S. over the period 1977-1987 with a 5-year gap. One of the main findings of Haltiwanger (1997) is that there is evidence to assume that entering plants displace less productive plants that eventually exit the market, but entering plants have a similar level of TFP compared to the firms that continue in the market. The Haltiwanger decomposition has been applied in different economies to analyse the firm selection process on TFP growth.

Foster et al. (2008) applied the Haltiwanger decomposition to microdata of the Census Manufactures in the U.S. for the period 1982-1997 with a 5-year gap. Foster et al. (2008) analysed the role of firms' dynamics on price at the firm level and TFP. The results indicated that entering businesses have higher TFP and lower prices than businesses that exit the market and incumbents. Additionally, the findings show that entering firms have lower prices because prices and TFP are crucial for young firms to survive. Another relevant result of Foster et al. (2008) is that the Haltiwanger decomposition understates the contribution of entering firms and overstates the contribution of continuing firms in TFP growth.

Other studies have applied the Haltiwanger decomposition in economies like China, Great Britain and New Zealand. Ding et al. (2016) measured TFP at the plant level in China and used the Haltiwanger decomposition by region and sector. They found that entering plants contribute to a larger extent to the increase of TFP in large and medium-sized industrial firms in China. Harris & Moffat (2019) estimated TFP at the plant level in the manufacturing sector of Great Britain during 1973-2012 and decomposed TFP growth using the Haltiwanger decomposition but also the Melitz & Polanec (2015) approach— Melitz-Polanec decomposition henceforth—. Their results indicate that, as expected, the Haltiwanger decomposition provided a higher contribution to the entering firms, while the Melitz-Polanec decomposition calculated a higher contribution to the continuers (between plants). This result is consistent with the findings in the paper of Harris (2021), which measured TFP at the plant-level in New Zealand. Harris (2021) indicated that entering plants contributed to a larger extent to TFP growth; by regions, the entering plants of Auckland had the higher contribution to TFP growth in New Zealand.

5.3.1 Calculation of TFP growth

TFP growth can be measured at different dimensions (e.g., geographical and sectoral) using the ln TFP aggregated and applying the first differences. It is possible to aggregate the ln TFP at the establishment level in Mexico by using the output's weights with the specification in equation 5.3 (Schreyer & Pilat 2001).

$$\ln\left(\widehat{TFP}_t\right) = \sum_{i=1}^{N_t} \theta_{it} \ln\left(\widehat{TFP}_{it}\right) \tag{5.3}$$

In equation 5.3, establishments are aggregated by year as $i = 1, \ldots, N_t$ and weights are calculated as the output share of the establishment i in year t on the total output in year t. Then, weights are measured as $\theta_{it} = Y_{it}/Y_t$. The calculation of the first difference of $\ln\left(\widehat{TFP}_t\right)$ between the year t and $t-k$ is equivalent to TFP growth, as equation 5.4 expresses. As the Economic Census has a 5-years gap $k = 5$.

$$\Delta\ln\left(\widehat{TFP}_t\right) = \ln\left(\widehat{TFP}_t\right) - \ln\left(\widehat{TFP}_{t-k}\right) \tag{5.4}$$

Equations 5.3 and 5.4 are applied to TFP estimations at the establishment level for the period 1998-2018 with a 5-years gap. Table 5.2 presents the results of the ln weighted average TFP in Mexico and the first differences during the period 1998.-2018 with a 5-years interval. The latter variable calculates TFP growth in Mexico by periods (Column 3).

Table 5.2: Calculation of TFP growth in Mexico, 1998-2018.[a/]

Year	(1) Weighted average TFP (ln)	(2)=Δ(1) Difference of weighted average TFP (ln)	(3)=(2)*100 / 5 TFP growth (%) p.a. by period
1998	-1.26		
2003	-1.03	0.23	4.58
2008	-1.23	-0.21	-4.13
2013	-1.22	0.01	0.22
2018	-1.24	-0.01	-0.26
Average TFP growth p.a. (1998-2018)			0.10

[a/] Negative rates of growth in red

Source: Own estimation using microdata of the Economic Census of Mexico

Column 3 in Table 5.2 presents TFP growth p.a. by periods in Mexico. Overall, TFP growth in Mexico followed a declining path during 1998-2018. This result is associated with the negative parameters of the time trend in the production functions (Table 4.8). From 1998 to 2003, TFP growth p.a. was 4.58%; during the period that covered the financial crisis (2003-2008), TFP growth dropped to -4.13%. In the period 2008-2013, TFP growth slightly recovered to 0.22%. Finally, during 2013-2018 TFP growth p.a. was negative at -0.26%. The average TFP growth in 20 years over the period 1998-2018 in Mexico was 0.10%. This result differs (but not to a large extent) from the negative average TFP growth of -0.48%, estimated by INEGI using the KLEMS model from 1998 to 2018. An explanation of the difference in TFP growth between the results of Table 5.2 and INEGI estimates is that the results of Table 5.2 exclude the sectors of utilities (NAICS 22) and the sector of management of companies (NAIJCS 55) (See Table 4.2 for the explanation). The evidence in Table 5.2 concludes that it has been a negligible contribution of TFP growth to the economic growth in Mexico during 1998-2018.

There can be disaggregated TFP growth by the contribution of states and economic sectors using equation 5.5. The contribution to national TFP growth aggregates observations across N_t^J, which represents the total number of establishments within the aggregation j in year t. The subscript j in this subsection can represent states or economic sectors.

$$\Delta \ln \left(\widehat{TFP}^*_{jt} \right) = \sum_{i=1}^{N_t^j} \theta_{it} \ln \left(\widehat{TFP}_{it} \right) - \sum_{i=1}^{N_{t-k}^j} \theta_{i,t-k} \ln \left(\widehat{TFP}_{i,t-k} \right) \tag{5.5}$$

Tables 5.3 and 5.4 extend the analysis of TFP growth by calculating the contribution of Mexican states and economic sectors to the national TFP growth by periods. The contribution to national TFP growth was measured with equation 5.5.

The last columns of Tables 5.3 and 5.4 indicates the average TFP growth contribution for the period 1998-2018, measured as $\Delta \ln \left(\widehat{TFP}^*_{jt} \right) / T$. Table 5.3 indicates that Mexico City is the state that contributed to a larger extent to the average TFP growth contribution in Mexico, with 0.602% during 1998-2018, followed by Campeche, which contributed on average a TFP growth of 0.267%, and the State of Mexico, which contributed 0.127% to TFP growth in Mexico for the period 1998-2018.

Table 5.4 indicates that the manufacturing sector of NAICS code 31 was the main sector that contributed to TFP growth in Mexico with 0.277% during 1998-2018, followed by the mining, quarrying, and oil and gas extraction (NAICS code 21) with a contribution to TFP growth of 0.207%. Data in Table 5.4 describes that two main sectors work as engines of TFP growth in the Mexican economy from 1998 to 2018: the manufacturing sector and the oil and gas extraction. These sectors were also relevant in the composition of the productive structure at the national level. According to Kaldor's laws, output growth in the manufacturing sector is highly correlated with output growth in the whole economy. For that reason, TFP growth in the manufacturing sector has a large determination in the TFP growth at the national level, and the high TFP growth can be explained due to the increasing RTS of this sector (Krugman 1979).

The results in Tables 5.3 and 5.4 indicate that Campeche and the economic sector of mining, quarrying, and oil and gas extraction highly contributed to national TFP growth during 1998-2018. This result indicates the relevance of the oil extraction industry in Mexico during the period 1998-2018. However, the oil industry in Mexico is declining due to emerging technologies and fewer oil

Table 5.3: Contribution of the states to national TFP growth (percentage %), 1998-2018.[a/] [b/]

State	Acronym	1998-2003	2003-2008	2008-2013	2013-2018	Average (1998-2018)
Mexico City	CDMX	0.890	0.389	0.357	0.771	0.602
Campeche	Camp.	1.981	-1.781	1.417	-0.551	0.267
State of Mexico	Mex.	0.607	-0.012	-0.042	-0.046	0.127
Veracruz	Ver.	0.102	-0.211	-0.047	0.367	0.053
Tlaxcala	Tlax.	0.053	0.001	-0.024	0.000	0.008
Guerrero	Gro.	0.004	-0.014	0.017	0.014	0.005
Michoacan	Mich.	0.165	-0.144	0.037	-0.039	0.005
Chiapas	Chis.	0.213	-0.347	0.066	0.075	0.002
Chihuahua	Chih.	-0.112	0.145	-0.053	0.012	-0.002
Durango	Dgo.	-0.007	0.029	-0.009	-0.022	-0.002
Yucatan	Yuc.	-0.003	-0.004	-0.101	0.097	-0.003
Colima	Col.	-0.000	-0.014	0.007	-0.008	-0.004
Nayarit	Nay.	-0.003	-0.007	-0.005	-0.005	-0.005
Oaxaca	Oax.	-0.034	-0.099	-0.115	0.217	-0.008
Morelos	Mor.	0.018	0.011	-0.073	0.013	-0.008
Zacatecas	Zac.	-0.018	-0.027	-0.020	0.028	-0.009
Puebla	Pue.	0.096	0.012	-0.067	-0.081	-0.010
Sinaloa	Sin.	-0.019	-0.012	-0.027	0.019	-0.010
Baja California Sur	BCS	0.007	-0.046	0.010	-0.020	-0.012
Tamaulipas	Tamps.	0.014	-0.349	0.142	0.142	-0.013
Tabasco	Tab.	0.644	-0.948	-0.026	0.265	-0.016
Hidalgo	Hgo.	0.005	-0.160	-0.072	0.148	-0.020
Sonora	Son.	0.091	-0.220	-0.125	0.162	-0.023
Jalisco	Jal.	-0.024	0.166	-0.001	-0.259	-0.029
Baja California	BC	0.026	-0.054	0.003	-0.122	-0.037
Quintana Roo	Q. Roo	-0.081	-0.066	0.024	-0.060	-0.046
San Luis Potosi	SLP	0.016	-0.069	-0.056	-0.170	-0.070
Aguascalientes	Ags.	-0.037	-0.016	-0.077	-0.168	-0.074
Queretaro	Qro.	0.035	-0.073	-0.161	-0.146	-0.086
Nuevo Leon	NL	0.007	-0.152	-0.218	-0.074	-0.109
Coahuila	Coah.	0.061	-0.087	-0.181	-0.371	-0.144
Guanajuato	Gto.	-0.118	0.033	-0.360	-0.453	-0.225
National		**4.578**	**-4.126**	**0.224**	**-0.264**	**0.103**

[a/] States are ranked from the highest to the lowest contribution to average TFP growth at the national level (1998-2018)

[b/] Totals by year at the national level are equivalent to totals in Table 5.2 rounded with 3 decimals

Source: Own calculation using microdata of the Economic Census of Mexico

Table 5.4: Contribution of the economic sectors to national TFP growth (percentage %), 1998-2018.[a/] [b/]

NAICS code	Economic Sector	1998-2003	2003-2008	2008-2013	2013-2018	Average (1998-2018)
31	Manufacturing (food, beverage etc.)	0.756	0.515	-0.026	-0.137	0.277
21	Mining, Quarrying, and Oil and Gas Extraction	3.278	-3.456	1.342	-0.338	0.207
32	Manufacturing (wood, paper, etc.)	0.342	-0.669	-0.358	1.174	0.122
48	Transportation	0.338	0.089	-0.057	0.066	0.109
52	Finance and Insurance	0.246	-0.520	0.347	0.289	0.091
23	Construction	-0.003	-0.271	0.390	0.081	0.049
81	Other services (except public administration)	0.074	0.097	0.001	-0.064	0.027
51	Information	-0.441	-0.048	0.120	0.445	0.019
43	Wholesale	-0.120	-0.023	-0.038	0.224	0.011
11	Agriculture, Forestry, Fishing and Hunting	0.031	0.012	0.016	-0.030	0.007
54	Professional, scientific, and technical services	-0.138	0.156	-0.024	0.019	0.003
49	Postal services and warehouse	0.005	-0.024	0.015	-0.012	-0.004
61	Educational services	-0.053	0.023	-0.070	0.051	-0.012
71	Arts, entertainment, and recreation	-0.044	-0.006	-0.027	-0.002	-0.020
53	Real estate, rental and leasing	-0.068	-0.047	0.028	-0.008	-0.024
62	Health care and social assistance	-0.037	-0.003	-0.069	0.007	-0.026
46	Retail trade	-0.245	-0.107	0.003	0.053	-0.074
56	Administrative and support of waste management and remediation services	-0.112	0.055	-0.093	-0.157	-0.077
72	Accommodation and food services	-0.118	0.067	-0.120	-0.143	-0.078
33	Manufacturing (primary metals, machinery, etc.)	0.887	0.034	-1.155	-1.783	-0.504
	National	**4.578**	**-4.126**	**0.224**	**-0.264**	**0.103**

[a/] Sectors are ranked from the highest to the lowest contribution to average TFP growth at the national level (1998-2018)

[b/] Totals by year at the national level are equivalent to totals in Table 5.2 rounded with 3 decimals

Source: Own calculation using microdata of the Economic Census of Mexico

reserves in the south of Mexico. For that reason, it is expected a declining trend in the TFP growth of Campeche in the coming years. Therefore, it is necessary that energy companies in Campeche, particularly PEMEX, begin the energy transition to explore alternative business opportunities related to the new energy technologies.[12] This transition might benefit TFP in Campeche and generate TFP spillovers in neighbour locations in the South of Mexico.

The calculation of the weighted average ln TFP during 1993 was omitted because that year mainly covers manufacturing establishments. Then, the calculation of the weighted average ln TFP in the manufacturing sector provides a longer period of coverage from 1993 to 2018 (NAICS codes 31, 32 and 33). Table 5.5 presents the results of the weighted average ln TFP in the manufacturing sector, the weighted average ln TFP in the first differences and TFP growth in Mexico from 1993 to 2018.[13]

Table 5.5: Calculation of TFP growth in the manufacturing sector of Mexico (percentage %), 1993-2018.[a/]

Year	(1) Weighted average TFP (ln)	(2)=Δ(1) Difference of weighted average TFP (ln)	(3)=(2)*100/5 TFP growth (%) p.a. by period
1993	-1.56		
1998	-1.54	0.02	0.33
2003	-1.50	0.05	0.91
2008	-1.48	0.01	0.23
2013	-1.54	-0.05	-1.04
2018	-1.59	-0.05	-1.02
Average TFP growth p.a. (1993-2018)			-0.12

[a/] Negative rates of growth in red

Source: Own estimation using microdata of the Economic Census of Mexico

Column 3 in Table 5.5 presents TFP growth p.a. by periods in the manufacturing sector of Mexico. TFP growth in Mexico has followed a declining path, and in recent years, the manufacturing TFP growth has been negative. In the period 1993-1998, TFP growth p.a. in the manufacturing sector was 0.33%. During the period 1998-2003, TFP growth p.a. slightly increased to 0.91%. In the period that covered the financial crisis (2003-2008), TFP growth was slightly positive at 0.23%. In the subsequent periods after the financial crisis, 2008-2013 and 2013-2018, TFP growth in the manufacturing sector remained negative at -1.04% and -1.02%, respectively. The average TFP growth in 25 years over the period 1993-2018 in Mexico was -0.12% (last row in Table 5.5).

[12] This is not easy because decisions in the Mexican energy sector can generate internal political disagreements. The energy sector and Mexican politics are strongly linked.

[13] In fact, the calculation of the weighted average ln TFP at different levels of aggregation (e.g. country, sector, state) implies that the sum of the weights across establishments in the same year have to be equal to one.

A deeper analysis of TFP growth in the manufacturing sector (NAICS 31-33) can be part of the future research agenda. There are three aspects in consideration for a future and deeper analysis of TFP growth of the Mexican manufacturing sector: (i) the measurement of the manufacturing sector, (ii) the structural change, (iii) the role of external competition.[14] The three considerations for future analysis of TFP growth in the manufacturing sector contemplate the following:

(i) Some studies argue that manufacturing TFP can be underestimated. The reason is that some industries of the service sector incorporate intangible efficiency into manufactured products, and those industries can be classified as knowledge-intensive services that produce intangible products. These sectors are underrepresented in the current NAICS, and knowledge-intensive services must be classified in the manufacturing sector.[15] The NAICS inadaptability to incorporate industries that produce intangible products in the manufacturing sector leads to underestimating these activities' contribution to manufacturing productivity.[16] Then, the inclusion of knowledge-intensive services is plausible to estimate TFP growth in the manufacturing sector.

(ii) In most countries, there has been a structural change due to the declining importance of the manufacturing sector. There can be three explanations for the structural change: the demand's inelasticity of manufacturing goods, the transference of manufacturing jobs from high-income countries to low-income countries, and the less intensive use of factors of production due to technological change.[17] In Mexico, structural change has been evident. The percentage share of manufacturing GDP in the total GDP of Mexico went from 40% to 30% between 1980 and 2019. Padilla-Perez & Villarreal (2017) argue that labour has been allocated from more productive activities to activities with lower productivity. Therefore, the structural change in Mexico has allocated labour to less productive activities. The declin-

[14]In addition, the disaggregation of weights and TFP in the measurement of TFP growth is essential in future calculations to examine whether TFP growth comes from the increase of weights or TFP.

[15]The categories in the SIC were defined in a period when the manufacturing activities were predominantly intensive in labour and the conventional manufacturing classification has current limitations in the digital era because knowledge-intensive services, small businesses and freelancers can be classified as manufacturing industries in the data collection of economic national accounts because these industries are dedicated to the knowledge production, intellectual property, and technology (Coyle 2016, Mullen et al. 2019, Hauge & O'Sullivan 2019).

[16]Hicks (2011) argues that the flaws in the NAICS can have consequences in the policy makers' efficiency. The reason is that most of the knowledge industries are underrepresented in the conventional industrial classification. These industries incorporate significant proportions of human capital and R&D. Thus, the limited information related to export and regional concentration of the knowledge industries can negatively impact the design and implementation of public policy.

[17]About the first explanation, Pitelis & Antonakis (2003) justify the structural change with the demand structure. The argument is that the elasticity of services is greater than one compared to the elasticity of manufactured products, which is relatively inelastic. Then the higher income goes to an increase in service demand rather than an increase in manufactured products. The second explanation is that outsourcing and labour flexibility partly explain the shift of a larger share of employment in services in some high-income countries. Berlingieri (2014) found that outsourcing is responsible for transferring manufacturing jobs from high-income countries to peripheral countries. The third explanation is that the manufacturing and agriculture sectors have had a greater technological change in their production processes, making these sectors less intensive in the use of factors of production, which is reflected in a lower share of GDP.

ing TFP growth in Mexican manufacturing can be associated with structural transformation. However, it is important to analyse whether other factors influenced at the same time TFP growth of the manufacturing sector and structural change in Mexico.

(iii) The role of external (international) competition can be a factor that affects TFP growth in Mexico. Table 5.5 shows that the declining path of TFP growth in the manufacturing sector began in 2003. Blyde & Fentanes (2019) pointed out an overall negative productivity shock to Mexican manufacturing establishments from Chinese competition. For that reason, it is relevant to analyse whether the inclusion of China in the World Trade Organisation (WTO) affected TFP growth in Mexico.

The previous aspects of analysis in TFP growth of the manufacturing sector are beyond this thesis, but there are important considerations for the future research agenda.

5.3.2 Firm selection and TFP growth

The decomposition of TFP growth accounts for quantifying the contribution of the firm selection (i.e. entering, surviving and exiting the market) to productivity growth. According to Melitz & Polanec (2015), the aggregation of $\ln\left(\widehat{TFP}_t\right)$ can be decomposed by the contribution of establishments entering and surviving in the market while the aggregation $\ln\left(\widehat{TFP}_{t-k}\right)$ can be decomposed as the contribution of establishments surviving and exiting the market. Then, equations 5.6 and 5.7 measure the contribution of the firm selection on the aggregated ln TFP for the years t and $t-k$.

$$\ln\left(\widehat{TFP}_t\right) = \sum_{i\in E}\theta_{it}\ln\left(\widehat{TFP}_{it}\right) + \sum_{i\in S}\theta_{it}\ln\left(\widehat{TFP}_{it}\right) \tag{5.6}$$

$$\ln\left(\widehat{TFP}_{t-k}\right) = \sum_{i\in S}\theta_{i,t-k}\ln\left(\widehat{TFP}_{i,t-k}\right) + \sum_{i\in X}\theta_{i,t-k}\ln\left(\widehat{TFP}_{i,t-k}\right) \tag{5.7}$$

Establishments are divided according to their selection group in equations 5.6 and 5.7. For instance, the group of establishments entering the market are described as $i \in E$, the group of establishments surviving is $i \in S$, and the group of establishments exiting the market is $i \in X$. Equations 5.6 and 5.7 are the basic accounting of the TFP growth decomposition, including firm selection.

Tables 5.6 and 5.7 explain the classification of establishments according to the groups of firm selection. Table 5.6 describes the number of establishments in the Economic Census of Mexico categorised by the number of periods remaining in the market during 1998-2018. Column 1 shows that establishments in the Economic Census can have a minimum of one period in the market but a maximum of five periods. For instance. Column 2 indicates that 1,359,497 establishments entered in 1998 and remained in the market for one period; 536,363 establishments entered in 1998 and stayed in the market for two periods; 232,367 survived for three periods, while 152,348 and 520,968 establishments remained for four and five periods, respectively. The same description applies to the subsequent years 2003-2018.

Table 5.6: The number of establishments in the Mexican market by period, 1998-2018.[a/]

Number of periods in the market	1998	2003	2008	2013	2018	Total by periods
One period	1,359,497					**1,359,497**
		945,838				**945,838**
			1,128,240			**1,128,240**
				968,404		**968,404**
					2,157,428	**2,157,428**
Two periods	536,363	536,363				**1,072,726**
		208,675	208,675			**417,350**
			357,150	357,150		**714,300**
				1,107,328	1,107,328	**2,214,656**
Three periods	232,367	232,367	232,367			**697,101**
		110,363	110,363	110,363		**331,089**
			715,718	715,718	715,718	**2,147,154**
Four periods	152,348	152,348	152,348	152,348		**609,392**
		295,388	295,388	295,388	295,388	**1,181,552**
Five periods	520,968	520,968	520,968	520,968	520,968	**2,604,840**
Total by years	**2,801,543**	**3,002,310**	**3,721,217**	**4,227,667**	**4,796,830**	**18,549,567**

[a/] Total observations in this Table are equivalent to Column 6 in Table 4.2 (obs. 18,817,567) minus observations omitted from 1993 in Table 3.2 (obs. 267,987)

Source: Own calculation using microdata of the Economic Census of Mexico.

Table 5.7: The number of establishments by groups: exiting, surviving and entering, 1998-2018.[a/]

Group of firms' selection	1998	2003	2008	2013	2018	Total by group
Exiting establishments $\in X$	1,359,497	1,482,201	1,569,282	1,588,265		**5,999,245**
Surviving establishments $\in S$	1,442,046	1,520,109	2,151,935	2,639,402		**7,753,492**
Total by years	**2,801,543**	**3,002,310**	**3,721,217**	**4,227,667**		**13,752,737**
Group of firms' selection	**1998**	**2003**	**2008**	**2013**	**2018**	**Total by group**
Entering establishments $\in E$		1,560,264	2,201,108	2,075,732	2,157,428	**7,994,532**
Surviving establishments $\in S$		1,442,046	1,520,109	2,151,935	2,639,402	**7,753,492**
Total by years		**3,002,310**	**3,721,217**	**4,227,667**	**4,796,830**	**15,748,024**

[a/] Total observations by years are equivalent to Table 5.6

Source: Own calculation using microdata of the Economic Census of Mexico

Data from Table 5.6 can be used to calculate the accounting of firm selection by classifying the Mexican establishments by entering, surviving and exiting groups. Table 5.7 uses the information from Table 5.6 to calculate the accounting of firm selection by classifying the establishments by groups of entering, surviving and exiting establishments. Table 5.7 calculates the accounting of firm selection by categorising the establishments i of year t and $t-k$ into four groups. On the one hand, establishments i of year $t-k$ are categorised into two groups: the group of exiting establishments

$i \in X$, and the group of surviving establishments $i \in S$. On the other hand, establishments i of year t are categorised into two groups: the group of entering establishments $i \in E$, and the group of surviving establishments $i \in S$.

Table 5.8 shows that the accounting in the firm selection implies that the sum of groups by year (i.e., exiting, surviving and entering establishments) is equal to the total number of establishments by year in the Economic Census. The 5-years gap in the microdata structure (Table 5.6) is a limitation for classifying entering, surviving and exiting establishments using the Economic Census. The reason is that the 5-years gap in the microdata structure can overestimate the number of entering and exiting establishments and underestimate the number of surviving establishments. Table 5.8 displays the information of Table 5.7 but in percentages by year.

Table 5.8: Percentage of establishments by groups: exiting, surviving and entering, 1998-2018.[a/]

Group of firms' selection	**1998**	**2003**	**2008**	**2013**	**2018**	**Total by group**
Exiting establishments	48.53%	49.37%	42.17%	37.57%		**43.62%**
Surviving establishments	51.47%	50.63%	57.83%	62.43%		**56.38%**
Total by years	**100%**	**100%**	**100%**	**100%**		**100%**
Group of firms' selection	**1998**	**2003**	**2008**	**2013**	**2018**	**Total by group**
Entering establishments		51.97%	59.15%	49.10%	44.98%	**50.77%**
Surviving establishments		48.03%	40.85%	50.90%	55.02%	**49.23%**
Total by years		**100%**	**100%**	**100%**	**100%**	**100%**

[a/] Percentages using data from Table 5.7
Source: Own calculation using microdata of the Economic Census of Mexico

Table 5.8 displays the percentage of establishments by groups in accounting firm selection. On average, the rate of exiting establishments during 1998-2013 in Mexico was 43.62%, while the survival rate was 56.38%. The rate of entering establishments during 2003-2018 in Mexico was 50.77%, and the surviving rate was 49.23%. The relevant fact about the microdata in the Economic Census structure is that many establishments are entering and exiting the market, and thus the Mexican market is dynamic. However, the dynamism has decreased because the rates of exiting and entering establishments have declined. The literature accounts that business churning is the process of entry, continuity and exit of firms in the economy and higher business churning leads to higher aggregated productivity (Anderton et al. 2019).[18]

Appendix F extended the analysis in the accounting of firm selection using data from the manufacturing sector in Tables F.1-F.3. The advantage of extending the analysis in the manufacturing sector is a longer period of coverage from 1993 to 2018, while most sectors only cover the period

[18] The high rates of entering establishments support the argument of weak instruments in the estimation of the SYS-GMM model due to limitations in the dynamic structure of the database.

1998-2018 (Table 3.2). Similar to the whole economy, the manufacturing sector is characterised by a dynamic process of entry and exit of manufacturing establishments in the market. On average, the rate of exiting establishments during 1993-2013 in the Mexican manufacturing sector was 46.26%, while the survival rate was 53.74%. The rate of entering establishments during 1998-2018 in the Mexican manufacturing sector was 54.07%, and the survival rate was 45.93% (Table F.3). Similar to the aggregated economy, business churning has decreased in manufacturing.

Appendix F also shows the rates of entry, survival and exit by economic sectors and states in Mexico during 1998-2018. Table F.4 shows that the economic sector with the lowest rate of entry is the agriculture sector, with 39.97% (NAICS 11), followed by the mining, quarrying, and oil and gas extraction, with 43.73% (NAICS 21), and then the retail trade sector with 47.11% (NAICS 46). Table F.5 shows that Mexico City has the lowest entry rate at 45.87%, followed by Zacatecas at 46.38% and Michoacan at 48.89%.

The basic accounting of TFP growth decomposition incorporates the firm selection of equations 5.6 and 5.7. TFP growth decomposition with firm selection can be applied to the categories of Mexican establishments (i.e. entering, surviving, exiting) in Table 5.7. The difference between equations 5.6 and 5.7 is the basic specification of the weighted average TFP growth that incorporates firm selection, as equation 5.8 shows.

$$\begin{aligned}\Delta \ln\left(\widehat{TFP}_t\right) = \left[\sum_{i\in E}\theta_{it}\ln\left(\widehat{TFP}_{it}\right) + \sum_{i\in S}\theta_{it}\ln\left(\widehat{TFP}_{it}\right)\right] - \Bigg[\sum_{i\in S}\theta_{i,t-k}\ln\left(\widehat{TFP}_{i,t-k}\right) + \\ \sum_{i\in X}\theta_{i,t-k}\ln\left(\widehat{TFP}_{i,t-k}\right)\Bigg]\end{aligned} \tag{5.8}$$

Equation 5.8 quantifies the contribution to the weighted average TFP growth $\Delta \ln\left(\widehat{TFP}_t\right)$ from the establishments that enter, survive and exit the market. However, TFP growth decomposition in equation 5.8 is limited because it does not calculate the reallocation of resources between and within establishments that survive in the market. The Haltiwanger and Melitz-Polanec decomposition quantifies the contribution within and between surviving establishments and the contribution of entering and exiting establishments on TFP growth. Both approaches are calculated in the following subsections.

5.3.3 Haltiwanger decomposition of TFP growth

In his seminal work, Haltiwanger (1997) argues that the aggregated TFP fluctuations are explained by the firm selection that generates a reallocation in the factors of production. Haltiwanger (1997) analysed TFP growth using the weighted and aggregated ln TFP in the first differences. The Haltiwanger decomposition of TFP growth classifies the variable $\ln\left(\widehat{TFP}_{it}\right)$ and the weights θ_{it} of the establishments i in the year t into groups of entering $i \in E$ and surviving establishments $i \in S$ while the variable $\ln\left(\widehat{TFP}_{i,t-k}\right)$ and the weights $\theta_{i,t-k}$ of the establishments, i in the year $t-k$ are classified as exiting $i \in X$ and surviving establishments $i \in S$.

The TFP growth decomposition of Haltiwanger (1997) disaggregates the weighted average ln TFP in the first differences into five components, as equation 5.9 specifies.

$$\Delta \ln\left(\widehat{TFP}_t\right) = \sum_{i\in S}\theta_{i,t-k}\left[\ln\left(\widehat{TFP}_{it}\right) - \ln\left(\widehat{TFP}_{i,t-k}\right)\right] + \sum_{i\in S}\left[\ln\left(\widehat{TFP}_{i,t-k}\right) - \ln\left(\overline{TFP}_{t-k}\right)\right][\theta_{it} - \theta_{i,t-k}] + \sum_{i\in S}\left[\ln\left(\widehat{TFP}_{it}\right) - \ln\left(\widehat{TFP}_{i,t-k}\right)\right][\theta_{it} - \theta_{i,t-k}] + \sum_{i\in E}\theta_{it}\left[\ln\left(\widehat{TFP}_{it}\right) - \ln\left(\overline{TFP}_{t-k}\right)\right] - \sum_{i\in X}\theta_{i,t-k}\left[\ln\left(\widehat{TFP}_{i,t-k}\right) - \ln\left(\overline{TFP}_{t-k}\right)\right] \tag{5.9}$$

The ln TFP in difference is an approximation of TFP growth. The first term in the Haltiwanger decomposition measures the increase of the ln TFP over time of the establishments that continue in the market (establishments surviving: within). The second term measures the dispersion between the ln TFP by the establishment $\ln\left(\widehat{TFP}_{i,t-k}\right)$ in relation to the average ln TFP in the period, $t-k$ expressed as $\ln\left(\overline{TFP}_{t-k}\right)$ multiplied by the change of weights over time $\theta_{it} - \theta_{i,t-k}$ (establishments surviving: between). The average TFP at the national level is measured as $\ln\left(\overline{TFP}_t\right) = \sum_{i=1}^{N_t}\ln\left(\widehat{TFP}_{it}\right)/N_t$. The third term complements the second term as it represents the covariance of the establishments with continuation in the market, considering the effect of the output weight change on the increase of the ln TFP (establishments surviving: cross). The sum of the first, second and third components of the Haltiwanger decomposition measures the contribution to the national TFP growth of the establishments with continuity in the Mexican market. The fourth term calculates the contribution to TFP growth of the entering establishments. The fifth term calculates the contribution to the national TFP growth of the establishments that exit the market.

Table 5.9 presents the results of the Haltiwanger decomposition of TFP growth in Mexico during the period 1998-2018. Column (1) of Table 5.9 displays TFP growth at the national level. The last row of Table 5.9 shows that the average annual TFP growth p.a. was 0.10% from 1998 to 2018. TFP growth is decomposed by the contribution of surviving, entering and exiting establishments. The last row of Column (2) shows that the contribution of surviving establishments to average TFP growth was -1.01% p.a. The contribution of survivors to TFP growth is divided into two: within and between surviving establishments in Columns (3) and (4), respectively.[19] Within surviving establishments, it was an average contribution to TFP growth p.a. of -1.45% and 0.44% between survivors for the period 1998-2018 (Columns 3 and 4 of Table 5.9). The average contribution

[19]The first term in the Haltiwanger decomposition measures the contribution to TFP growth of surviving establishments within. The second and third terms in the Haltiwanger approach equals the contribution of TFP growth within surviving establishments between.

of the entering establishments to TFP growth p.a. (1998-2018) was 0.92%, and -0.20% for the establishments exiting the market (Columns 5 and 6). The contribution of net entrants to TFP growth is measured as the contribution of entering establishments discounting the contribution of exiting establishments. The last row in Column (5) shows that the contribution of net entrants to TFP growth was 1.11% p.a.

Table 5.9: Haltiwanger decomposition of TFP growth in Mexico (growth rates %), 1998-2018 [a/]

Period	(1)=(2)+(5) TFP growth (%) p.a. by period	(2)=(3)+(4) Surviving	(3) Surviving (within)	(4) Surviving (between)	(5)=(6)-(7) Net entrants	(6) Entering	(7) Exiting
1998-2003	4.58	0.50	0.46	0.04	4.08	3.02	-1.06
2003-2008	-4.13	-3.05	-5.24	2.18	-1.07	-0.58	0.49
2008-2013	0.22	-1.43	-1.09	-0.34	1.65	1.76	0.11
2013-2018	-0.26	-0.06	0.06	-0.12	-0.20	-0.52	-0.31
Total 1998-2018	**0.10**	**-1.01**	**-1.45**	**0.44**	**1.11**	**0.92**	**-0.20**

[a/] Negative rates of growth in red

Source: Own estimation using microdata of the Economic Census of Mexico

Table 5.9 shows evidence that surviving establishments in the Mexican market contributed negatively to TFP growth in -1.01% p.a. On the contrary, the contribution of net entrants to TFP growth was 1.11% p.a. Therefore, the results of the Haltiwanger approach show that the surviving establishments pull TFP growth downwards, but the net entrants push TFP growth upwards. Within surviving establishments, it was a negative contribution to TFP growth, while it was a positive contribution to TFP between establishments. This result indicates that the main reason for the Mexican economy's low TFP growth is that surviving establishments have a negative TFP growth over time (1998-2018). In particular, during 2003-2008 and 2008-2013, surviving establishments concentrated significant negative contributions to TFP growth (Table 5.9). Therefore, the financial crisis of 2008-2009 originated a negative contribution of surviving establishments to TFP growth. Since the financial crisis, establishments have not recovered their pace of TFP growth.

Results in Table 5.9 can be associated with the empirical evidence of Levy-Algazi (2018). Levy-Algazi (2018) indicated that the Mexican economy has firms with pervasive dynamics because establishments with low TFP (or negative) enter and remain in the market while establishments with positive TFP exit the Mexican market. According to the results in Table 5.9, there is initial evidence to confirm a dysfunctional firm selection in Mexico. The dysfunctional firm selection implies that establishments with negative TFP growth survive in the market.

In Schumpeterian models, firm selection is a process of 'creative destruction' in which entering and surviving establishments in the market have high productivity, while establishments with low productivity exit the market (Kehrig 2011). Aghion et al. (2001, p. 564) state that "small firms exit more frequently, but the ones that survive tend to grow faster than the average growth rate". The reason is that the condition of survival makes firms with continuity in the market more productive than the average. For instance, Bartelsman & Doms (2000) found that the pattern of firms in Canada is that unsuccessful entrants have a higher probability of no survival, and the successful ones survive and grow in output and productivity. For that reason, the condition of survival in the theoretical selection model is that surviving firms increase their size and productivity over time (Jovanovic 1982, Hopenhayn 1992, Hsieh & Klenow 2014).

Table 5.9 shows a partial process of 'creative destruction' in Mexico because net entrants contributed positively to TFP growth while surviving establishments contributed negatively. Then, it can be argued that the business creation process pushes upward TFP growth in the Mexican economy, which is in line with the Schumpeterian theory. However, the business with continuity in the market pulls downward TFP growth, which is a contrary prediction of a virtuous economy from the Schumpeterian perspective (Aghion et al. 2015). This result is in line with some papers in the literature. For instance, Hsieh & Klenow (2014) found that surviving establishments in Mexico underperform compared to the surviving plants in the U.S.[20]

This research adopts the concept of Levy-Algazi (2018) and Ros-Bosch (2019) that a dysfunctional business churning in Mexico allows firms with negative TFP growth to survive in the Mexican market pulling the aggregated TFP growth downwards. This finding can open alternative lines of future research about the causes that make the Mexican economy permissive by allowing unproductive establishments to survive in the market.

Fried et al. (2008, p. 12) indicated that the ultimate success of productivity is profits. Therefore, productivity is an indicator of financial performance. The importance of productivity at the microeconomic level is that TFP is commonly associated with a condition of firm survival in a competitive environment because more productive firms generally have higher output, revenue and profits, as well as lower prices (Olley & Pakes 1996, Hopenhayn 1992, Melitz & Polanec 2015). However, in an emergent economy like Mexico with a large informal sector, the survival condition can be limited in a non-competitive environment that restricts the TFP growth of surviving establishments.

There are reasons to assume that the tolerance of the Mexican economy by allowing the survival of unproductive establishments comes from the informal sector because the informal sector is characterized by low productivity. Early theories of Development Economics account that the formal (capitalist) sector is more productive because its production process is intensive in the use of capital. In contrast, the informal (subsistence) sector is labour-intensive and uses obsolete cap-

[20] Hsieh & Klenow (2014) found that the life cycle of surviving establishments in Mexico increases at a slower pace than the life cycle of plants in the U.S. Therefore, Mexican establishments with continuity in the market grow slower than their counterpart in the U.S. The slow life cycle in Mexico can be associated with the negative TFP growth of surviving establishments.

ital (Lewis 1954). The lack of fulfilling the rule of law and the lack of capital endowments in some establishments has allowed permission and tolerance for producers to expand the informal sector in Mexico. The expansion of the informal sector can be a crucial factor that generates pervasive incentives for establishments to follow the inertia of subsistence. The condition of subsistence disincentives capital accumulation and causes low profits, savings, and investment. These factors generate unproductive surviving establishments in the context of informality in the Mexican economy.

Using the Haltiwanger approach to calculate the TFP growth decomposition at Mexico's subnational and sectoral levels can shed light on the states and sectors causing the dysfunctional business churning and influencing TFP growth downwards. The contribution of each state (or sector) j to TFP growth at the national level used the same specification of equation 5.9. The difference is that the establishments have to be aggregated across the groups of surviving establishments in state (sector) j (S_j), entering establishments (E_j) and exiting establishments (X_j). The contribution to the national TFP growth by states or economic sectors j can be measured with the Haltiwanger approach using equation 5.10.

$$\Delta \ln\left(\widehat{TFP}^{H}_{jt}\right) = \sum_{i\in S_j}^{N_t^j} \theta_{i,t-k}\left[\ln\left(\widehat{TFP}_{it}\right) - \ln\left(\widehat{TFP}_{i,t-k}\right)\right] + \sum_{i\in S_j}^{N_t^j}\left[\ln\left(\widehat{TFP}_{i,t-k}\right) - \ln\left(\overline{TFP}_{t-k}\right)\right][\theta_{it} - \theta_{i,t-k}] + \sum_{i\in E_j}^{N_t^j}\left[\ln\left(\widehat{TFP}_{it}\right) - \ln\left(\widehat{TFP}_{i,t-k}\right)\right][\theta_{it} - \theta_{i,t-k}] + \sum_{i\in E_j}^{N_t^j}\theta_{it}\left[\ln\left(\widehat{TFP}_{it}\right) - \ln\left(\overline{TFP}_{t-k}\right)\right] - \sum_{i\in X_j}^{N_t^j}\theta_{i,t-k}\left[\ln\left(\widehat{TFP}_{i,t-k}\right) - \ln\left(\overline{TFP}_{t-k}\right)\right] \tag{5.10}$$

The variable $\Delta \ln\left(\widehat{TFP}^{H}_{jt}\right)$ measures TFP growth contribution of the disaggregation j (state or sector) to TFP growth at the national level using the Haltiwanger approach. The calculation of the Haltiwanger decomposition by states or sectors is straightforward. The only difference between equation 5.9 and 5.10 is that the latter equation aggregates the total establishments in j and t, which is represented by N_t^j.

The results present the Haltiwanger approach on its geographical and sectoral dimension using the average TFP growth contribution by states and sectors to simplify the exposition of the equation 5.10. The measurement of the average TFP growth contribution is $\Delta \ln\left(\widehat{TFP}^{H}_{jt}\right)/(T-t)$. The period $T-t$ covers 1998-2018 by states (or sectors) j. In addition, the results of the geographical and sectoral dimension of TFP growth present the contribution of survivors (first three terms in equation 5.10) and net entrants (fourth term minus fifth term of equation 5.10) The Haltiwanger decomposition at the spatial level is presented in Table 5.10. The information in Table 5.10 allows for analysing of whether survivors or net entrants determine the states that contributed most to national TFP growth. Column (1) of Table 5.10 incorporates states' contribution to average national TFP growth from 1998 to 2018. Column (1) is equivalent to the last Column of Table 5.2. Columns (3) and (4) report the results for TFP growth decomposition with the Haltiwanger approach of surviving establishments (within and between) and net entrants.

The last row of Column (1) in Table 5.10 indicates that the average TFP growth at the national level for the period 1998-2018 was 0.105% p.a., the contribution of the survivors was -1.010% p.a., and net entrants contributed in 1.114% p.a (similar sum of Table 5.9). Table 5.10 describes that 13 states contributed positively to TFP growth in Mexico using the Haltiwanger approach. On the contrary, 18 states contributed negatively with this approach. Table 5.10 shows that only six Mexican states followed a virtuous Schumpeterian firm selection in which survivors and net entrants had positive TFP growth from 1998 to 2018. In addition, 53% of the states concentrated a positive contribution of surviving establishments to TFP growth, while 31% of the states had a positive TFP growth from net entrants.

Particularly, Campeche had a high contribution to TFP growth, but this contribution mainly comes from net entrants. As Campeche is primarily dedicated to oil extraction, the negative contribution of survivors to TFP growth and the positive contribution from net entrants can come from the oil extraction sector. On the contrary, Table 5.10 displays that most states that contributed negatively to TFP growth are associated with the negative contribution of survivors and net entrants. For that reason, most of the states in Mexico follow a dysfunctional Schumpeterian process regarding the negative contribution of survivors and net entrants on TFP growth. The second state with the highest contribution to average TFP growth was Mexico City. The high contribution can be associated with the positive effects of agglomeration on TFP.

Table 5.10: Haltiwanger decomposition of average TFP growth by states in Mexico, 1998-2018.[a/]

State	Acronym	(1)=(2)+(3) TFP growth (%) p.a. (1998-2018)	(2) Survivors	(3) Net entrants
Campeche	Camp.	0.294	-0.794	1.088
Mexico City	CDMX	0.134	0.094	0.041
Veracruz	Ver.	0.037	0.013	0.025
Sonora	Son.	0.012	0.004	0.008
Oaxaca	Oax.	0.010	0.006	0.004
Tlaxcala	Tlax.	0.005	0.005	-0.001
Zacatecas	Zac.	0.004	0.004	0.000
State of Mexico	Mex.	0.004	0.023	-0.019
Durango	Dgo.	0.003	0.004	-0.001
San Luis Potosi	SLP	0.003	0.015	-0.012
Puebla	Pue.	0.003	0.016	-0.013
Guerrero	Gro.	0.002	0.001	0.001
Yucatan	Yuc.	0.000	0.006	-0.006
Colima	Col.	-0.000	0.000	-0.000
Hidalgo	Hgo.	-0.001	0.004	-0.005
Tamaulipas	Tamps.	-0.001	0.009	-0.010
Nayarit	Nay.	-0.002	0.000	-0.002
Morelos	Mor.	-0.003	-0.002	-0.001
Baja California Sur	BCS	-0.004	-0.000	-0.004
Nuevo Leon	NL	-0.004	0.008	-0.012
Sinaloa	Sin.	-0.005	-0.002	-0.003
Michoacan	Mich.	-0.014	-0.006	-0.007
Aguascalientes	Ags.	-0.017	-0.012	-0.005
Queretaro	Qro.	-0.019	-0.003	-0.016
Quintana Roo	Q. Roo	-0.021	-0.006	-0.015
Baja California	BC	-0.024	-0.027	0.003
Chihuahua	Chih.	-0.028	-0.021	-0.007
Jalisco	Jal.	-0.036	-0.003	-0.033
Chiapas	Chis.	-0.038	-0.093	0.055
Coahuila	Coah.	-0.039	-0.021	-0.018
Tabasco	Tab.	-0.073	-0.181	0.107
Guanajuato	Gto.	-0.079	-0.050	-0.029
Total 1998-2018		**0.105**	**-1.010**	**1.114**

[a/] States are ranked from the highest to the lowest contribution to average TFP growth at the national level (1998-2018)

Source: Own estimations with information from the Economic Census (INEGI)

Table 5.11 measures the Haltiwanger decomposition of TFP growth by economic sector following equation 5.10. Column (1) in Table 5.11 shows the contribution of TFP growth to the national level by economic sectors. Furthermore, Columns (2) and (3) measure TFP growth regarding the contribution of survivors and net entrants. The last row of Table 5.11 indicates the average TFP growth by economic sector and the contribution of survivors and net entrants to TFP growth at the national level.

Table 5.11 displays that six of the 20 economic sectors contributed positively to Mexico's national average TFP growth using the Haltiwanger approach from 1998 to 2018. Three economic sectors contributed to a large extent to national TFP growth that includes Mining, Quarrying, and Oil and Gas Extraction (NAICS code 21), Finance and Insurance sector (NAICS code 52) and Manufacturing (food, beverage and tobacco etc.) (NAICS code 31). In particular, the large contribution of the oil extraction activities is related to the high contribution to the national TFP growth of Campeche. The positive contribution of net entrants to TFP growth implies that new competitors in oil extraction activities have pushed TFP growth upward. Due to its large size, the heavy manufacturing sector (NAICS code 33) and the wholesale and retail trade sector (NAICS code 43 and 46) are relevant sectors that pull TFP growth downwards.

Table 5.11 displays that only three sectors had a virtuous Schumpeterian process with a positive contribution of surviving and net entrants establishments to TFP growth. On the contrary, nine sectors had a negative contribution from surviving and net entrants establishments, making a dysfunctional Schumpeterian process evident in most sectors. The evidence of the Haltiwanger decomposition at different levels (regional and sectoral) indicates that most states/sectors with positive TFP growth are the result of positive contribution from surviving establishments, while most states/sectors with negative TFP growth come from a negative contribution of surviving and net entrants establishments. For that reason, surviving establishments push TFP growth upwards so that states/sectors contribute positively to average TFP growth in Mexico. Campeche and the Mining, Quarrying, and Oil and Gas Extraction (NACIS code 22) concentrated the contribution of net entrants to TFP growth to a large extent, which is associated mainly with oil extraction activities. The contribution of net entrants to TFP growth was 1.114%; of which net entrants in Campeche contributed 1.088%, and oil extraction activities contributed 1.273% (Tables 5.10 and 5.11). Therefore, the positive contribution of net entrants to TFP growth in Mexico is highly concentrated in locations and sectors related to oil extraction activities.

Table 5.11: Haltiwanger decomposition of average TFP growth by sectors in Mexico (2-digit of NAICS code), 1998-2018.[a/]

NAICS code	Economic Sector	(1)=(2)+(3) TFP growth (%) p.a. (1998-2018)	(2) Surviving	(3) Net entering
21	Mining, Quarrying, and Oil and Gas Extraction	0.225	-1.049	1.273
52	Finance and Insurance	0.150	0.128	0.022
31	Manufacturing (food, beverage and tobacco etc.).	0.078	0.078	0.000
48	Transportation	0.020	0.005	0.014
23	Construction	0.009	0.015	-0.006
32	Manufacturing (wood, paper, printing and related supporting activities etc.)	0.003	0.017	-0.014
81	Other services (except public administration)	-0.004	0.011	-0.014
56	Administrative and support of waste management and remediation services	-0.004	-0.035	0.031
11	Agriculture, Forestry, Fishing and Hunting	-0.006	-0.004	-0.001
46	Retail trade	-0.007	-0.021	0.013
71	Arts, entertainment, and recreation	-0.009	-0.006	-0.002
49	Postal services and warehouse	-0.009	-0.004	-0.005
61	Educational services	-0.015	-0.012	-0.003
62	Health care and social assistance	-0.017	-0.013	-0.004
53	Real estate, rental and leasing	-0.017	-0.018	0.000
51	Information	-0.025	-0.009	-0.016
72	Accommodation and food services	-0.034	0.013	-0.047
43	Wholesale	-0.042	-0.029	-0.013
54	Professional, scientific, and technical services	-0.043	-0.026	-0.017
33	Manufacturing (primary metals, machinery, computers and electronics, etc.).	-0.148	-0.051	-0.097
	Total 1998-2018	**0.105**	**-1.010**	**1.114**

[a/] Sectors are ranked from the highest to the lowest contribution to average TFP growth at the national level (1998-2018)

Source: Own estimations with information from the Economic Census (INEGI)

In summary, the negative contribution of surviving and net entrants establishments is pulling TFP growth downwards in most states and sectors in Mexico. Designing and implementing industrial strategies that work as leverage for TFP growth in surviving and net entrants establishment is necessary. A positive outcome of industrial strategies is to generate a virtuous Schumpeterian process in the Mexican economy in which surviving and net entrants contribute positively to TFP growth at the national level and its disaggregations by states and sectors.

The Haltiwanger decomposition was applied to TFP growth in the manufacturing sector (NAICS 31-33) using equation 5.9 to measure the contribution of survivors and net entrants. The reason to measure the TFP growth decomposition in the manufacturing sector is that this sector can be analysed in a more extended period from 1993 to 2018. The results in Table 5.12 indicate that the annual average of TFP growth p.a. in the Mexican manufacturing sector during 1993-2018 was -0.12%. Survivors in the market contributed -0.04%, while net entrants contributed -0.08%. Similar to the Haltiwanger decomposition of TFP growth at the national level, the manufacturing activities indicate a dysfunctional business churning and inefficient allocation of resources because unproductive establishments remain in the market, and net entrants contribute negatively to TFP growth in Mexico.

Table 5.12: Haltiwanger decomposition of TFP growth in the manufacturing sector (NAICS 31-33) of Mexico, 1993-2018 [a/]

Period	**(1)=(2)+(3)** **TFP growth (%) p.a. by period**	**(2)** **Survivors**	**(3)** **Net entrants**
1993-1998	0.33	0.31	0.02
1998-2003	0.91	0.75	0.16
2003-2008	0.23	0.25	-0.03
2008-2013	-1.04	-0.87	-0.18
2013-2018	-1.02	-0.63	-0.39
Total 1993-2018	**-0.12**	**-0.04**	**-0.08**

[a/] Negative rates of growth in red

Source: Own estimations using the Economic Census Mexico collected by INEGI

The TFP growth decomposition in the manufacturing sector using the Haltiwanger approach gives evidence regarding the contribution to TFP growth of survivors and net entrants in a longer period. Table 5.12 displays that the dysfunctional firm selection process with negative TFP growth of survivors and net entrants began after the global financial crisis of 2008. This result shows that the manufacturing sector's TFP growth can be divided into two time intervals. The first time interval is 1993-2008 and the second is 2008-2018. From 1993 to 2008, the manufacturing sector had a positive TFP growth associated with a virtuous Schumpeterian process due to the positive contribution of survivors and net entrants to TFP growth. The only exception is 2003-2008, in which net entrants contributed negatively to TFP growth. After the financial crisis, the second time interval (2008-2018) indicates that the manufacturing sector's TFP growth decreased associated with a dysfunctional Schumpeterian process. From 2008 to 2018, surviving and net entering establishments in the Mexican manufacturing sector contributed negatively to TFP growth. Therefore, the economic crisis negatively affected the supply-side, affecting establishments' TFP growth in the Mexican manufacturing sector.

5.3.4 Melitz-Polanec decomposition of TFP growth

Foster et al. (2008) argued that the Haltiwanger decomposition understates the entering firms' contribution and overstates the surviving firms' contribution to TFP growth. For that reason, this section implements the Melitz-Polanec decomposition to TFP growth in Mexico. Melitz & Polanec (2015) proposed an extension of the Olley & Pakes (1996) productivity decomposition to quantify the contribution of surviving, entering, and exiting firms to the aggregated productivity growth. According to Melitz & Polanec (2015), the basic concept of Olley & Pakes (1996) is that the weighted average ln TFP can be decomposed into the contribution of the unweighted average TFP and the covariance of the weighted TFP, disaggregated by weights and unweighted TFP. Equation 5.11 shows the basic concept of Olley & Pakes (1996).

$$\ln\left(\widehat{TFP}_t\right) = \frac{1}{N_t}\sum_{i=1}^{N_t}\ln\left(\widehat{TFP}_{it}\right) + \sum_{i=1}^{N_t}\left(\ln\left(\widehat{TFP}_{it}\right) - \ln\left(\overline{TFP}_t\right)\right)\left(\theta_{it} - \bar{\theta}_t\right) \tag{5.11}$$

The average weighted ln TFP is equal to the mean of the unweighted ln TFP by year (first term of equation 5.11), and the covariance of the weights and the unweighted TFP (second term of equation 5.11), which can be expressed as $\operatorname{cov}\left(\theta_{it}, \ln\left(\widehat{TFP}_{it}\right)\right)$. In equation 5.11 the variable $\bar{\theta}_t$ is the mean of the weights measured as $\bar{\theta}_t = \sum_{i=1}^{N_t}\theta_{it}/N_t$. Melitz & Polanec (2015) extended equation 5.11 to the basic accounting of firm selection in equation 5.8 to quantify the contribution of establishments entering, surviving and exiting the market to the aggregated TFP growth. Equation 5.12 displays TFP growth using the Melitz-Polanec decomposition of TFP growth.

$$\begin{aligned}\Delta\ln\left(\widehat{TFP}_t\right) = \frac{1}{N_t}\sum_{i\in S}\Delta\ln\left(\widehat{TFP}_{it}\right) + \sum_{i\in S}\Delta\operatorname{cov}\left(\theta^S_{it}, \ln\left(\widehat{TFP}_{it}\right)\right) + \\ \sum_{i\in E}\theta^E_{it}\left\{\sum_{i\in E}\theta^E_{it}\ln\left(\widehat{TFP}_{it}\right) - \sum_{i\in S}\theta^S_{it}\ln\left(\widehat{TFP}_{it}\right)\right\} - \\ \sum_{i\in X}\theta^X_{i,t-k}\left\{\sum_{i\in X}\theta^X_{i,t-k}\ln\left(\widehat{TFP}_{i,t-k}\right) - \sum_{i\in S}\theta^S_{i,t-k}\ln\left(\widehat{TFP}_{i,t-k}\right)\right\}\end{aligned} \tag{5.12}$$

The first term of equation 5.12 measures the contribution within surviving establishments and the second term measures the contribution between establishments. The sum of the first and the second terms is the total contribution of surviving establishments to TFP growth. The third and fourth terms of equation 5.12 measure the contribution of entering and exiting establishments to TFP growth, respectively. The weights in equation 5.12 are crucial for the Melitz-Polanec decomposition. The necessary condition is that the sum of the weights of entrants and survivors in the year t is $\sum_{i\in E}\theta_{it}^{E}+\sum_{i\in S}\theta_{it}^{S}=1$ and the sum of weights of exiters and survivors in the year $t-k$ is $\sum_{i\in E}\theta_{i,t-k}^{X}+\sum_{i\in S}\theta_{i,t-k}^{S}=1$. This condition is related to the basic accounting of the TFP growth decomposition in Table 5.7.[21]

Table 5.13 presents the results of Melitz-Polanec decomposition during 1998-2018. Column (1) of Table 5.13 presents TFP growth by period. TFP growth is disaggregated by the contribution of surviving (within and between), entering and exiting establishments (Columns 2-7 in Table 5.13). Column (1) measures the contribution of firm selection of TFP growth. In the last row of Table 5.13, TFP growth p.a. (1998-2018) was 0.10%. The contribution within surviving establishments was -0.69%, and between establishments was -0.66%. In total, the surviving establishments contributed -1.34% to TFP growth (Column 2). The contribution of the entering establishments to TFP growth was 1.36%, while the contribution of exiting establishments was -0.09%. The contribution of the net entrants to TFP growth is 1.45% p.a. for the period 1998-2018.

Table 5.13: Melitz-Polanec decomposition of TFP growth at the national level by years in Mexico, 1998-2018 [a/]

Period	(1)=(2)+(5) TFP growth (%) p.a. by period	(2)=(3)+(4) Surviving	(3) Surviving (within)	(4) Surviving (between)	(5)=(6)-(7) Net entrants	(6) Entering	(7) Exiting
1998-2003	4.58	0.43	-0.26	0.69	4.16	4.15	-0.01
2003-2008	-4.13	-3.59	-7.33	3.74	-0.54	-0.74	-0.20
2008-2013	0.22	-2.21	2.70	-4.91	2.43	2.70	0.26
2013-2018	-0.26	-0.01	2.15	-2.15	-0.26	-0.69	-0.43
Total 1998-2018	**0.10**	**-1.34**	**-0.69**	**-0.66**	**1.45**	**1.36**	**-0.09**

[a/] Negative rates of growth in red

Source: Own estimations using the Economic Census Mexico collected by INEGI

There are differences and similarities in the comparison between the Haltiwanger and the Melitz-Polanec decomposition. On the one hand, the differences are two. The first is that the Haltiwanger decomposition underestimates the contribution of entering establishments and overestimates the contribution of surviving establishments on TFP growth compared to the Melitz-Polanec decomposition. The second is that surviving establishment (between) negatively contributed to TFP growth in the Melitz-Polanec decomposition, while it is a positive contribution of surviving establishments (between) in the Haltiwanger decomposition. The results of the Melitz-Polanec approach provide

[21]The condition that $\sum_{i\in E}\theta_{it}^{E}+\sum_{i\in S}\theta_{it}^{S}=1$ and $\sum_{i\in E}\theta_{i,t-k}^{X}+\sum_{i\in S}\theta_{i,t-k}^{S}=1$ is crucial, which in Melitz & Polanec (2015) is represented by $s_{S2}+s_{E2}=1$ and $s_{S1}+s_{X1}=1$. This condition allows to keep the identity in the decomposition of Melitz & Polanec (2015) as they explain with their notation that the weighted average TFP in period 2 is $\Phi_2=s_{S2}\Phi_{S2}+s_{E2}\Phi_{E2}=\Phi_{S2}+s_{E2}\left(\Phi_{E2}-\Phi_{S2}\right)$ and similarly the weighted average TFP in period 1 is $\Phi_1=s_{S1}\Phi_{S1}+s_{X1}\Phi_{X1}=\Phi_{S1}+s_{X1}\left(\Phi_{X1}-\Phi_{S1}\right)$.

a robustness analysis of the Haltiwanger approach results. Overall, both approaches conclude that surviving establishments pull TFP growth downwards while net entrants push TFP growth upwards (1998-2018). Similar to the Haltiwanger decomposition, the Melitz-Polanec approach also displays that during the periods 2003-2008 and 2008-2013, there was a significant negative contribution to TFP growth (Table 5.13). For that reason, there can be confirmed that the negative economic shock of the financial crisis (2008-2009) mainly affected the TFP growth of surviving establishments. Since that period, the TFP growth of surviving establishments has not recovered. In summary, according to the Haltiwanger and Melitz-Polanec decomposition, there is enough evidence to support the argument that the Mexican economy is prone to allowing the survival of unproductive establishments generating a dysfunctional business churning that pulls down TFP growth in Mexico. In addition, encouraging entering establishments in the market benefit TFP growth in Mexico.

The results in Table 5.13 indicate that the negative impact of exiting firms implies that high-productivity firms exit the market while low-productivity firms remain. This result suggests that there are misallocations in the Mexican economy. The previous findings align with the research of Levy-Algazi (2018), which explains that productive establishments have exited the Mexican market, and unproductive firms have replaced them. The problem is that the informal sector in Mexico allows unproductive and small establishments to survive, creating a dysfunctional firm dynamic that contributes negatively to the aggregated TFP. According to Levy-Algazi (2018), there are asymmetries in applying fiscal policies because large and productive establishments face higher regulatory tax burdens that inhibit their enlargement or cause such firms to exit the market. In addition, firms that exit the market can face financial constraints, which is a factor that creates misallocation in Mexico, as Iacovone et al. (2022) suggests. Financial constraints imply that young and small firms, even firms with innovation activities, can face collateral constraints (i.e. tangible assets) to access credit. As a result, there can be inferred that financial constraints inhibit firms from growing or staying in the Mexican market. A deeper evaluation of the TFP growth decomposition is needed to link TFP growth with establishments' characteristics, such as taxes and financial constraints. This evaluation can confirm whether taxes and financial constraints create misallocations and inhibit TFP growth in Mexico.

The results of TFP determinants and TFP growth decomposition can seem contradictory. On the one hand, the results of the TFP determinants indicated that age increases TFP at the establishment level. On the other hand, the decomposition of the TFP growth shows that surviving establishments have contributed negatively to TFP growth. Three complementary explanations clarify the differences in the effect of age and survival on TFP. The first explanation is that TFP growth within surviving establishments dropped significantly during the period covering the financial crisis (2003-2008), and this pattern is independent of the effect of the establishment's age on TFP. During this period, the surviving establishments experienced a decrease in TFP and weights, resulting in a significant drop in TFP growth within surviving establishments (Tables 5.9 and

5.13).[22] The second explanation is that excluding the period which covers the crisis (2003-2008), the rest of the periods in which TFP growth within surviving establishments decreased can be the result of the decrease of weights rather than the decrease of TFP. The third explanation is that the negative TFP growth between surviving establishments measures the decrease of TFP dispersion across surviving establishments, and this concept does not conflate with the explanation of the positive effect of age on TFP. It is relevant to mention that age and survival (in the TFP growth decomposition) are not fully comparable because they measure different concepts. As it was explained, the TFP growth decomposition of surviving establishments includes more concepts than productivity evolution over time, which can be comparable to age. Apart from the productivity evolution over time, survival in the TFP growth decomposition comprises using weights and measuring TFP dispersion between surviving establishments. The latter two components make the concept of survival differ from the concept of age. In summary, although age and survival can infer similar definitions, the reality is that, in practice, they measure different concepts. Thus the effect of survival and age on TFP are not comparable.

The findings of this research about the higher contribution of net entrants to TFP growth are consistent with the theory that entrants have a more significant contribution to TFP growth (Olley & Pakes 1996, Melitz & Polanec 2015). However, data frequency (periodicity) is crucial in determining to what extent surviving establishments contribute to TFP growth. Foster et al. (2001, p. 314) state that "[...] studies that focus on high frequency variation [...] tend to find a small contribution of net entry to aggregate productivity growth while studies over a longer horizon find a large role for net entry". Then, it is appropriate to confirm the findings of the TFP growth decomposition of this research using data with higher frequency (periodicity), which is considered in the future research agenda.

The Melitz-Polanec approach can be applied to measure the TFP growth contribution by states and sectors regarding the contribution of surviving and net entrants establishments. The Melitz-Polanec decomposition at the geographical and sectoral dimension measures the TFP growth contribution of the disaggregation j (state or sector) to TFP growth at the national level, which is specified as the variable $\Delta \ln \left(\widehat{TFP}_{jt}^{MP}\right)$. It is possible to transform the TFP growth decomposition with the Melitz-Polanec approach at the national level in equation 5.12 $\Delta \ln \left(\widehat{TFP}_t\right)$ to the TFP growth disaggregation by states or sectors $\Delta \ln \left(\widehat{TFP}_{jt}^{MP}\right)$. For that transformation, it is necessary to aggregate the contribution of survivors, entering and exiting establishments across states/sectors j expressed as S_j, E_j and X_j, respectively. In addition, the fifth and sixth terms regarding the contribution of entering and exiting establishments have to include the weights at the national level for groups of entering and exiting establishments, expressed as $\sum_{i\in E}\theta_{it}^{E}$ and $\sum_{i\in X}\theta_{i,t-k}^{X}$.[23]

[22] In the same period (2003-2008), TFP growth between establishments increased significantly. This result can indicate that during a period of crisis, there is a significant productivity reallocation between surviving establishments that get reflected in a large TFP dispersion (an increase of productivity of surviving establishments between)

[23] The use of the weights at national level is necessary to keep the identity in the state/sector contribution to the

Equation 5.13 measures the TFP growth contribution $\Delta \ln\left(\widehat{TFP}_{jt}^{MP}\right)$ by state (or sector) j using the Melitz-Polanec approach.

$$\Delta \ln\left(\widehat{TFP}_{jt}^{MP}\right) = \frac{1}{N_t^j}\sum_{i\in S_j}\ln\left(\widehat{TFP}_{it}\right) - \frac{1}{N_{t-k}^j}\sum_{i\in S_j}\ln\left(\widehat{TFP}_{i,t-k}\right) + \sum_{i\in S_j}\operatorname{cov}\left(\theta_{it}^{S_j}, \ln\left(\widehat{TFP}_{it}\right)\right) - \sum_{i\in S_j}\operatorname{cov}\left(\theta_{i,t-k'}^{S_j}\ln\left(\widehat{TFP}_{i,t-k}\right)\right) + \sum_{i\in E}\theta_{it}^{E}\left\{\sum_{i\in E_j}\theta_{it}^{E_j}\ln\left(\widehat{TFP}_{it}\right) - \sum_{i\in S_j}\theta_{it}^{S_j}\ln\left(\widehat{TFP}_{it}\right)\right\} - \sum_{i\in X}\theta_{i,t-k}^{X}\left\{\sum_{i\in X_j}\theta_{i,t-k}^{X_j}\ln\left(\widehat{TFP}_{i,t-k}\right) - \sum_{i\in S_j}\theta_{i,t-k}^{S_j}\ln\left(\widehat{TFP}_{i,t-k}\right)\right\} \tag{5.13}$$

In equation 5.13, the variable $\ln\left(\widehat{TFP}_{jt}^{MP}\right)$ measures the contribution to TFP growth in the disaggregation j (state or sector) to the national TFP growth using the Melitz-Polanec approach. The first four terms in equation 5.13 are equivalent to the TFP growth contribution of surviving establishments. In sum, the first four terms measure the contribution of surviving establishments $i \in S_j$ in the state (or sector) j to TFP growth at the national level. In addition, The fifth and sixth terms of equation 5.13 measure the contribution of the entering $i \in E_j$ and exiting establishments $i \in X_j$ in the state (or sector) j to TFP growth at the national level. In comparison to equation 5.12, the fifth and sixth terms of equation 5.13 are multiplied by the weights $\sum_{i\in E}\theta_{it}^{E}$ and $\sum_{i\in X}\theta_{it}^{X}$, respectively.

The geographical and sectoral dimensions of TFP growth decomposition with the Melitz-Polanec approach use the average TFP growth contribution in each state/sector j, which is measured as $\Delta \ln\left(\widehat{TFP}_{jt}^{MP}\right)/(T-t)$. The period $T-t$ covers 1998-2018 by states (or sectors) j. The results of the Melitz-Polanec decomposition present the contribution of survivors (first four terms in equation 5.13) and net entrants (fifth term minus sixth term of equation 5.13) by the level of disaggregation j (state or sector). Tables 5.14 and 5.15 measure the average TFP growth contribution between 1998 and 2018 by states and economic sectors, respectively. The average TFP growth contribution is disaggregated by states or sectors using the Melitz-Polanec approach with the specification of equation 5.13. Table 5.14 displays the results of the Melitz-Polanec decomposition by states which allows for analysing whether survivors or net entrants are responsible for high contributions to TFP growth across states.

The last row of Table 5.14 displays that the total TFP growth p.a. for the period 1998-2018 was 0.106% p.a. Survivors contributed -1.345% p.a., and the net entrants contributed 1.450% p.a.

average weighted ln TFP at national level. This condition can be expressed with the notation of Melitz & Polanec (2015) where Φ_2^j is the state/sector contribution in period $t = 2$ and Φ_1^j is the state contribution in period $t-k = 1$. Then the use of weights at national level $s_{S2} + s_{E2} = 1$ and $s_{S1} + s_{X1} = 1$ will fulfil the following conditions necessary for the decomposition $\Phi_2^j = s_{S2}\Phi_{S2}^j + s_{E2}\Phi_{E2}^j = \Phi_{S2}^j + s_{E2}\left(\Phi_{E2}^j + \Phi_{S2}^j\right)$ and $\Phi_1^j = s_{S1}\Phi_{S1}^j + s_{X1}\Phi_{X1}^j = \Phi_{S1}^j + s_{X1}\left(\Phi_{X1}^j + \Phi_{S1}^j\right)$

Table 5.14: Melitz-Polanec decomposition of average TFP growth by states in Mexico, 1998-2018.[a/]

State	Acronym	(1)=(2)+(3) TFP growth (%) p.a. within the state (1998-2018)	(2) Survivors	(3) Net entrants
Mexico City	CDMX	0.402	0.121	0.281
Nuevo Leon	NL	0.091	0.051	0.039
Oaxaca	Oax.	0.043	0.002	0.041
Yucatan	Yuc.	0.041	0.016	0.025
Sonora	Son.	0.033	0.023	0.011
Coahuila	Coah.	0.032	0.011	0.020
Tamaulipas	Tamps.	0.026	0.037	-0.010
Chihuahua	Chih.	0.017	-0.002	0.019
Veracruz	Ver.	0.016	-0.030	0.046
Hidalgo	Hgo.	0.011	0.005	0.007
Baja California	BC	0.010	-0.019	0.029
Aguascalientes	Ags.	0.008	-0.002	0.010
San Luis Potosi	SLP	0.004	0.024	-0.020
Durango	Dgo.	0.002	-0.000	0.002
Morelos	Mor.	-0.001	-0.020	0.019
Colima	Col.	-0.003	-0.000	-0.003
Zacatecas	Zac.	-0.007	0.002	-0.009
Nayarit	Nay.	-0.007	-0.002	-0.005
Tlaxcala	Tlax.	-0.008	-0.012	0.004
Michoacan	Mich.	-0.011	-0.021	0.010
Sinaloa	Sin.	-0.013	-0.002	-0.011
Baja California Sur	BCS	-0.014	-0.003	-0.011
Jalisco	Jal.	-0.025	0.004	-0.028
Quintana Roo	Q. Roo	-0.028	-0.001	-0.028
Guanajuato	Gto.	-0.034	-0.036	0.002
Guerrero	Gro.	-0.034	-0.032	-0.003
Puebla	Pue.	-0.039	-0.023	-0.015
Queretaro	Qro.	-0.049	-0.005	-0.044
Campeche	Camp.	-0.051	-0.950	0.899
State of Mexico	Mex.	-0.064	-0.110	0.046
Chiapas	Chis.	-0.074	-0.144	0.070
Tabasco	Tab.	-0.170	-0.226	0.056
Total 1998-2018		**0.106**	**-1.345**	**1.450**

[a/] States are ranked from the highest to the lowest contribution to average TFP growth at the national level (1998-2018)

Source: Own estimations using the Economic Census Mexico collected by INEGI

Then, the sum of Table 5.14 is similar to the sum of Table 5.13. The disaggregation of the TFP growth decomposition by states using the Melitz-Polanec approach provides different results to the Haltiwanger approach. The results in Table 5.14 show that 14 states contributed positively to the average TFP growth in Mexico using the Melitz-Polanec approach, while 13 positively contributed with the Haltiwanger approach. On the contrary, 18 states contributed negatively to the TFP growth with the Melitz-Polanec approach, while 19 states had a negative contribution using the Haltiwanger approach were identified. The Melitz-Polanec approach estimates more states with a positive contribution to average TFP growth because this approach calculates a higher contribution of net entrants across states than the estimation of the Haltiwanger approach.

It is important to notice that the disaggregation of TFP growth decomposition by states in Tables 5.10 and 5.14 followed a different calculation method.[24] Therefore, the ranking of TFP growth contribution across states differs between the Melitz-Polanec and the Haltiwanger approach. The Haltiwanger approach estimated that Campeche and Mexico City had the largest TFP growth contribution, while the Melitz-Polanec approach calculated that Mexico City and Nuevo Leon were the states with the highest contribution. Particularly, the Haltiwanger approach overstates the contribution of surviving and net entrants in the states of Campeche and Mexico City compared to the Melitz-Polanec approach. There were identified seven states that contributed positively to average TFP growth in Mexico using both approaches, Haltiwanger and Melitz-Polanec. Those states include Mexico City, Veracruz, Sonora, Oaxaca, Durango, San Luis Potosi and Yucatan.

Table 5.14 describes that most of the states with the highest contribution to average TFP growth in Mexico have a positive contribution to TFP growth from survivors or net entrants, which is a virtuous Schumpeterian firm selection to TFP growth. Conversely, most states with negative TFP contributions have a negative contribution from survivors and net entrants, with a dysfunctional firm selection on TFP growth. This result is similar to the Haltiwanger approach. Therefore, both approaches confirm that states with a positive contribution to average TFP growth in Mexico follow a virtuous Schumpeterian process. On the contrary, most states with negative TFP growth contributions had a dysfunctional Schumpeterian process on TFP growth.

Table 5.15 measures the Melitz-Polanec decomposition of TFP growth at the sector level using the weighted average TFP growth for the period 1998-2018 $\Delta \ln \left(\widehat{TFP}_{jt}^{MP}\right)/(T-t)$. The purpose of Table 5.15 is to examine whether a higher contribution to TFP growth in Mexico at the sectoral level comes from survivors or net entrants.

The total weighted average TFP growth across sectors was 0.106% p.a. for the period 1998-2018, the survivors contributed -1.345% p.a., and the net entrants contributed 1.450% p.a. Similar to the results at the state level. The Melitz-Polanec approach estimates more sectors with positive

[24]This difference also applies to the calculation of TFP growth contribution by states in Table 5.3. This implies that there is a difference in the variables $\Delta \ln \left(\widehat{TFP}_{jt}^{*}\right)$, $\Delta \ln \left(\widehat{TFP}_{jt}^{H}\right)$ and $\Delta \ln \left(\widehat{TFP}_{jt}^{MP}\right)$ from equation 5.5, equation 5.10 and equation 5.13

Table 5.15: Melitz-Polanec decomposition of average TFP growth by sectors in Mexico (2 digits of NAICS), 1998-2018.[a/]

NAICS ID	Economic Sector	(1)=(2)+(3) TFP growth (%) p.a. (1998-2018)	(2) Surviving	(3) Net entering
32	Manufacturing (wood, paper, printing and related supporting activities etc.)	0.405	0.113	0.292
52	Finance and Insurance	0.324	0.296	0.029
31	Manufacturing (food, beverage and tobacco etc.).	0.269	0.078	0.191
33	Manufacturing (primary metals, machinery, computers and electronics, etc.).	0.171	0.051	0.121
51	Information	0.129	0.038	0.091
43	Wholesale	0.067	0.049	0.019
48	Transportation	0.057	-0.007	0.064
49	Postal services and warehouse	-0.002	-0.006	0.005
61	Educational services	-0.006	-0.010	0.004
23	Construction	-0.008	-0.006	-0.002
71	Arts, entertainment, and recreation	-0.010	0.000	-0.010
11	Agriculture, Forestry, Fishing and Hunting	-0.024	-0.025	0.001
62	Health care and social assistance	-0.033	-0.025	-0.009
53	Real estate, rental and leasing	-0.043	-0.024	-0.019
54	Professional, scientific, and technical services	-0.075	-0.069	-0.006
56	Administrative and support of waste management and remediation services	-0.082	-0.024	-0.058
72	Accommodation and food services	-0.112	-0.016	-0.096
81	Other services (except public administration)	-0.161	-0.158	-0.004
21	Mining, Quarrying, and Oil and Gas Extraction	-0.291	-1.255	0.964
46	Retail trade	-0.471	-0.345	-0.126
	Total 1998-2018	**0.106**	**-1.345**	**1.450**

[a/] Sectors are ranked from the highest to the lowest contribution to average TFP growth at the national level (1998-2018)

Source: Own estimations using the Economic Census Mexico collected by INEGI

TFP growth contributions than the Haltiwanger approach due to a higher contribution of net entrants. In addition, most of the sectors with positive TFP growth disaggregation followed a virtuous Schumpeterian process with the positive contribution of survivors and net entrants. In contrast, sectors with negative TFP growth had a dysfunctional firm selection on TFP growth.

The Haltiwanger approach estimated that Campeche and the Mining, Quarrying, and Oil and Gas Extraction sector (NAICS code 21) had the largest contribution to the average TFP growth in Mexico while the Melitz-Polanec calculated that Campeche and the sector with NAICS code 21 are among the lowest contribution to average TFP growth at the national level. The reason is that the Haltiwanger approach overestimated the contribution of survivors and net entrants in comparison to the Melitz-Polanec approach. Therefore, there is a different ranking of states and sectors according to their contribution to TFP growth using the Haltiwanger and the Melitz-Polanec approach. There were identified three sectors that contributed positively to average TFP growth in Mexico using the Haltiwanger and the Melitz-Polanec approaches: Finance and Insurance (NAICS code 52), Manufacturing (food, beverage and tobacco etc.) (NAICS code 31) and Transportation (NAICS code 48).

The Haltiwanger and Melitz-Polanec approach displays the same effect of a negative contribution of survivors and a positive effect of net entrants to TFP growth in Campeche and the sector dedicated to oil extraction and gas extraction. This result can indicate that the openness in the energy market related to entering establishments with activities of oil extraction and exploration has positively contributed to TFP growth in the sector of Mining, Quarrying, and Oil and Gas Extraction sector (NAICS code 21)

Table 5.16 applies the Melitz-Polanec decomposition to the TFP growth of the manufacturing sector for a longer period that covers from 1993 to 2018. Table 5.16 indicate that the total weighted average TFP growth p.a. in the Mexican manufacturing sector was -0.12%; survivors contributed in -0.05%, while net entrants contributed in -0.07%. Similar to the Melitz-Polanec decomposition of TFP growth at the national level, the manufacturing activities indicate a dysfunctional business churning because unproductive establishments remain, and net entrants contribute negatively to TFP growth in the Mexican manufacturing sector.

The Melitz-Polanec approach in the manufacturing sector has similarities and differences compared to the Haltiwanger approach. The similarity is that both approaches calculated a negative contribution of survivors and net entrants to TFP growth in the manufacturing sector from 1998 to 2018. The difference is that the Haltiwanger approach measured a positive association between the TFP growth of survivors and net entrants (in most periods), and the Melitz-Polanec decomposition measured a negative association between the contribution of survivors and net entrants. This result implies that the Haltiwanger approach measured an effect of complementarity in the TFP growth because when the survivors increased their contribution to TFP growth, the net entrants complemented the positive impact and vice-versa. The Melitz-Polanec decomposition implies a

Table 5.16: Melitz-Polanec decomposition of TFP growth in the manufacturing sector by years in Mexico, 1998-2018 [a/]

Period	**(1)=(2)+(3) TFP growth (%) p.a. by period**	**(2) Survivors**	**(3) Net entrants**
1993-1998	0.34	0.38	-0.04
1998-2003	0.91	0.94	-0.03
2003-2008	0.23	0.29	-0.06
2008-2013	-1.04	-1.16	0.12
2013-2018	-1.02	-0.71	-0.31
Total 1993-2018	**-0.12**	**-0.05**	**-0.07**

[a/] Negative rates of growth in red

Source: Own estimation using microdata of the Economic Census of Mexico

substitution effect, which means that the positive TFP growth of survivors is substituted by the negative TFP growth of net entrants and vice-versa.

Overall, the results of the TFP growth decomposition using the Haltiwanger and the Melitz-Polanec approach display that surviving establishments in the market at the national, sectoral and state levels contribute negatively to TFP growth in Mexico. The exercise of TFP growth decomposition is relevant to account for how the micro-performance and micro-heterogeneity of TFP using the firm selection drives the macro performance of aggregated TFP growth in Mexico. The Schumpeterian theory accounts for the fact that an efficient business churning generates efficient resource allocations that contribute positively to TFP growth from entrants and surviving establishments. If there is no efficient business churning, there is room for implementing economic policy to improve firm selection.

The results of TFP growth using the Haltiwanger and Melitz-Polanec approach indicate that survivors pull downward TFP growth. Then, it is appropriate that policymakers promote a more active role of horizontal and vertical industrial strategies that boost TFP growth by incentivising the TFP determinants in surviving establishments (See the TFP determinants that impact positively on TFP in Table 4.8). In particular, industrial strategies can be applied more actively in surviving establishments of states and economic sectors that contribute negatively to TFP growth in Mexico. In addition, net entrants push TFP growth upward. For that reason, an active industrial strategy that incentive and support the opening of businesses can contribute to TFP growth positively. The Chapter on Conclusions derives recommendations for industrial strategies considering the firm selection and its impact on TFP growth in Mexico.

Iacovone et al. (2022) measured the TFP growth decomposition in Mexico using the methodology of Melitz & Polanec (2015). Iacovone et al. (2022, p. 53) presented the TFP growth by intervals of 5 years that cover each Census period in Mexico from 1993 to 2018. However, the TFP growth in the period 1993-1998 is problematic because, in that period, data from the Economic Census in Mexico primarily covered establishments of the manufacturing sector and excluded services. For that reason, there is more plausible to consider the period 1998-2018 in the estimation of TFP growth in Mexico by Iacovone et al. (2022), because the period 1998-2018 covers the statistical universe of establishments in the Mexican economy, not only the manufacturing sector. According to results in Iacovone et al. (2022, p. 53), an average annual TFP growth of -0.331% can be calculated in the period 1998-2018. The TFP growth decomposition indicates that the component within firms is closely correlated with the TFP growth, while the contribution of entering establishments to TFP growth is positive over the whole analysis period (1993-2018). This thesis calculated a TFP growth of 0.10%, which is close to the estimation of Iacovone et al. (2022). The component of net entrants, particularly entering firms, is the component that is highly correlated with TFP growth using the Haltiwanger and Melitz-Polanec decomposition.

There can be two factors that explain the differences in the TFP growth decomposition between Iacovone et al. (2022) and this thesis. The first factor is that this thesis measures TFP with a production function including a mark-up correction and estimated with the Wooldridge model, while Iacovone et al. (2022) estimated TFPR with a Cobb-Douglas and the Ackerberg-Caves-Frazer correction. This can be the main explanation for different results in the TFP growth decomposition. The second factor of difference is the measurement of weights. This thesis used the relative importance of a firm's output (revenue), while Iacovone et al. (2022) used added-value. The reason for using output weights is to keep consistency because the production functions estimated in this thesis have an output orientation. However, output and added-value weights are not the main reason for different TFP growth decomposition results. According to Melitz and Polanec (2015; p. 369-370), TFP with added-value orientation and added-value weights leads to similar results to TFP with output orientation and output weights.

The recent paper of Dias & Robalo (2021) pointed out a substantial difference when productivity is weighted and aggregated in levels compared to the aggregation of weighted log-productivity. The difference in the productivity aggregations is critical because different productivity aggregations change the results of the productivity growth decomposition. Dias & Robalo (2021) explain that the difference between productivity aggregations results from Jensen's inequality.[25] The empirical literature on the TFP growth decomposition uses ln TFP aggregated across observations which is referred to as geometric TFP growth, and it is represented as $\Delta \ln \left(\widehat{TFP_t}\right)^G = \sum_{i=1}^{N} \theta_{it} \ln\left(TFP_{it}\right) - \sum_{i=1}^{N} \theta_{i,t-1} \ln\left(TFP_{i,t-1}\right)$.

However, the aggregation of TFP in levels leads to different conclusions in the TFP growth

[25] Dias & Robalo (2021, p. 5) pointed out that "Jensen's inequality states that $g(E(X)) \geq E(g(X))$ for any concave function $g()$". For that reason, Jensen's inequality in the TFP aggregation using the function ln() implies that $\ln\left(\sum_{i=1}^{N} \theta_{it} TFP_{it}\right) \geq \sum_{i=1}^{N} \theta_{it} \ln\left(TFP_{it}\right)$.

decomposition, which is referred to as arithmetic TFP growth and is measured as $\Delta \ln \left(\widehat{TFP_t}\right)^A = \left[\sum_{i=1}^{N} \theta_{it} TFP_{it} - \sum_{i=1}^{N} \theta_{i,t-1} TFP_{i,t-1}\right] / \sum_{i=1}^{N} \theta_{i,t-1} TFP_{i,t-1}$. For that reason, the Jensen's inequality between TFP growth in levels (arithmetic) is higher or equal to TFP growth measured with logarithms (geometric) $\Delta \ln \left(\widehat{TFP_t}\right)^A \geq \Delta \ln \left(\widehat{TFP_t}\right)^G$.[26]

Chapter 5 used two different measures of TFP aggregation. In section 5.2, there was used the decomposition of weighted average TFP (in levels) to examine the geographical and sectoral dimensions of productivity in Mexico. In section 5.3, there was used the weighted average ln TFP to measure the TFP growth decomposition. The use of different TFP aggregations is due to the author´s preference to choose a metric which represents with veracity the productivity in Mexico. The use of the weighted average TFP provided a better representation of the geographical and sectoral dimension of TFP in Mexico, while the use of weighted average TFP in ln provided a better representation of the TFP growth decomposition in Mexico. The choice of one method of TFP aggregation above another relies on the researcher's preferences and the questions addressed, as Dias & Robalo (2021) suggest. The TFP growth decomposition can be extended by using TFP in levels as part of the future research agenda. The Appendix in Melitz & Polanec (2015) explains the productivity growth decomposition of a productivity index in levels, which can be applied to future research. The extension and comparison of different TFP aggregations using arithmetic and geometric TFP growth can confirm the effect of firm selection on TFP growth regarding the contribution of surviving, entering and exiting establishments in Mexico in the future research agenda.

[26] The reason for the Jensen's inequality is that the weights change the moments in the productivity distribution and thus in the arithmetic and geometric growth. Dias & Robalo (2021, p. 31) concluded "we suggest using the arithmetic mean whenever the analysis is based on labour productivity (. . .) so that their changes match the changes in labour productivity that can be computed from the National Accounts aggregate data." About the selection in the aggregation of TFP, Dias & Robalo (2021) argue that the selection may depend on the research preferences and questions addressed.

Chapter 6

Analysis of results 3: Regional TFP convergence

6.1 Overview of Chapter 6

This Chapter analyse regional TFP convergence in Mexico. Chapter 6 uses weighted TFP at the state and municipality level measured in Section 5.2.1 to test the hypothesis of TFP convergence. This research contributes to the literature because not many studies use TFP as the analysis metric to examine productivity convergence. Table 6.1 summarises the content of Chapter 6 by analysing two metrics: beta-convergence and sigma-convergence disaggregated at the state and municipality levels. There are three sections in Chapter 6. Section 6.2 presents the theory of convergence. This section explains beta-convergence using TFP. Typically, beta-convergence is measured with econometric techniques using neoclassical convergence models. This section includes the spatial convergence model with the contribution of Spatial Econometrics to the convergence analysis. Section 6.2 includes the concept of sigma-convergence as a complementary measurement to beta-convergence. Section 6.3 presents evidence about the TFP evolution across Mexican states and municipalities to analyse the stylised facts of the weighted TFP between 1998 and 2018. Finally, Section 6.4 presents the measurement of TFP beta-convergence and TFP sigma-convergence at the state and municipality levels.

Table 6.1: Measurement of regional TFP convergence in Mexico

Metric	Disaggregation
TFP beta-convergence	State Municipality
TFP sigma-convergence	State Municipality

Source: Own elaboration

6.2 Theory of convergence

There are three concepts related to economic convergence: (i) absolute convergence, (ii) conditional convergence and (iii) club convergence (Galor 1996). The concept of absolute convergence refers to the process of economic growth in which the economies will end up with the same output level and production per worker in the long run. This concept comes from the neoclassical economic growth theory introduced by the Solow (1956) model. Absolute convergence accounts for a pattern of economic growth in which emergent economies grow faster and reach the same income per capita compared to high-income economies in the long run. However, there is more evidence in the literature that economic growth leads to a conditional convergence between economies. The process of conditional convergence predicts that economies with different initial endowments (i.e. factors of production) and output will converge to different levels of output and factors of production determined by the economic structure and its absorptive capacity (Barro & Sala-i Martin 1992). In addition, club convergence proposes that a cluster of economies with similar structural characteristics converge to the same level of steady-state (level of factors of production) in the long run.

According to the economic growth theory, there are two mechanisms for economic convergence: diminishing RTS and absorptive capacity (Durlauf et al. 2009). On the one hand, the Solow (1956) neoclassical growth model emphasises that diminishing RTS is a mechanism that slows down economic growth in the long run to approach the steady-state. Therefore, the neoclassical theory of economic growth predicts that larger economies grow at a slower pace due to diminishing RTS while small economies grow at a faster pace as those economies are far towards the approach of the steady state. On the other hand, Durlauf et al. (2009) pointed out that endogenous growth models account for the fact that economies behind the technological frontier have the potential for rapid advancement due to the installation of capital embodying the technological frontier. In addition, absorptive capacity in economies behind the technological frontier induces productivity growth with a positive effect on the catch-up process (Griffith et al. 2003, 2004). [1]

[1]For instance, R&D is a factor that can benefit the catch-up effect through improvements in TFP growth. Grif-

Convergence represents the capacity of economic growth to reduce initial disparities of economic development (i.e., measured by the GDP per capita). The concept of convergence can be applied to other economic indicators and geographical delimitations beyond macroeconomic studies. This research applies the convergence analysis to TFP. The analysis of TFP convergence reflects the capacity of TFP growth (growth efficiency) in an economy to reduce initial TFP (efficiency) disparities with other economies. Then, absolute TFP convergence ensures that economies approach similar efficiency conditions in the steady-state. In the long term, similar levels of efficiency are associated with similar levels of economic development (Klenow & Rodriguez-Clare 1997). In addition, TFP convergence is relevant to the endogenous growth theory to examine if economies behind the technological frontier are developing the absorptive capacity to catch-up with the technological frontier.[2] Ultimately, TFP convergence aims to generate better conditions to achieve more equity in living standards through absorptive capacity and increases in efficiency.[3]

The literature points out two measurements of convergence. The first measurement is beta-convergence, and the second is sigma-convergence. In a nutshell, beta-convergence measures the catch-up process and sigma-convergence measures the evolution of disparities. Sala-i Martin (1996) defines a mathematical relationship of negative causality between beta-convergence and sigma-convergence. The mathematic negative relationship beta-sigma implies that the more vigorous the catch-up process is, the lower the economies' disparities. This section reviews both measurements.

Chapter 6 measures TFP convergence across geographical locations in Mexico, including states and municipalities. The relevance of the TFP convergence at the subnational level in Mexico is to examine the reverse of productivity across geographical locations over time. The reverse of TFP across locations implies analysing if a location with low productivity is growing faster to catch-up with high-productivity locations. The TFP catch-up process is the reverse of the productivity weakness at the subnational level because low-productive locations are improving their initial conditions over time to reach higher productivity levels and a higher living standard. In the literature, the catch-up process is measured with beta-convergence. In addition, it is relevant to examine whether productivity inequalities are reducing across geographical locations by measuring sigma-convergence. This analysis aims to determine whether the distribution of TFP across locations has reduced productivity inequalities within Mexico over time. The evolution of the distribution of

fith et al (2004) define two roles or "faces" of the R&D. The first channel is when R&D generates innovation, lowering costs, and then TFP and production increase. If new products replace the existing ones through a Schumpeterian process of creative destruction, greater efficiency and better technology are reached, pushing the PPF upward. The second channel is the development of "tacit" knowledge. This concept refers to the identification, assimilation and exploitation of innovations made by a context of other firms and R&D actors (e.g. universities and research institutes), which is expected to generate improvements in TFP.

[2] The analysis of TFP convergence can be catalogued as the core of examination on convergence across economies. The reason is that TFP convergence explains if TFP drives economic convergence based on endogenous growth. At the macro level, endogenous growth theory explains that economic growth results from internal forces that reflect increases in TFP by accumulating human capital and innovation (Mankiw et al. 1992, Griffith et al. 2003).

[3] For instance, Figure 1.6 displays that there is a negative relationship between labour productivity and poverty across Mexican states.

TFP across geographical locations can be measured using sigma-convergence.

6.2.1 Beta-convergence

Sala-i Martin (1996, p. 2) defines beta-convergence as "[the] negative relation between the growth rate of income per capita and the initial level of income". Therefore, the convergence process determines whether poor economies grow faster than rich economies to catch up with them. During the 1990s and 2000s, several studies analysed convergence in GDP (income) per capita.[4] Therefore, the rule of 2% convergence is a simplification in the literature because convergence speed varies depending on the case study. This research proposes that models of GDP convergence can be adapted to measure TFP beta-convergence.

This research measures TFP convergence across states and municipalities in Mexico. For that reason, the specification of models to measure TFP convergence includes weighted TFP at the state and municipality levels calculated in Chapter 5. The author is unaware of previous research on TFP convergence in Mexico with a detailed parametric (econometric) analysis. Most recent studies examining Mexico's productivity convergence use labour productivity as the analysis metric with geographical disaggregation at the state or the municipality level (Díaz-Dapena et al. 2019, Castellanos-Sosa 2020, Cabral et al. 2020, Mendoza-Velázquez et al. 2020). Therefore, this research fills the gap in the literature about regional TFP convergence in Mexico.

There are few studies of TFP convergence in the literature due to the lack of information about TFP. At the country level, sources of information such as the World KLEMS data or the Penn World Table provide data to analyse TFP convergence across countries. However, TFP convergence with a regional orientation implies estimating TFP with data at the regional level and then examining the convergence measurements (i.e. beta-convergence, sigma-convergence). For instance, Byrne et al. (2009), Escribá-Pérez & Murgui-García (2018), and Burda & Severgnini (2018) measured TFP at the regional level using the calculation of growth accounting in Italy, European regions and Germany, respectively.[5] Subsequently, they estimated different models that account for TFP convergence across regions. Otsuka & Goto (2016) calculated TFP with a non-parametric method using regional data at a prefectural level in Japan, and then Otsuka & Goto (2016) evaluated TFP convergence. Most of the studies that analyse TFP convergence use data at the regional level.

[4] Young et al. (2008) pointed out that the literature on convergence concludes that beta-convergence is similar across economies, and there can be a rule in which economies converge at the speed of 2% p.a. Esquivel (1999) summarised convergence studies and argued that there is a variation across economies and time in estimating beta-convergence. The values of beta-convergence can fluctuate from 1% to 4.5%.

[5] Byrne et al. (2009) and Burda & Severgnini (2018) measured TFP at the regional level in Germany and Italy by using the identity of the growth accounting specified as $Y/L = TFP(K/Y)^{1-\alpha/\alpha}$, which expresses that labour productivity is positively associated with TFP. The measurement of TFP in both studies consisted of defining the parameter α. Burda & Severgnini (2018) set $\alpha = 0.33$, and they tested convergence using a panel data model following convergence to the frontier. Byrne et al. (2009) set α as the share of labour cost to value-added, and they tested convergence using panel data models of unit roots.

The author considers that using TFP estimations from microdata is a more refined variable for analysing TFP convergence.

The measurement of beta-convergence can be derived from the Solow-Swan model (Barro & Sala-i Martin 1992, p. 54-59). In the neoclassical theory of economic growth, beta-convergence reflects the speed that the economy approaches its steady-state in which the capital and output are constant over time. The extension of this theoretical neoclassical convergence framework applied to TFP can be interpreted as the approach of an economy to its maximum TFP level in the steady-state. Barro & Sala-i Martin (1992, p. 230) empirically measured convergence across U.S. states with a regression in which the average income growth per capita is the dependent variable of the initial income level per capita.[6] Therefore, the point of departure to measure TFP beta-convergence is to specify average TFP growth in location j as a function of the initial value of TFP in location j. Then, beta-convergence is the parameter β of a cross-section that includes the weighted TFP as the main analysis variable in a cross-section estimated with OLS, as equation 6.1 specifies.

$$\left[\ln\left(\widetilde{TFP}_{jT}\right) - \ln\left(\widetilde{TFP}_{j1}\right)\right]/T = \alpha + \beta \ln \widetilde{TFP}_{j1} + \varepsilon_j \tag{6.1}$$

Equation 6.1 uses a cross-section model where the dependent variable $\left[\ln\left(\widetilde{TFP}_{jT}\right) - \ln\left(\widetilde{TFP}_{j1}\right)\right]/T$ approximates the average weighted TFP growth in the geographical location j between the initial year 1 and the last year T. The initial year is 1998 ($t = 1$), and the last year is 2018 (T). The subscript j represents the geographical delimitation that represents a state or a municipality, depending on the level of disaggregation of the TFP analysis. The variable $\ln\left(\widetilde{TFP}_{j1}\right)$ is the initial level of weighted ln TFP during 1998.

Equation 6.1 can be labelled as the neoclassical TFP convergence model (regression). The parameter α is the common steady-state for the locations j's and ε_j is the error term in the geographical location j. The parameter β measures convergence (divergence) across geographical locations per annum. If there is TFP convergence across locations, the parameter β is negative ($\beta < 0$). A negative value of β means that lower initial weighted TFP in the location j is associated with higher weighted TFP growth, and high initial levels of TFP is associated with lower TFP growth rates. On the other hand, if β is positive ($\beta > 0$), there is divergence across geographical locations j's. In case the parameter β is not statistically significant means that $\beta = 0$ and locations are in equilibrium which indicates neither TFP convergence nor TFP divergence.

The main variable analysed in equation 6.1 is the weighted TFP ($\widetilde{TFP}_{jT}$) in the location j and year t. Therefore, the precise meaning in the case of TFP convergence is that locations with low weighted TFP during 1998 had a larger increase in the weighted TFP growth than their counterparts over the period 1998-2018. On the contrary, locations with high weighted TFP during 1998 had a smaller increase in their weighted TFP growth from 1998 to 2018. As a result, geographical

[6] Quah (1993) catalogued the specification of the convergence model as "Barro regressions".

locations with an initial low weighted TFP catch-up with locations with a high weighted TFP.

Rey & Montouri (1999, p. 145) stated that in the neoclassical convergence model, "Implicitly, each region has been viewed as an independent entity and the potential for observational interactions across space has largely ignored". In addition, Rey & Montouri (1999) pointed out that spillovers are key mechanisms that contribute to convergence, and the omission of spatial dependence in the specification of the beta-convergence model can lead to misspecification.[7] In the survey of Harris (2011), there are three models that measure beta convergence in a cross-section: (i) the neoclassical convergence model estimated with OLS, (ii) the beta-convergence model with spatial dependence in the independent variable, and (iii) the beta-convergence model with spatial dependence in the error term. The latter two models consider spatial spillovers as crucial variables in determining convergence.

Rey & Gallo (2009) pointed out that studies about economic convergence at the subnational level have adopted the strategy to include Spatial Econometrics in the analysis. These models are labelled spatial convergence models, which account for spatial dependence.[8] Spatial Econometrics account for the economic interactions between regions due to proximity by including a W matrix, which represents the spillover effects of production between economies. The W matrix is an approximation to measure the interregional linkages under the idea of Tobler (1970, p. 236), "everything is related to everything else, but near things are more related than distant things."

The neoclassical model to measure TFP convergence in equation 6.1 can have spatial dependence, and the inclusion of a W matrix is necessary. This model can be defined as the TFP spatial convergence. Stakhovych & Bijmolt (2009) suggested that an initial exploratory analysis to identify spatial dependence can measure spatial autocorrelation using Moran's I statistics, the Kelejian-Robinson test, and Lagrange Multiplier (LM). Rey & Gallo (2009) pointed out that in addition to Moran's index, other studies that analyse convergence use the Getis–Ord. Anselin (1988, p. 323) pointed out that Moran's index is the most common test for spatial autocorrelation.

This research adopts the classic detection of spatial dependence by using Moran's index in the variables included in the neoclassical model of TFP convergence. There are three variables in equation 6.1 which can have spatial dependence: (i) the independent variable (average weighted TFP growth), (ii) the dependent variable (lagged TFP,) and (iii) the error term. Elhorst (2010) proposes a strategy for estimating spatial models, which consists of specifying the W matrix in the variables with spatial dependence. In the case of spatial dependence in the three variables, Elhorst

[7] Rey & Montouri (1999) extended the convergence analysis of income per capita across states of the U.S. in the period 1929-1994 to test for spatial dependence and the results indicated that there is positive spatial dependence in the income per capita across states. Rey & Montouri (1999) indicated that the spatial dependence is due to clusters of income per capita.

[8] Spatial dependence explains that regions in the vicinity (periphery) determine the region of analysis (centre) and vice versa. For that reason, the interregional feedback generates economic spillovers. These economic interactions generate spillover and get reflected in the data as spatial dependence, which is also consistent with the NEG models of centre-periphery.

(2010) proposes the Manski model as the most general model in Spatial Econometrics that accounts for spatial lags in all the variables. Equation 6.2 suggests a spatial TFP convergence model with spatial lags in all the variables.

$$\left[\ln\left(\widetilde{TFP}_{jT}\right)-\ln\left(\widetilde{TFP}_{j1}\right)\right]/T=\alpha+\beta\ln\left(\widetilde{TFP}_{j1}\right)+\rho W\left[\ln\left(\widetilde{TFP}_{jT}\right)-\ln\left(\widetilde{TFP}_{j1}\right)\right]/T+ \gamma W\ln\left(\widetilde{TFP}_{j1}\right)+\lambda W\varepsilon_j+\varepsilon_j \tag{6.2}$$

Equation 6.2 is a cross-section beta-convergence model that includes the W matrix in the three variables, and the parameters ρ, γ and λ measure spatial effects in the dependent variable, independent variable and the error term of the location j, respetively. The dimension of the W matrix is $M \times M$, where M is the total number of geographical locations j in the cross-section. In most of the studies of Applied Spatial Econometrics, the W matrix can be contiguous or inverse distance. Stakhovych & Bijmolt (2009) suggested estimating the spatial models with different specifications in the W matrix. The strategy of Stakhovych & Bijmolt (2009) consisted of selecting the W matrix that maximises the log-likelihood, which is associated with the minimum values of the Information Criteria (IC) tests. This criterion for selecting the W matrix ensures the best goodness of fit in the spatial model. Alternatively, Stakhovych & Bijmolt (2009, p. 407) proposed that "using the most simple spatial weights matrix, first-order contiguity (if the theory does not suggest otherwise), offers the second-best option.". In the spatial convergence model, $\beta < 0$ indicates TFP convergence, $\beta > 0$ indicates TFP divergence, and $\beta = 0$ indicates that the locations are in equilibrium. [9]

In equation 6.2, the parameter ρ measures the spillovers of TFP growth across geographical locations. The parameter λ measures the spatial autocorrelation of the error term, and the parameter γ estimates the spatial lag of the initial levels of weighted TFP on TFP growth. According to Jadhav & Viswanathan (2022), the parameter γ can be described as the parameter of spatial convergence and this criterion comes from the framework of Anselin (2003).[10] Empirical research that analyses economic convergence using techniques of Spatial Econometrics do not usually focus on analysing the parameters that account for spatial spillovers. The main objective of the convergence analysis using Spatial Econometrics is the correction of spatial autocorrelation to overcome bias in the parameters (Rey & Montouri 1999, Rey & Gallo 2009).

According to the framework of Anselin (2003, p. 162), equation 6.2 includes spatial multipliers. This equation can be expressed as $(I-\rho W)([\ln\left(\widetilde{TFP}_{jT}\right)-\ln(\widetilde{TFP}_{j1})]/T)=\alpha+(I+$

[9]The variable $\left[\ln\left(\widetilde{TFP}_{jT}\right)-\ln\left(\widetilde{TFP}_{j1}\right)\right]/T$ is the same as the dependent and independent variables in equation 6.2. The difference is that the inclusion of the weighted matrix W in the independent variable denotes the effect of TFP growth from the periphery to the centre. Then, the variable $W\left[\ln\left(\widetilde{TFP}_{jT}\right)-\ln\left(\widetilde{TFP}_{j1}\right)\right]/T$ describes the effect of TFP growth from the vicinity of the region j.

[10]Jadhav & Viswanathan (2022) analysed the income convergence at the sub-state level in India and focused on the spatial convergence aspect.

$\rho_1 W)\beta \ln \widetilde{TFP}_{j1} + (I + \lambda W)\varepsilon_j$, where the parameter ρ_1 represents the spatial lag of the initial levels of TFP across regions j. Therefore, the parameter $\gamma = \rho_1 * \beta$. The parameter γ measures spatial convergence because it incorporates the parameter of beta convergence β and the spatial lag ρ_1. Jadhav & Viswanathan (2022) concluded that when the parameter $\gamma > 0$ reflects spatial convergence because $\beta < 0$ and $\rho_1 < 0$. On the contrary, when the parameter $\gamma < 0$ suggests spatial divergence because $\beta < 0$ and $\rho_1 > 0$. In both cases, it is assumed that there is beta-convergence because $\beta < 0$.

The strategy to estimate the parameter β and to test TFP convergence at the state and municipality level in Mexico consists of the following steps:

1. To measure beta-convergence using the neoclassical model (regression).
2. To identify potential spatial dependence using Moran's index in the variables included in the neoclassical model.
3. In the case of spatial dependence, there is specified a spatial convergence model including the variables with spatial dependence, as Elhorst (2010) proposed, which accounts a specification strategy from general to specific. In the case of non-significant spatial parameters, the spatial model can be constrained to define more specific spatial models.
4. The spatial convergence model is tested with different W matrices (e.g. contiguity, inverse distance). The selection of the best W matrix is based on the matrix that provides the best goodness of fit, as Stakhovych & Bijmolt (2009) proposed.

Harris et al. (2011) argue that the W matrix imposes a priori an arbitrary structure of regional interaction based on contiguity or inverse distance. The W matrix has been criticised because the economic structure of spatial dependence of the W matrix is untested and could lead to a miss-specification in regional models. For that reason, the W matrix can be contentious because it collapses the economic linkages between regions into a single weighted matrix. This matrix can hide and omit alternative linkages from the regional economic structure. Harris et al. (2011) highlight the importance of the appropriate measurement of the economic linkages between regions because different measurements can lead to different results in applied regional economics. Therefore, Harris et al. (2011) proposed that there can be alternative measurements for the economic linkages to the standard approach of the W matrix that include (i) W matrix built with first-step regression residuals, (ii) W matrix capturing neighbourhood linkages measured with non-parametric approaches, (iii) W hybrid matrix that includes contiguity and distance effects that can measure technological proximity and transportation times, (iv) X matrix that includes proxy variables of linkages. The advantage of the X matrix is that it can be incorporated straightforwardly into the regression. Harris et al. (2011, p. 255-263) reviews the proxy variables that can be included in the X matrix. Those variables reflect a 'learning region' operating with MAR and Jacobian externalities.

Although Harris et al. (2011) proposed alternative approaches to the W matrix, this work did not propose a quantitative test about the most plausible measurement of economic linkages. The literature does not define the best or correct measurement of unobserved economic linkages between regions. Instead, ad-hoc measurements are an ongoing debate. As McMillen (2010, p. 121) states, "... the paradox of most spatial econometric models is that ... their very use is an admission that the true model structure is unknown". Therefore, the open question about "what is an appropriate measurement of economic linkages among regions?" is the allowance for the answer "to use different approaches to measure economic linkages according to economic theory and available data". A robustness test in applied economics could examine whether the spillover effect remains positive (or negative) in the presence of different measurements of economic linkages. Chapter 6 adopts the approach that the W matrix of contiguity or inverse distance is a plausible measurement of economic linkages among Mexican locations. However, a future line of research could incorporate additional measurements of economic linkages.

6.2.2 Sigma-Convergence

Quah (1993) proposed that sigma-convergence is the most straightforward metric to analyse convergence as it measures if the income distribution across economies becomes more equitable. Monfort (2008, p. 5) defines the concept of sigma-convergence as "[the] reduction of disparities among regions in time". Beta-convergence and sigma-convergence are related as both measurements analyse the reduction of disparities between economies. However, beta-convergence emphasises that economic growth is a convergence mechanism with high-income economies. The literature accounts for Standard Deviation (S.D.) as the metric of sigma-convergence, but other indices that measure inequality can be complementary such as the Gini coefficient, the Atkinson index, the Mean Logarithmic Deviation (MLD) and the Theil index (Monfort 2008).[11]

This subsection uses the work of Sala-i Martin (1996) to define the mathematical relationship between beta-convergence and sigma-convergence. In his seminar paper, Sala-i Martin (1996) concluded that convergence of GDP per capita reduces GDP per captia inequalities between economies (or regions). The proposition of Sala-i Martin (1996) can be expressed using TFP, which implies that TFP convergence across regions is necessary but not sufficient to reduce TFP inequalities between regions. Equation 6.3 explains the speed of TFP convergence at the national level.

$$\ln\left(\widetilde{TFP}_t\right) = \alpha + (1-\beta)\ln\left(\widetilde{TFP}_{t-1}\right) + v_i \tag{6.3}$$

[11] The empirical study of Monfort (2008) relates beta-convergence and sigma-convergence in Europe. Monfort (2008) argues that there is a beta-convergence process in the European Union among the groups of countries EU-15 and EU-27. Monfort (2008) estimated that the magnitude of beta-convergence was not constant. From the 1970s and 1990s, there was a stronger beta-convergence process, which generated a reduction in sigma-convergence in the group EU-15. The group of EU-27 also showed a reduction in the sigma-convergence from the 1990s to the early 2000s.

The transformation of 6.3 leads to the neoclassical model in equation 6.1. The calculation of the variance of weighted TFP across economies j's in time t is defined as follows:

$$\sigma_t^2 = \frac{1}{N_t^j} \sum_{j=1}^{J} \left(\widetilde{TFP}_{jt} - \tilde{\mu}_t \right)^2 \tag{6.4}$$

In 6.4, the variable $\tilde{\mu}_t$ is the mean of $\widetilde{TFP}_{jt}$ across economies j's in time t. From equation 6.4, the following equation derives the evolution of σ^2 over time with an autoregressive process.

$$\sigma_t^2 \cong (1-\beta)\sigma_{t-1}^2 + \sigma_u^2 \tag{6.5}$$

According to equation 6.5, the condition of beta-convergence in the interval $-1 < \beta < 0$ is necessary so that the variance (disparities) decreases over time. If there is beta-divergence in the interval $1 > \beta > 0$, the variance increases over time. Sala-i Martin (1996) defines the steady state of equation 6.5 as follows:

$$\sigma^2 = \frac{\sigma_u^2}{[1-(1-\beta)^2]} \tag{6.6}$$

Equation 6.6 indicates that when β increases, the steady state σ^2 decreases. The replacement of σ_u^2 of equation 6.5 into 6.6 is the solution for the evolution of sigma over time σ_t^2 in the function of the steady-state of the variance σ^2.

$$\sigma_t^2 = \sigma^2 + (1-\beta)^2 \left(\sigma_{t-1}^2 + \sigma^2 \right) \tag{6.7}$$

In equation 6.7, as long as $\sigma^2 < \sigma_{t-1}^2$, the increase of β decreases σ_t^2 until reaching the steady-state σ^2, which is the negative relationship between β and σ^2. For that reason, beta-convergence (catching-up process) is a necessary condition but not sufficient for sigma-convergence (reduction of disparities) because other conditions depend on the values of σ^2 and σ_{t-1}^2. Equation 6.7 implies that the more vigorous the catch-up process is, the lower the economies' disparities. The calculation of sigma-convergence using weighted TFP at the geographical level j is specified as follows.

$$\sigma_t = \sqrt{\frac{\sum_{j=1}^{J} (\ln(\widetilde{TFP}_{jt}) - \tilde{\mu}_t)^2}{N_t^j}} \tag{6.8}$$

Equation 6.8 measures the S.D. of the weighted TFP in ln at the level of disaggregation j

by year as the sigma-convergence. In equation 6.8, the variable $\tilde{\mu}_t$ is the mean of weighted TFP (ln) across locations j in year t, and N_t^j is the number of geographical locations j in the year t. The level of disaggregation j can be state or municipality level. [12] Beta-convergence and sigma-convergence of TFP measure different concepts of efficiency. On the one hand, beta-convergence measures efficiency catch-up among economies (i.e., states, municipalities, etc.). On the other hand, sigma-convergence measures the increase/decrease of efficiency disparities between economies (i.e., states, municipalities, etc.). Higher values of sigma-convergence indicate that TFP disparities between states are increasing, while lower values of sigma-convergence indicate a reduction of TFP disparities. Chapter 6 measures TFP sigma-convergence and tests the prediction of Sala-i Martin (1996). In the case of a TFP catch-up process across locations in Mexico, there might be a reduction of TFP disparities across locations.

6.3 Regional convergence and productivity disparities in Mexico

Several studies in Mexico have examined the convergence process (or divergence) across geographical locations in Mexico using GDP (or gross output) per capita as the analysis metric. Still, studies have yet to analyse productivity convergence across Mexican regions. The analysis of productivity convergence is relevant because productivity gaps are the primary driver of persistent regional disparities over time. This section has two objectives. The first objective is to summarise studies on convergence and productivity disparities across Mexican regions to provide a perspective on regional convergence across Mexican locations. The second objective is to give evidence on TFP disparities across states and municipalities in Mexico between 1998 and 2018 using the weighted TFP from Chapter 5.

According to the literature, there can be an association between economic growth and GDP per capita convergence in Mexico. For instance, Esquivel (1999) concluded that there was an intense economic convergence across Mexican states from 1940 to 1960, reducing income disparities in those locations. The decades from 1940 to 1960 are associated with high GDP growth in Mexico according to Esquivel (2010).[13] Conversely, the lack of economic convergence between Mexican states from 1960 to 1995 is related to low economic growth rates and financial instabilities (Esquivel 2010). Esquivel (1999) considered that efforts to decrease regional disparities in Mexico should be associated with a higher provision of infrastructure and human capital in less developed states.[14]

[12] Sigma-convergence uses weighted TFP in ln to keep proportionality in relation to beta-convergence because beta-convergence uses variables in ln. For instance, Ram (2018) measured sigma-convergence of income in ln, as he described that variable as SDLOG.

[13] Esquivel (1999) measured a beta-convergence of 1.1% p.a. at the state level in Mexico from 1940 to 1995. This result is explained because there was an intense regional convergence in Mexico from 1940 to 1960. However, there was no evidence of regional convergence from 1960 to 1995.

[14] The provision of regional capabilities that incentive economic development is a determinant factor in regional convergence in Mexico. The results of Garduño Rivera (2014) indicate that education and infrastructure positively impact value-added per worker in Mexican municipalities.

The literature on regional convergence in Mexico accounts that another determinant of convergence (divergence) is the economic integration between Mexico and the U.S. Empirical studies that analyse convergence in Mexico with long time series or panel data divide the analysis into pre-NAFTA (before 1994) and post-NAFTA (after 1994). The literature review compiled by Díaz-Dapena et al. (2019) accounts for relevant facts about economic convergence across regions in Mexico that can be summarised as follows. (i) Mexican states with economic linkages have grown more than their counterparts, but there has been no significant increase after NAFTA. In addition, the capacity growth in Mexico City was reduced after NAFTA, and then the agglomeration of economic activities in Mexico was reduced. (ii) Trade reforms affected Mexico City and the poorest states (mainly in the south of Mexico). (iii) There was an intense convergence process across Mexican regions pre-NAFTA; post-NAFTA convergence continued with a slower pattern. In addition, there is an increasing disparity between Northern states and the rest of the regions in the period post-NAFTA.[15] (iv) There is evidence to suggest that there are clubs of convergence in Mexico at the state level as the result of a wide heterogeneity.[16]

In recent years, there have been an increasing number of studies analysing regional productivity convergence in Mexico due to the data available from the Economic Census of Mexico. The studies of Cabral et al. (2020) and Castellanos-Sosa (2020) are two recent papers that estimated labour productivity convergence in Mexican regions. Castellanos-Sosa (2020) estimated a convergence model with data disaggregated by states and sectors (state-sector). After accounting for sector and state fixed effects, Castellanos-Sosa (2020) concluded that the convergence rate increased during the global financial crisis. However, in the long-term, the financial crisis affected the convergence of states and sectors. In addition, Castellanos-Sosa (2020) argued that the labour productivity convergence pattern barely changed in the North of Mexico, while most of the changes occurred in the South and Center of Mexico. Cabral et al. (2020) estimated labour productivity convergence across Mexican states and municipalities using data from the manufacturing sector of the Economic Census from 1993 to 2013 with a 5-years gap. Cabral et al. (2020) estimated a parameter of beta-convergence equivalent to 0.16 at the state level and 0.48 at the municipality level estimated with a Spatial Durbin Error Model (SDEM). Associated with the beta-convergence estimations, Cabral et al. (2020) calculated a half-life period of convergence equivalent to 99.4 years and 26.5 years at the state and municipality levels, respectively.

[15] Díaz-Dapena et al. (2019) analysed the effect of NAFTA on productivity convergence using the value-added per worker at the municipality level. The parametrical result of Díaz-Dapena et al. (2019, p. 5522) indicated that there is a strong and statistically significant convergence across municipalities in Mexico over the period pre-NAFTA (1980-1993) while in the period post-NAFTA (1998-2008), the parameter of convergence is not statistically significant. In addition, proximity to the border between Mexico-U.S. benefited the value-added growth during the post-NAFTA period, indicating that proximity to the U.S. increases value-added per worker at the municipality level. However, proximity to Mexico City had a non-significant effect on the increase of value-added per worker pre-NAFTA and post-NAFTA.

[16] Mendoza-Velázquez et al. (2020) tested the hypothesis of club convergence across Mexican states from 1940 to 2015. The result of Mendoza-Velázquez et al. (2020) is that Mexican states have four convergence clubs in the intersection of four characteristics (i) high and low income and (ii) high and low inequality

Labour productivity is a metric biased in economic sectors with intense use of capital (Sargent & Rodriguez 2001). Therefore, TFP is a more reliable metric in the analysis of productivity convergence. There are few studies of TFP convergence across regions, and the author is unaware of a study that analyses TFP convergence across Mexican regions. There are some studies of TFP convergence in other economies. For instance, Byrne et al. (2009) found a lack of TFP convergence in Italian regions from 1970 to 2001.[17] The parametrical results in Burda & Severgnini (2018, p. 206) found TFP convergence in Germany from 1993 to 2011. However, Burda & Severgnini (2018) did not provide a plausible interpretation of the convergence parameters.[18] Otsuka & Goto (2016) found TFP convergence across Japanese regions from 1980 to 2010.[19] Finally, Escribá-Pérez & Murgui-García (2018) found a conditional TFP convergence in 121 European regions from 1995 to 2007.[20]

Harris (2011) argues that there are problems defining appropriate geographical delimitation to analyse productivity convergence. This research considers that the analysis of TFP convergence across Mexican states provides a clearer idea of the big 'picture' that describes the regional TFP in Mexico. A higher regional disaggregation of the TFP considers the analysis of the weighted TFP at the municipality level to confirm the results at the state level. The following subsection presents evidence about the weighted TFP disparities across states and municipalities in Mexico from 1998 to 2018. The results indicate that the geographical structure of productivity in Mexico was rigid from 1998 to 2018 because the distribution of high and low productive geographical locations remained without significant changes over 20 years.

The persistence of productivity disparities results from agglomeration economies that generate locations with high and low productivity. Externalities shape the economic and geographical structure of productivity in Mexico. Some geographical locations have comparative advantages, increasing RTS and minimising costs that make them more productive than their counterparts. The issue is that some geographical locations needed to catch up to the productive leaders in 1998

[17] Byrne et al. (2009) attributed the lack of convergence in their study to a limitation (bias) in estimating TFP with data at the regional level.

[18] The parametrical results in Burda & Severgnini (2018, p. 206) found a negative relationship with statistical significance between the rates of TFP growth and lagged values of TFP, but those parameters have large magnitudes. Burda & Severgnini (2018) did not provide a plausible interpretation of the convergence parameters. Instead, this study focused on the TFP gap between the East and West of Germany, mainly explained by manufacturing construction and other production activities. In addition, the absorptive capacity only operates in East Germany and helps backwards states the most.

[19] TFP convergence in Japanese regions suggests that the accumulation of technological knowledge in each region is a source of sustainable growth in the long term. Otsuka & Goto (2016) consider that regional-specific factors related to technological progress explain regional economic development and its contribution to national economic growth. However, Otsuka & Goto (2016) appreciate that the omission of spillovers is a limitation in measuring TFP convergence in their study.

[20] Escribá-Pérez & Murgui-García (2018) analysed the TFP catch-up in European regions using models of Spatial Econometrics to account for regional spillovers in determining TFP growth rates. In addition to the catching-up analysis, this study measures the effect of regulations and labour markets on TFP growth in 121 European regions during 1995-2007. The study suggests that human and technological capital and factors related to market regulation have been determinants of TFP growth and convergence.

and remained with low productivity levels in 2018. Applying fiscal policy to reduce disparities across geographical locations in Mexico is not enough (Angeles-Castro et al. 2019). Therefore, there is room for implementing public policy (i.e., industrial strategies) to boost productivity in low-productive locations and rebalance the geographical structure of productivity in Mexico.

6.3.1 TFP disparities at the state level

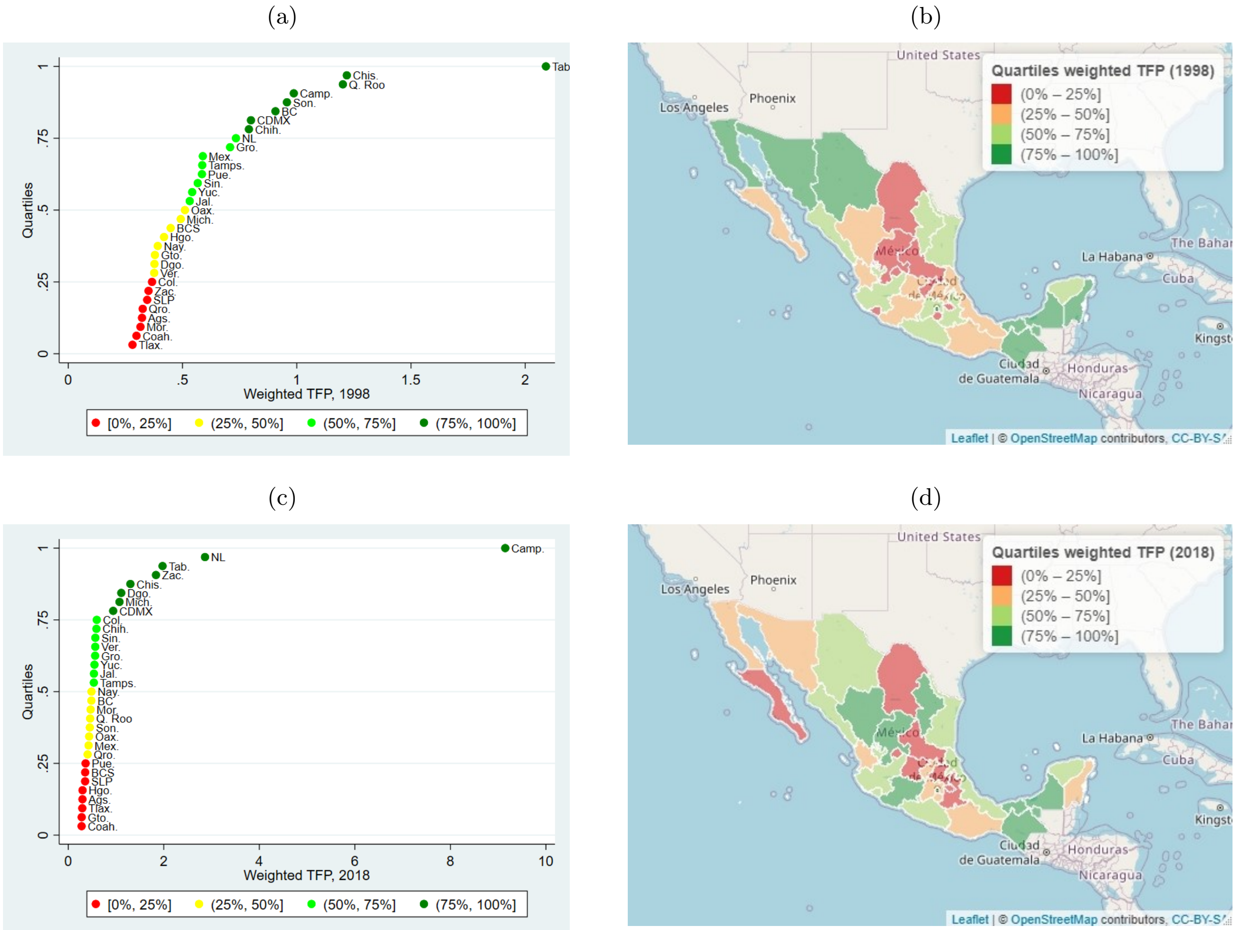
This subsection presents initial evidence about TFP disparities across Mexican states using weighted TFP in 1998 and 2018. Figure 6.1 displays the cumulative function of weighted TFP at the state level classified by quartiles and its spatial distribution in 1998 (Figure 6.1a and 6.1b) and 2018 (Figure 6.1c and 6.1d). The analysis period in Figure 6.1 is relevant for the Mexican economy because NAFTA was signed in 1994. Since that year, the Mexican economy has begun a close economic partnership with the U.S. For that reason, Figure 6.1 displays the evolution of the TFP at the state level after NAFTA, which is the beginning of an intense process of economic openness in Mexico.

The cumulative weighted TFP function at the state level between 1998 (Figure 6.1a) and 2018 (Figure 6.1c) indicates major changes in the composition of the weighted TFP distribution at the state level in the top quartile. In 1998, Tabasco (Tab) was the state with the highest weighted TFP, but in 2018 Tabasco was the third state with the highest TFP. From 1998 to 2018, two states increased their weighted TFP to reach the highest two positions in the top quartile: Nuevo Leon (N.L.) and Campeche (Camp). [21] The high increase in weighted TFP in Nuevo Leon was generated by activities related to manufacturing and trade. In addition, TFP increase in activities related to oil extraction and production was the main cause of the increase of weighted TFP in Campeche from 1998 to 2008. States in lower quartiles had a positive increase of weighted TFP between 1998 and 2018 (Figure 6.1a and 6.1c). This characteristic can be better illustrated in the subsequent Figure 6.3. As a result, the changes of positions across states in the top quartile of weighted TFP distribution and the positive increase of weighted TFP in states in lower quartiles are initial stylised facts to conduct the TFP convergence analysis.

Figures 6.1b and 6.1d show changes in the spatial distribution structure using weighted TFP at the state level between 1998 and 2018. For that reason, Mexico has had a particular geographical productivity structure for over 20 years. There can be identified three clusters of states with high levels of weighted TFP, including (i) some northern states of Mexico that share a border with the U.S., (ii) highly populated states such as Mexico City and Jalisco, and (iii) Campeche and Tabasco which are states characterised by a large industry of oil extraction. Figure E.2 in Appendix E illustrates the three clusters of high TFP in Mexico with a more defined spatial distribution using

[21] In the comparison of Figures 6.1a and 6.1c., the growth of weighted TFP in Campeche, Nuevo Leon, Tabasco and Zacatecas is significant because these four states increased their weighted TFP (above 2) from 1998 to 2018, and that is the reason why the scale of the axis in Figure 6.1a is substantially different to 6.1c.

Figure 6.1: The cumulative function of weighted TFP at the state level, categorised by quartiles and its spatial distribution during (a, b) 1998 and (c, d) 2018.[a/][b/]



[a] Names of the Mexican states in alphabetical order (abbreviation of the name in parenthesis): Aguascalientes (Ags.) — Baja California (BC) — Baja California Sur (BCS) — Campeche (Camp.) — Chiapas (Chis.) — Chihuahua (Chih.) — Coahuila De Zaragoza (Coah.) — Colima (Col.) — Durango (Dgo.) — Guanajuato (Gto.) — Guerrero (Gro.) — Hidalgo (Hgo.) — Jalisco (Jal.) — Mexico City (CDMX) — Michoacan De Ocampo (Mich.) — Morelos (Mor.) — Nayarit (Nay) — Nuevo Leon (NL) — Oaxaca (Oax.) — Puebla (Pue.) — Queretaro (Qro.) — Quintana Roo (Q. Roo) — San Luis Potosi (SLP) — Sinaloa (Sin.) — Sonora (Son.) — State of Mexico (Mex.) — Tabasco (Tab.) — Tamaulipas (Tamps.) — Tlaxcala (Tlax) — Veracruz De Ignacio De La Llave (Ver.) — Yucatan (Yuc.) — Zacatecas (Zac.)

[b/] Link to the interactive map 6.1b 6.1d

Source: Own estimation using microdata of the Economic Census of Mexico.

average TFP at the state level.

Between 1998 and 2018, there were three relevant changes in the weighted TFP across states: (i) contiguous states to the northern states increased their weighted TFP to reach higher quartiles in the TFP distribution while northern states that share a border with the U.S. decreased their weighted TFP and had a lower position in the TFP distribution, (ii) contiguous states to Jalisco, which is a large populate state, increased their weighted TFP significantly while contiguous states of Mexico City decreased their weighted TFP and their position in the TFP distribution, and (iii) Campeche increased its TFP over the period 1998-2018 due to the oil production and energy activities while Tabasco kept a high weighted TFP (See Subsection 5.2.2). Overall, there can be three factors that generate spillovers of productivity in Mexico: (i) international trade (i.e. economic integration Mexico-U.S.), (ii) agglomeration economies (e.g., contiguity to high-populated areas) and (iii) activities related with the energy sector.

Although three factors generate productivity spillovers in Mexico, the international trade between Mexico and U.S. is the most plausible factor of productivity spillovers across Mexican states. In 1998 the economic relationship between Mexico and the U.S. intensified due to NAFTA. That situation benefited activities of import and export in northern Mexican states due to their proximity to the U.S. As a result, NAFTA caused states sharing a border with the U.S. to have a higher weighted TFP than most of the states, which have a position in the top two quartiles of the weighted TFP distribution —in dark green and green— (i.e., Baja California, Chihuahua, Nuevo Leon, and Tamaulipas).[22] In 2018, some states sharing a border with the U.S. decreased their weighted TFP to the bottom two quartiles —in yellow and red— (i.e. Sonora, Baja California and Coahuila). However, other northern states still had higher weighted TFP than the rest, with positions in the top two quartiles in 2018 (i.e. Chihuahua, Nuevo Leon and Tamaulipas). In contrast, contiguous states to the North of Mexico (i.e., Zacatecas, Durango and Sinaloa) increased their weighted TFP to reach a position in the top two quartiles. For that reason, the economic integration of Mexico-U.S. generated productivity spillovers to the northern Mexican states, their contiguous states and states that attracted foreign firms during 1998-2018.[23]

The literature accounts that the manufacturing productivity in North Mexico has had gains due to its proximity to the U.S. and policies of open trade that incentive firms to export to the U.S. For instance, Fuentes & Fuentes (2002) measured TFP in the manufacturing sector using a translog function by regions from 1978 to 1988. Fuentes & Fuentes (2002) found that in the analysis period, the manufacturing region grew in labour, capital and productivity. In addition, the productivity increase in the northern region results from the outward-oriented policies that include the free-trade zone on the border of the U.S.-Mexico and the assembly exporting industry. Díaz Bautista (2017) measured TFP by manufacturing industries using the Tornqvist-Theil index. Díaz Bautista (2017)

[22] The higher weighted TFP during 1998 in the states mentioned can be better observed in Figure 6.3

[23] Figure 6.1 displays that contiguous states to the North of Mexico had a transition from yellow and red to green, which denotes the change of position from bottom to top quartiles in the weighted TFP distribution.

argue that trade liberalisation has generated a reallocation of economic activity across geographical locations that favours northern states closer to the U.S. Before the trade liberalisation, Mexico followed a strategy of import substitution that benefited the internal market, and thus larger cities in central Mexico generate larger economies of scale. Díaz Bautista (2017) estimated a positive TFP growth of 2.8% in the manufacturing sector between 1985 and 1989. In addition, Iacovone et al. (2022) provide evidence that manufacturing is more productive in North Mexico because that region concentrates spatially on the GVC. Then, several papers in the literature argue that the North of Mexico has become more productive than other regions due to outward-oriented policies that include the free-trade zone on the border of the U.S. and trade agreements.

6.3.2 TFP disparities at the municipality level

This subsection presents initial evidence about TFP disparities across Mexican municipalities using weighted TFP in 1998 and 2018. Figure 6.2 presents the cumulative function of weighted TFP at the municipality level classified by quartiles and its spatial distribution in 1998 (Figure 6.2a and 6.2b) and 2018 (Figure 6.2c and 6.2d).

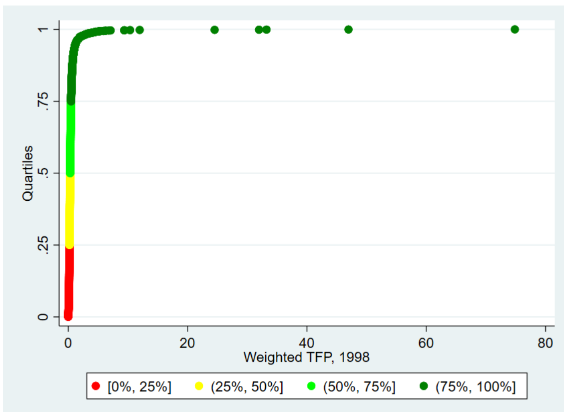
Two characteristics of the cumulative weighted TFP function are important to explain. The first characteristic is the comparison in time from 1998 and 2018 between Figure 6.2a and Figure 6.2c. The first characteristic comprises the change of position across municipalities in the top quartile. In 2018, there was a change of position across municipalities at the top of the distribution of weighted TFP in comparison to 1998.[24] In addition, municipalities in lower quartiles of weighted TFP had a positive growth of weighted TFP, which can be better illustrated in the subsequent Figure 6.5. These results can be initial evidence to explore the potential convergence of weighted TFP across municipalities. The second characteristic is a higher continuity of the cumulative weighted function at the municipality level (Figures 6.2b and 6.2d) compared to the state level (Figures 6.1b and 6.1d). Therefore, the discontinuity of the cumulative function of weighted TFP at the state level reflects the aggregation bias. The aggregation bias implies that the disaggregation by municipalities of the weighted TFP at the state level reflects a more precise representation of TFP heterogeneity, which depicts a continuous cumulative function of the weighted TFP across municipalities.

The weighted TFP of the Mexican municipalities in Figure 6.2 displays a different spatial distribution compared to the state level in Figure 6.1 using quartiles of weighted TFP. The reason is that there are municipalities in the bottom quartiles of weighted TFP within northern states in the top quartiles of the weighted TFP distribution in 1998 and 2018. The spatial distribution of productivity shows contrasts in the South of Mexico. On the one hand, more municipalities in Southeast Mexico are in the top quartiles of weighted TFP between 1998 and 2018, particularly

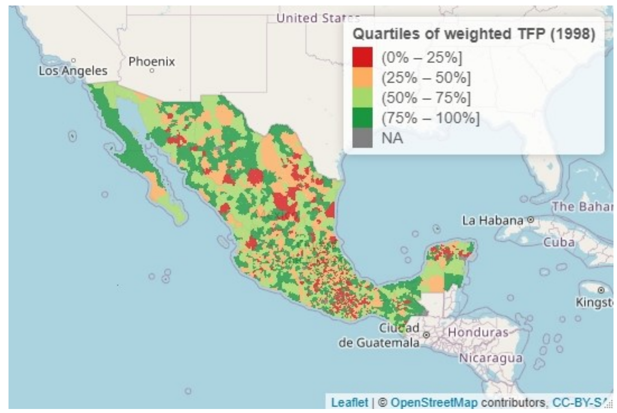
[24] See the changes of the rankings between 1998 and 2018 in the link of interactive maps in the footnote of Figure 6.2

Figure 6.2: The cumulative function of weighted TFP at the municipality level, categorised by quartiles and its spatial distribution during (a, b) 1998 and (c, d) 2018.[a/]

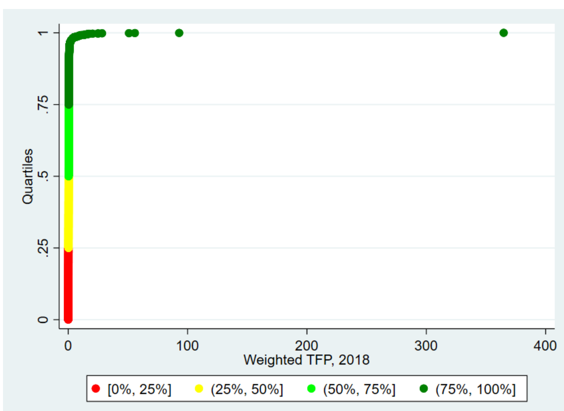
(a)



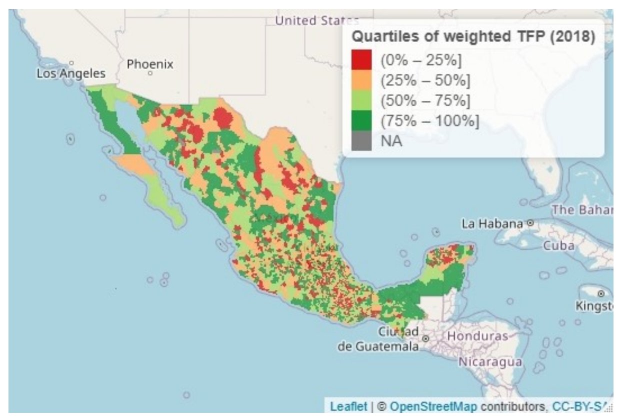
(b)



(c)



(d)



[a/] Link to the interactive map 6.2b 6.2d

Source: Own estimation using microdata of the Economic Census of Mexico.

within the states of Chiapas, Campeche and Tabasco. Efficiency in energy and tourism activities can explain the high levels of weighted TFP in southeastern municipalities of Mexico. On the other hand, most of the municipalities in the bottom quartiles of the weighted TFP distribution were concentrated in Oaxaca (southwest of Mexico) between 1998 and 2018. However, the number of municipalities in the bottom quartiles in Oaxaca decreased over 20 years (1998-2018). Figure E.3 in Appendix E extends the spatial distribution of TFP at the municipality level using average TFP between 1998 and 2018. The results in E.3 confirm a significant proportion of municipalities with low average TFP in Oaxaca and Guerrero.

The calculation of weighted TFP at different geographical levels shows that higher aggregation of the weighted TFP hides the TFP heterogeneity in Mexico. For that reason, using weighted TFP at the municipality level can be a more appropriate analysis metric for regional TFP convergence. In addition, the spatial distribution of the weighted TFP at the municipality level shows potential spatial autocorrelation. The reason is that Figure 6.2 provides a clear picture of clusters with contiguous municipalities of high and low weighted TFP. Figures 6.1 do not clearly show TFP spatial autocorrelation because there are states with high weighted TFP contiguous to states with low weighted TFP.

Figures 6.1 and 6.2 display large TFP inequalities across Mexican regions. The Mexican government has explored different public policy options to close the regional productivity gap and rebalance the spatial distribution of productivity in the last decades. However, the large regional productivity inequality is persistent, particularly in the stages of Oaxaca and Guerrero. For instance, the Mexican Plan of Development during the administration 2012-2018 made explicit that one of the main government objectives was to democratize productivity (Mexican-Government 2013). In addition, one of the roles of fiscal policy in Mexico is to reduce socio-economic and productivity inequalities across geographical locations. The Minister of Treasure has a redistribution policy across states and municipalities to compensate for the economic disparities. This policy means that a proportion of the taxes generated by high-income locations are reallocated to low-income locations to rebalance the spatial economic structure. The fiscal policy of redistribution across regions is known in Mexico as article 33 (Ramo 33, in Spanish).[25]

The implementation of an industrial strategy is another option of public policy that is plausible to explore in the following years in Mexico to rebalance the spatial distribution of TFP in Mexico and to level-up TFP in the South of Mexico, particularly in low-productive regions (e.g. Guerrero

[25] Angeles-Castro et al. (2019) analysed the redistributive effects of the fiscal policy of Ramo 33 on the Mexican states. They concluded that fiscal policy with an orientation of redistribution between states (i.e. inter-states) reduces the income gap between high-income and low-income states. In particular, the reduction of the income gap is larger in states with the lowest incomes. However, the fiscal policy is insufficient to generate conditional convergence at the state level. Angeles-Castro et al. (2019) examined the effect of fiscal policy on reducing inequality within states (i.e., intra-state), and there was no redistribution effect at the state level. On the contrary, fiscal policy has generated higher inequality within states. This result presumes that high-income households or firms benefit to a larger extent from the fiscal policy Ramo 33, and the objective of this policy to reduce inequalities within the state is not accomplished.

and Oaxaca). There should be special attention to increasing TFP in Oaxaca because that state has the municipalities with the lowest weighted TFP in Mexico (Figure 6.2). Industrial strategies can comprise horizontal and vertical strategies. On the one hand, horizontal strategies imply implementing programs oriented to increase the determinants that positively affect TFP. In addition, these programs can also have an orientation to create a production linkage (e.g., import, export) between establishments in low-productive states and the U.S. Vertical strategies can imply creating externalities so that low-income regions increase their production capabilities. There can be an increase in intangible capabilities related to the absorptive capacities (e.g., higher quality in the programs of universities, degrees related to science and technology, R&D activities), but there can also be an increase in tangible capabilities (e.g., more efficient transport infrastructure, adaptation of new technology).

6.4 TFP convergence in Mexico

This section estimates the models of TFP convergence presented in section 6.2 using the weighted TFP at the state and municipality levels. The purpose is to test whether there was a TFP convergence across Mexican states and municipalities between 1998 and 2018. There are two following subsections. In the first subsection, the analysis of TFP convergence is disaggregated at the state level. The second subsection analyses TFP convergence at the municipality level. There are two measurements of TFP convergence in each subsection: beta-convergence and sigma-convergence.

The results of this section indicate that there is no TFP convergence at the state level due to the aggregation bias. The aggregation bias cause outliers in the relationship between TFP growth and initial TFP levels across states that make the parameter β statistically non-significant over the period 1998-2018. The economic reason for the outliers with high TFP growth is that there are states with centre-periphery spillovers. However, at the municipality level, there was estimated with the Neoclassical model of beta-convergence, but the spatial convergence model did not improve the parametric results. The weighted TFP of the Mexican municipalities converged at a rate of 0.21% p.a. from 1998 to 2018, and it would take 323 years for half the TFP gap across municipalities to be eliminated.

The measurement of sigma-convergence reveals no significant changes in the TFP disparities across Mexican states. The reduction of TFP disparities across Mexican states in the period that covers the financial crisis (2003-2008) illustrates that the reduction of disparities was for an incorrect economic functioning because most of the states reduced their TFP levels during that period. A successful reduction of TFP disparities has to be parallel to increasing the weighted TFP at the national level and TFP convergence. Then, using sigma-convergence and other inequality metrics must be used with caution to determine if reducing inequality and disparities responds to the correct economic reasons.

According to Sala-i Martin (1996), there is a negative mathematical relationship between beta-convergence and sigma-convergence, indicating that periods with stronger convergence are associated with a decrease in disparities. The TFP analysis at the municipality level can describe the relationship between beta-convergence and sigma-convergence. The consistent TFP beta-convergence across Mexican municipalities over the period 1998-2018 caused a sustained reduction of TFP disparities across municipalities that reflect a downward trend of the sigma-convergence from 1998 to 2018. Then, TFP catch-up between municipalities reduces inequalities in terms of efficiency. This research accounts for using weighted TFP at the municipality level to better analyse TFP beta-convergence and sigma-convergence because TFP at the municipality level overcomes the aggregation bias at the state level.

There is a good outcome for the economic policy at the subnational level in Mexico if a productivity catch-up process is achieved alongside a better distribution of productivity across Mexican locations. This achievement of the economic policy implies a negative beta-convergence and a downward trend in the evolution of the sigma-convergence over time. However, achieving the productivity catch-up and reducing productivity inequalities across Mexican locations is not enough if this process is slow. A slow productivity catch-up and marginal reductions of productivity inequalities suggest that there is room for implementing economic policy oriented to accelerate the catch-up process and the inequality reduction of productivity. The design and implementation of local industrial strategies can be instruments of economic policy oriented to increase productivity at the state and municipality levels in Mexico.

Iacovone et al. (2022) sustains a similar argument that there is absolute convergence of TFP at the municipality level, but no convergence across states. Iacovone et al. (2022) argue that most of the states have a set of municipalities that push productivity growth upwards, while states in the South of Mexico are characterised to have few municipalities that drive productivity growth at the state level. Therefore, Southern states do not converge when TFP is analysed at the state level. The online appendix of Iacovone et al. (2022) presents the graphic representation of TFP convergence in Mexico. However, neither the main document nor the online appendix provides parametrical results of the statistical significance of beta-convergence and its magnitude.

Iacovone et al. (2022) measured the beta-convergence across states and municipalities from 1993 to 2018, but the Economic Census of 1993 only covers manufacturing activities, and the rest of the period covers all the economic activities (See Table 3.2). For instance, the period of analysis (1993-2018) in the convergence of labour productivity of Cabral et al. (2020) is valid because that paper analysed labour productivity only in the manufacturing sector. As a result, the estimation of TFP convergence in Iacovone et al. (2022) can be biased because the period analysed covers different economic activities. This thesis arrived at the same conclusion as Iacovone et al. (2022) that there is no TFP convergence across states, but there is TFP convergence across municipalities. From a statistical perspective, this thesis argues that the aggregation bias hides the TFP heterogeneity within states. Therefore, the aggregation bias leads to different convergence results when different levels of geographical disaggregation are analysed. This thesis complements the TFP convergence by measuring the convergence rate and the half-life period. The TFP convergence is robust by using two metrics of TFP aggregation (weighted and average TFP in Appendix I).

6.4.1 TFP convergence at the state level

Beta-convergence

This subsection estimates TFP convergence models using the weighted TFP at the state level in a cross-section of 32 states. The estimation of beta-convergence follows the four-step strategy in section 6.2. Therefore, the initial model to measure TFP convergence accounts for the neoclassical convergence (regression) model in equation 6.1. This model is estimated with OLS and provides initial evidence indicating if weighted TFP at the state level converged over 1998-2018. Table 6.2 shows the parametrical results of the TFP neoclassical convergence model.

Table 6.2: Neoclassical models of regional convergence (regression) using weighted TFP at the state level, 1998-2018

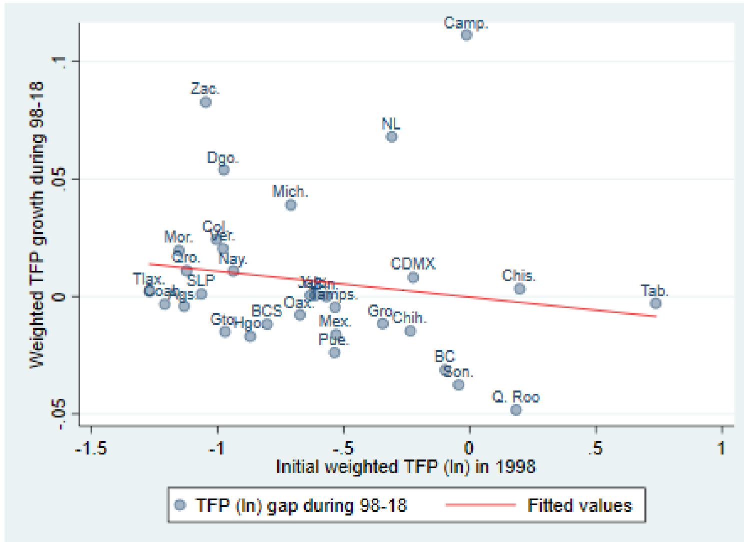
Parameters	Variables	Dependent weighted TFP growth (1998-2018)
β	Initial weighted TFP (1998)	-0.011
		(0.013)
α	Constant	-0.000
		(0.012)
Observations		32

Robust standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1
Source: Own estimation using microdata of the Economic Census of Mexico

Table 6.2 reports that the parameter β is not statistically significant. Therefore, the evidence suggests that there is not beta-convergence regarding weighted TFP across states from 1998 to 2018. Figure 6.3 displays a scatter plot of the neoclassical regional convergence model using the result from Table 6.2. In the x-axis, it is the initial ln TFP in 1998 ln $\left(\widetilde{TFP}_{j1}\right)$ and in the y-axis, it is the average weighted TFP growth from 1998 to 2018 $\left[\ln\left(\widetilde{TFP}_{jT}\right) - \ln\left(\widetilde{TFP}_{j1}\right)\right]/T$.[26]

[26] There is important to point out that the measurement of TFP growth in the convergence analysis is different to the TFP growth decomposition in Chapter 5. The disaggregated measurement of TFP growth in Figure 6.3 is measured as $\left[\ln\left(\sum_{i=1}^{N_t^j}\theta_{it}TFP_{it}\right) - \ln\left(\sum_{i=1}^{N_t^j}\theta_{i,t-1}TFP_{i,t-1}\right)\right]/T$ while the measurement of TFP growth in Tables 5.9 and 5.13 is measured as $\left[\sum_{i=1}^{N}\theta_{it}\ln\left(TFP_{it}\right) - \sum_{i=1}^{N}\theta_{i,t-1}\ln\left(TFP_{i,t-1}\right)\right]/T$. Jensen's inequality presented in section 5.4 accounts that the measurement of TFP growth in this Chapter 6 presents larger magnitudes. There-

Figure 6.3: Neoclassical model (regression) of regional convergence using weighted TFP at the state level, 1998-2018.



Source: Own estimation using microdata of the Economic Census of Mexico.

Although Figure 6.3 displays a negative slope in the regression line (Fitted values), indicating beta-convergence, the parameter β is not statistically significant (Table 6.2). The large outliers in Figure 6.3 are the main cause for no statistical significance in the parameter β. Figure 6.3 displays three states as outliers in the sample. These outliers are states characterised by high levels of weighted TFP growth, including the states Zacatecas (Zac), Campeche (Camp) and Nuevo Leon (N.L.). The outliers in Figure 6.3 deserve a particular explanation as follows.

- Zacatecas is a state with a low TFP in 1998, but this state had a high TFP growth from 1998 to 2018. TFP growth in Zacatecas has been driven by productivity growth in secondary economic sectors (NAICS code 21, 23, 31-33).

- Campeche is a particular case in Mexico because the oil industry mainly drives the economy of this state. Previous evidence showed that the increase in oil extraction in the oil state-owned company, PEMEX's, generated a significant TFP growth in Campeche during 2003. Then, the oil industry is the cause of a high TFP growth in Campeche during the period 1998-2018.

- Nuevo Leon (N.L.) had a high weighted TFP growth from 1998 to 2018. The explanation for the high productivity growth in N.L. is the geographical proximity to the U.S., which can generate a spillover effect. This spillover effect can be more significant than in other northern Mexican states because Monterrey (the main municipality in N.L.) and its metropolitan area are closer to dynamic cities in Texas, such as Houston and Dallas.

fore, the magnitudes of TFP growth across states in Figure 6.3 is larger than TFP growth in Tables 5.9 and 5.13. In particular, the inequality in the measurement of TFP growth in Nuevo Leon and Campeche is more evident.

The conclusion of the beta-convergence at the state level is that there is no apparent TFP convergence over the period 1998-2018. This research argues that the lack of significant TFP convergence at the state level is due to an aggregation bias. The aggregation bias generated outliers in the sample at the state level (e.g. N.L., Camp and Zac), making the parameter β non-significant. The aggregation bias implies that the productivity spillover centre-periphery can explain the high TFP growth in Nuevo Leon and Campeche. For instance, Monterrey is a municipality in Nuevo Leon which can generate a high productivity spillover that causes a high TFP increase in contiguous areas. Thus, the aggregation of weighted TFP across municipalities in Nuevo Leon has a high TFP growth between 1998 and 2018 due to the spillovers in the Metropolitan area of Monterrey (i.e., contiguous municipalities to Monterrey).[27]

Imbs et al. (2005) argue that aggregation bias is a characteristic in which time-series and panel data fail to control heterogeneity in the data. For that reason, the estimation of parametric approaches leads to different results as long as the data is more disaggregated. The aggregation bias has been documented in several papers on regional convergence in the Mexican economy. For instance, Castellanos-Sosa (2020) disaggregated the data at the state-sector level to include more observations on the convergence estimation. Garduño Rivera (2014) accounts that studies about the spatial distribution of economic activity at the state level severely reduce the number of observations and mask the geographical heterogeneity of the economic activity. In addition, Garduño Rivera (2014) argues that using more disaggregated databases improves the precision of the parameters. The reason is that the parameters approximate their real values as long as the sample increases.

Other studies imply aggregation bias in the analysis of productivity convergence in Mexico. Díaz-Dapena et al. (2019) used data on the value-added per worker at the municipality level to analyse the effect of NAFTA on productivity convergence. Díaz-Dapena et al. (2019) argued that using data at the state level implies losing a large part of the heterogeneity that explains the convergence process in Mexico. In order to provide evidence of large geographical heterogeneity in Mexico, Díaz-Dapena et al. (2019) calculated a Theil index of the value-added per worker disaggregated by the inequality between and within states. The results of Díaz-Dapena et al. (2019, p. 5520) quantified a larger contribution within states rather than between states to explain the inequality of value-added per worker in Mexico. Therefore, it is more appropriate to use data disaggregated at the municipality level that accounts for productivity heterogeneity.

For a deeper analysis, the parameter β was estimated to analyse TFP convergence in 1998-2003, 2003-2008, 2008-2013 and 2013-2018. Table 6.3 displays the analysis of the beta-convergence by periods which allows examining whether there were periods between 1998 and 2018 with TFP convergence across states using the specification of the neoclassical convergence model in equation 6.1.

[27] The same effect of spillover centre-periphery applies in the states of Campeche and Zacatecas.

Table 6.3: Neoclassical models of regional convergence by periods using weighted TFP at the state level, 1998-2018

Parameters	Variables	1998-2003	2003-2008	2008-2013	2013-2018
β	Initial weighted TFP (1998)	0.037	-0.136***	-0.136	-0.024
		(0.067)	(0.013)	(0.086)	(0.024)
α	Constant	0.051	-0.156***	-0.110	0.053
		(0.059)	(0.020)	(0.098)	(0.033)
Observations		32	32	32	32

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1
Source: Own estimation using microdata of the Economic Census of Mexico

Table 6.3 displays that over the period 2003-2008, the parameter β was negative and statistically significant. For that reason, Table 6.3 indicates that the only period in which there was beta-convergence of weighted TFP at the state level was from 2003 to 2008. The evidence from Chapter 5 suggested that during 2003-2008, the Mexican economy had a deficient performance due to the global financial crisis of 2008 and 2009. For instance, Figure 5.1 indicates that the weighted TFP in Mexico had its largest drop from 2003 to 2008. In addition, Table 5.2 shows that TFP growth in Mexico fell to -4.13%. For that reason, the association between the convergence and the effect of the crisis of 2008-2009 suggests that the economic crisis affected TFP growth of states with high initial levels of TFP. The TFP convergence across states during the financial crisis does not characterise a virtuous catch-up process that relies on TFP growth from the least productive states. Instead, the evidence of Table 6.3 suggests that the TFP catch-up was at the expense of the crisis, severely constraining the TFP growth of the most productive states in Mexico while the least productive states continued with positive rates of TFP growth.

The theory of convergence account that spillover effects from contiguous states can determine the TFP growth at the state level (Rey & Montouri 1999, Rey & Gallo 2009, Harris 2011, Escribá-Pérez & Murgui-García 2018, Cabral et al. 2020). Therefore, exploring whether there is evidence of spatial dependence in the variables included in the beta-convergence model at the state level is appropriate. Three variables can present spatial dependence from equation 6.1, including the independent variable, dependent variable, and error term. Elhorst (2010) proposes to test spatial dependence in all the sources that can present spatial dependence. The first variable is the weighted TFP growth $\ln\left(\widetilde{TFP}_{jT}\right) - \ln\left(\widetilde{TFP}_{j1}\right)$, the second variable is the initial level of weighted TFP $\ln \widetilde{TFP}_{j1}$ and the third variable is the residual ϵ_j. Table 6.4 presents the estimation of Moran's Index applied to the three variables included in the neoclassical model using the routine of Kondo (2018).

The results in Table 6.4 indicate that the null hypothesis of no spatial autocorrelation is rejected

Table 6.4: Evaluation of spatial dependence in the variables of the TFP convergence model using weighted TFP at the state level, 1998-2018

Dependent Variable	$\left[\ln\left(\widetilde{TFP}_{jT}\right) - \ln\left(\widetilde{TFP}_{j1}\right)\right]/T$	$\ln \widetilde{TFP}_{j1}$	ε_j
Moran's I	-0.045	0.113	-0.040
E(I)	-0.032	-0.032	-0.032
SE(I)	0.032	0.033	0.031
Z(I)	-0.399	4.426	-0.247
P-value(I)	0.690	0.000	0.805
Number of observations	32	32	32

Source: Own estimation using microdata of the Economic Census of Mexico

in two variables included in the convergence model described as weighted TFP growth and residuals (See Columns 2 and 4 in Table 6.4). Therefore, the variables included in the neoclassical convergence model (regression) display spatial dependence. The spatial distribution of weighted TFP in Figure 6.1d displays that contiguous areas of states with high productivity can have neighbours with high weighted TFP levels. For instance, Figure 6.1d shows states with high weighted TFP surrounding high productive states in the North and Southeast of Mexico. Therefore, estimating a spatial convergence model using the weighted TFP at the state level is convenient, as there is evidence of spatial dependence in two of the variables included in Table 6.4.

The estimation strategy defines the specification of the spatial TFP convergence model. There are two relevant considerations for specifying the spatial TFP convergence model. The first consideration specifies the spatial model from general to particular, as Elhorst (2010) proposed. Elhorst (2010, p. 13) defines a taxonomy of the spatial model, and the most general specification is the Manski model, which was initially proposed in the paper of Manski (1993). The Manski model includes spatial lags in the independent variable, dependent variable and error term. If the parameters that measure the spatial lags are non-significant, it is appropriate to exclude those variables to generate a more specific spatial model.

The second consideration in the spatial TFP convergence model specification consists of evaluating different specifications of the W matrix and selecting the matrix that provides the best goodness of fit. Stakhovych & Bijmolt (2009) proposed that the selection of the W matrix has to consider the minimisation of the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). Alternatively, Stakhovych & Bijmolt (2009) proposed that the most simple W matrix is the best option because a W matrix with less connectivity is less restricted to identifying the true spillovers generated in the data. About this argument, Stakhovych & Bijmolt (2009, p. 396) found that "the first order contiguity weights matrix identifies the true model more frequently than other matrices".

Appendix H compares competitive specifications that estimate the spatial TFP convergence model using weighted TFP at the state level in Table H.1. The selected spatial TFP convergence model from Table H.1 follows a specification à la Manski that includes spatial lags in the dependent variable, the independent variable and the error term, as equation 6.2 specifies. The specification includes an inverse distance matrix W matrix to capture the TFP spillovers across Mexican municipalities. The selection process consisted of choosing the W matrix that provided the best goodness of fit across models with the minimum AIC and BIC (See Table H.1 in Appendix H for more details).[28]. Table 6.5 presents the parametrical results of the spatial model of regional TFP convergence using weighted TFP at the state level.

Table 6.5: Spatial model of regional TFP convergence using weighted TFP at the state level, 1998-2018.[a/]

Parameters	Variables	Spatial convergence model ($W4$ matrix)
β	Initial weighted TFP (1998)	-0.015
		(0.014)
ρ	W weighted TFP growth (1998-2018)	0.043
		(0.057)
γ	W Initial weighted TFP (1998)	-0.530
		(1.101)
λ	W Error	-0.551
		(1.125)
α	Constant	0.030
		(0.034)
Observations		32
R-squared pseudo		0.0419
AIC		-117.9
BIC		-109.1

Standard errors in parentheses

*** p¡0.01, ** p¡0.05, * p¡0.1

[a/] $W4$ matrix: inverse distance matrix

Source: Own estimation using microdata of the Economic Census of Mexico.

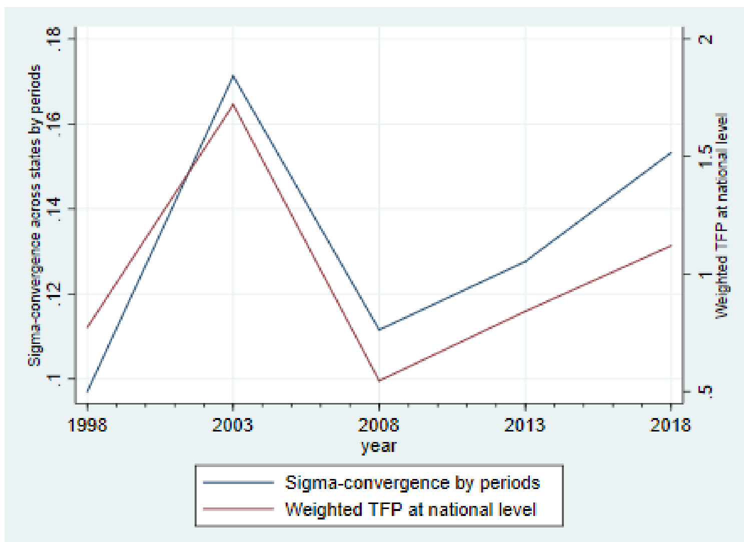
Table 6.5 indicates that there is not TFP beta-convergence across states in Mexico because β is not statistically significant. In addition, none of the parameters that measure spatial spillovers were statistically significant, including ρ, λ and γ. For that reason, the implementation of the spatial model of TFP convergence does not improve the estimation of the neoclassical (regression) model. The conclusion of this subsection is that there is not beta-convergence using weighted TFP at the state level in Mexico, which can be the result of an aggregation bias Imbs et al. (2005).

[28]However, the choice of the W matrix is not consistent with less degree of connectivity (less restriction) to detect the spillovers that arise from Moran's index Stakhovych & Bijmolt (2009), Farber et al. (2009)

Sigma-convergence

This subsection calculated the TFP disparities across Mexican states by measuring sigma-convergence. Figure 6.4 presents the estimation of the time-series of the sigma-convergence across states σ_t in relation to the weighted TFP at the national level $\widetilde{TFP}_t$ for the period 1998-2018. Overall, the results indicate that the TFP dispersion between states increases (decreases) when the weighted TFP at the national level grows (declines) from 1998 to 2013. As a result, the growth of the weighted TFP at the national level is at the expense of increasing productivity disparities. Figure 6.4 indicates that sigma-convergence increased from 1998 to 2018, which reflects the fact of no beta-convergence across states when weighted TFP is examined

Figure 6.4: Sigma-convergence using weighted TFP at the state level and weighted TFP at the national level, 1998-2018.



Source: Own estimation using microdata of the Economic Census of Mexico.

In the period that covers the financial crisis (2003-2008), the reduction of TFP disparities in Figure 6.4 cannot be attributed to the correct economic functioning. The financial crisis caused a decrease in TFP growth, a TFP divergence among states and a reduction in TFP disparities. The TFP divergence, alongside the reduction of TFP disparities, responds to a severe decrease of TFP growth in states with low levels of TFP, while TFP growth in states of high TFP was not affected to a larger extent. The financial crisis caused many states to reduce their TFP and decrease TFP growth. Thus, the reduction of TFP disparities during the financial crisis reflects that most Mexican states were less efficient. Beta-convergence confirms this result at the state level in the period 2003-2008 (Table 6.3).

The use of sigma-convergence and other inequality metrics (e.g. Gini coefficient, Atkinson index, and Theil index) must be used with caution. The reduction of TFP disparities across Mexican states during the financial crisis (2003-2008) illustrates the reduction of disparities for incorrect economic functioning. Then inequality cannot be raw metrics examined superficially, and the analysis has to consider whether the reduction of inequalities was for a correct economic functioning, such as the reduction of TFP disparities in the period 2013-2018.

For the whole period 1998-2018, sigma-convergence did not change significantly. Sigma-convergence was 0.9 and 0.15 in 1998 and 2018, respectively. The increased weighted TFP disparities across states over time result from the lack of beta-convergence across states from 1998 to 2018 (Table 6.2). As long as there is no TFP beta-convergence across states, sigma-convergence remained without decreasing from 1998 to 2018.

6.4.2 TFP convergence at the municipality level

Beta-convergence

This section estimates neoclassical models to test the hypothesis of TFP convergence among Mexican municipalities, which is a higher geographical disaggregation than the state level in the previous section. The advantage of using weighted TFP at the municipality level in the convergence analysis is to provide evidence of whether higher disaggregation leads to different results in estimating beta-convergence. Estimating beta-convergence using the weighted TFP at the state level can hide or mask a large TFP heterogeneity and a different pace of TFP growth across geographical locations in Mexico. For that reason, weighted TFP at the municipality level presents a deeper diagnosis to overcome the aggregation bias effect on TFP convergence.

Table 6.6 shows the results in estimating the beta-convergence with the neoclassical models (regression) specification in equation 6.1. Table 6.6 shows that the parameter $\beta < 0$ and is statistically significant. The beta-convergence indicates that Mexican municipalities converged on TFP from 1998 to 2018. This result contradicts Table 6.2, which indicates evidence of no TFP convergence across Mexican states. For that reason, weighted TFP at the municipality level leads to different convergence results in Mexico.

Table 6.6 found absolute TFP convergence across Mexican municipalities as the convergence model accounts that the initial TFP level is the only explanatory variable for TFP growth. In addition, the empirical research measures conditional convergence by including control variables in the convergence model to explain that convergence speed as conditional to the control variables. De la Fuente (2000) argues that some empirical papers on conditional convergence include variables of endogenous growth that capture differential fundamentals across economies. Those fundamentals include variables that could affect returns to scale, technological absorption and structural change. Regarding the factors that affect TFP growth, this research found determinants that positively impact TFP, such as age, managerial efforts to reduce costs, industrial concentration and MAR externalities. On the other hand, Jacobian externalities and population density negatively affect TFP. This research argues that TFP determinants benefit or affect the pace of TFP convergence. The beta-convergence analysis conditional to growth determinants is beyond the research objectives. However, an extension of the TFP convergence model can be considered, including control variables.

Table 6.6: Neoclassical models of regional convergence (regression) using weighted TFP at the municipality level, 1998-2018

Parameters	Variable	Neoclassical model (Regression)
β	Initial weighted TFP (1998)	-0.042***
		(0.001)
α	Constant	-0.041***
		(0.001)
Observations		2,421

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1
Source: Own estimation using microdata of the Economic Census of Mexico

Figure 6.5 displays a graphical representation of the neoclassical model (regression) using the results from Table 6.6. The x-axis presents the initial weighted TFP in ln at the municipality level during 1998 $\widetilde{TFP}_{j1}$ and the y-axis presents the average TFP growth from 1998 to 2018 $\left[\ln\left(\widetilde{TFP}_{jT}\right) - \ln\left(\widetilde{TFP}_{j1}\right)\right]/T$.

Figure 6.5: Neoclassical model (regression) of regional convergence using weighted TFP at the municipality level, 1998-2018.

Source: Own estimation using microdata of the Economic Census of Mexico.

The negative slope of the 'regression line' in Figure 6.5 displays graphically that the parameter beta is negative $\beta < 0$, which indicates that, on 'average' the Mexican municipalities had a convergence process. Figure 6.5 indicates better goodness of fit in the 'regression line' compared to Figure 6.3. Weighted TFP at the municipality level indicates that higher TFP disaggregation avoids outliers. For that reason, a higher data disaggregation allows overcoming the aggregation bias effect on TFP convergence. Weighted TFP at the municipality level estimates better goodness of fit in the neoclassical model (regression), which allows the statistical significance of the parameter β.

Table 6.7 presents the estimation of the neoclassical (regression) model by 5-year intervals from 1998 to 2018. The results in Table 6.7 presents the parameter β in four periods 1998-2003, 2003-2008, 2008-2013 and 2013-2018. The estimation of the parameter β with the neoclassical model measures TFP convergence in all the periods, and they are statistically significant (Table 6.7).

Table 6.7: Neoclassical models of regional convergence by periods using weighted TFP at the municipality level, 1998-2018

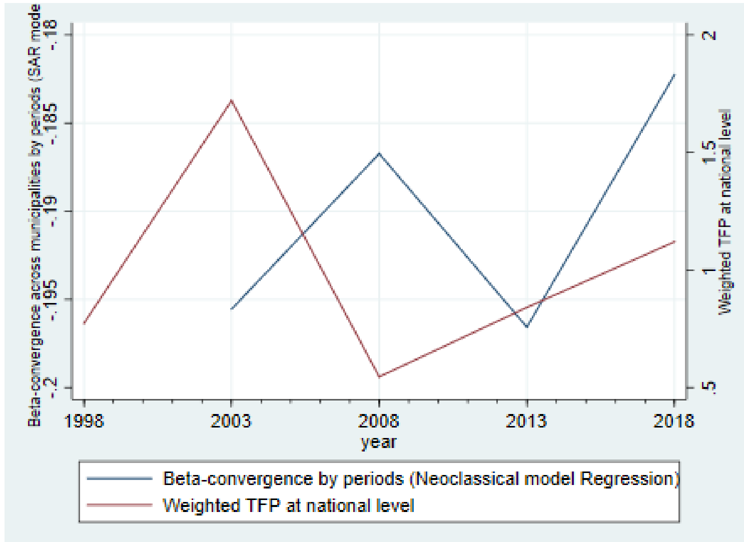
Parameters	Variables	1998-2003	2003-2008	2008-2013	2013-2018
β	Initial weighted TFP (1998)	-0.196***	-0.187***	-0.197***	-0.182***
		(0.002)	(0.003)	(0.002)	(0.003)
α	Constant	-0.182***	-0.241***	-0.215***	-0.211***
		(0.003)	(0.004)	(0.003)	(0.003)
Observations		2,420	2,421	2,421	2,421

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1
Source: Own estimation using microdata of the Economic Census of Mexico.

Figure 6.6 presents the time-series of beta-convergence β in relation to the weighted TFP at the national level $\widetilde{TFP}_t$ over the period 1998-2018. Figure 6.6 indicates a negative relationship between the time-series of β and the $\widetilde{TFP}_t$ during the period 1998-2013, while in the period 2013-2018 the variables β and $\widetilde{TFP}_t$ followed a positive direction. This result indicates that from 1998 to 2013 the increase of weighted TFP aggregated at the national level $\widetilde{TFP}_t$ produce a stronger TFP beta-convergence across Mexican municipalities. During the period that includes the financial crisis (2003-2008), the decrease of $\widetilde{TFP}_t$ generated a weak TFP convergence process measured by β. In the period 2013-2018, the increase in weighted TFP ($\widetilde{TFP}_t$) is associated with a weak TFP beta-convergence β across municipalities. The period 1998-2013 shows evidence of the correct economic functioning because there was a stronger TFP convergence across municipalities β when there was an increase in the weighted TFP in Mexico $\widetilde{TFP}_t$. However, the period 2013-2018 indicates that the increase in weighted TFP in Mexico reduced the TFP convergence at the municipality level.

Similar to the previous section, spatial dependence was tested with Moran's index in the three variables included in the neoclassical model (regression) of weighted TFP at the municipality level. Moran's index was estimated using the routine of Kondo (2018). The routine of Kondo (2018) uses the inverse distance W matrix to increase the power of the spatial autocorrelation test (Farber et al.

Figure 6.6: Beta-convergence by periods using weighted TFP at the municipality level and the weighted TFP at the national level, 1998-2018.



Source: Own estimation using microdata of the Economic Census of Mexico.

2009).[29] Table 6.8 presents the results regarding spatial dependence on weighted TFP growth, the initial levels of weighted TFP, and the error term from the estimation of the neoclassical model (regression).

The results in Table 6.8 indicate that the null hypothesis of no spatial autocorrelation is not rejected in the three variables of the neoclassical model. For that reason, there is no evidence for the application of techniques of Spatial Econometrics in the TFP convergence analysis using weighted TFP at the municipality level. The results from Table 6.6 provide sufficient evidence to conclude beta-convergence across municipalities in Mexico using weighted TFP from 1998 to 2018.

The estimation of β in Table 6.6 allows calculating the half-life period of TFP convergence across municipalities, which is necessary to eliminate TFP disparities across municipalities in Mexico by 50%. This document replicated the calculation of the convergence rate as Cabral et al. (2020, p. 28) specified as $b = -\ln(1+\beta)/T$ and the half-life period is calculated with the expression $v = \ln(\widetilde{TFP}^*_{jt} - \widetilde{TFP}_{jt})/b$. The convergence rate b is calculated by replacing the value of β from Table 6.6. The half-life period v is calculated by replacing the gap $\widetilde{TFP}_{jt} - \widetilde{TFP}^*_{jt} = 2$ and the value of the convergence rate b.

The results indicate that the absolute convergence rate b is 0.21% using the weighted TFP at the municipality level, and it would take 323 years for half the weighted TFP gap to be elim-

[29] Farber et al. (2009) concluded that a higher degree of connectivity reduces the probability of spatial autocorrelation. Therefore, the inverse distance matrix in the routine of Kondo (2018) increases the degree of connectivity and augments the precision of the spatial autocorrelation test. For that reason, Stakhovych & Bijmolt (2009) proposed that the second-best option in the specification of a spatial model is the inclusion of a W matrix with less connectivity because that matrix Is less restricted and increases the probability of finding spatial lags.

Table 6.8: Evaluation of spatial dependence in the variables of convergence model using weighted TFP at the municipality level, 1998-2018

Dependent Variable	$\left[\ln\left(\widetilde{TFP}_{jT}\right) - \ln\left(\widetilde{TFP}_{j1}\right)\right]/T$	$\ln \widetilde{TFP}_{j1}$	ε_j
Moran's I	0.022	0.044	0.037
E(I)	0.000	0.000	0.000
SE(I)	0.001	0.001	0.001
Z(I)	23.852	47.538	40.819
P-value(I)	0.000	0.000	0.000
Number of observations	2,421	2,421	2,421

Source: Own estimation using microdata of the Economic Census of Mexico

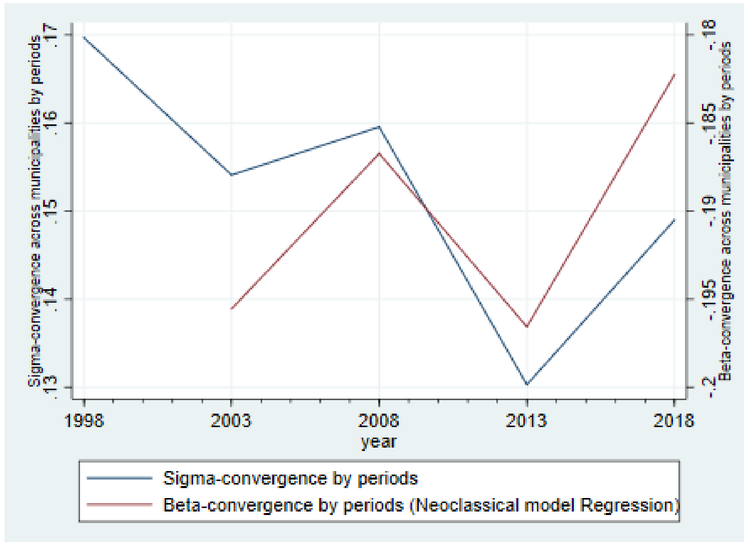
inated. Cabral et al. (2020) calculated the absolute convergence rate of labour productivity at the municipality level of 2.62%, and the half-life period is 26.50 years. Compared to the results of Cabral et al. (2020) analysing labour productivity convergence, the convergence rate and the half-life period calculation show that the weighted TFP convergence across municipalities is very slow.

Sigma-convergence

The calculation of sigma-convergence using weighted TFP at the municipality level is specified in equation 6.8. The sigma-convergence indicates the dispersion among the weighted TFP of the Mexican municipalities by year. Higher values of sigma-convergence indicate that the TFP disparities between municipalities are increasing, while lower values of sigma-convergence indicate a reduction of TFP disparities. Figure 6.7 presents the time-series of the sigma-convergence at the municipality level σ_t in relation to the time-series of β from Table 6.7.

The relationship between the time-series of beta-convergence β and sigma-convergence σ_t using data of weighted TFP at the municipality level can be analysed more straightforwardly than the results at the state level. The reason is that for the whole period 1998-2018, there was TFP convergence $\beta < 0$ and a reduction of TFP disparities because σ_t follows a decreasing trend (Figure 6.7). Sala-i Martin (1996) states that periods with intensified convergence reduce disparities. The results in Figure 6.7 indicate that a prolonged period of TFP convergence decreased TFP disparities across Mexican municipalities from 1998 to 2018. Therefore, a consistent TFP convergence process reduces TFP disparities over extended periods. This research proposes that industrial strategies can be implemented to accelerate TFP convergence and alleviate the productivity problem in the Mexican economy. The next Chapter 7 of the Conclusion derives recommendations for public policy-oriented to increase TFP in Mexico.

Figure 6.7: Sigma-convergence and beta-convergence using weighted TFP at the municipality level by periods, 1998-2018.



Source: Own estimation using microdata of the Economic Census of Mexico.

6.5 Extending the analysis of TFP convergence

Appendix I extends the TFP convergence analysis but uses the average TFP as the analysis metric. The similarities between weighted and average TFP are that there was no found TFP beta-convergence across states, and the evidence suggests that the lack of convergence responds to an aggregation bias. Furthermore, there was beta-convergence across municipalities using weighted and average TFP. A convergence rate of 0.21% and a half-life period of 323 years were calculated using the weighted TFP. The convergence rate was 0.20% and a half-life period of 340 years when the average TFP was examined. Finally, the decreasing trend of sigma-convergence gives evidence of the reduction of disparities in weighted and average TFP across municipalities. The decreasing pattern of sigma-convergence responds to the continuous periods of beta-convergence at the municipality level in Mexico from 1998 to 2018.

Chapter 7

Conclusion

7.1 Concluding remarks

"Productivity isn't everything, but, in the long run, it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker" (Krugman 1997). This PhD thesis examined productivity in Mexico to analyse the mechanisms that benefit productivity in the economy. Productivity growth is not sufficient, but it is necessary to improve Mexico's living standards in the long term. This research used TFP at the establishment level as the fundamental metric of productivity analysis. In current economic research, estimating and analysing TFP at the micro-level (e.g., firms, plants and establishments) is crucial because this granular analysis allows a deeper understanding of TFP and the factors that affect or benefit the productivity of businesses. The estimation of TFP at the micro-level enables the extrapolation of the TFP analysis at a higher level of aggregation, such as at the regional, sectoral (i.e. meso level) and ultimately at the country level (i.e. macro level). The TFP transition in the level of analysis from micro-meso-macro reflects economic 'pointillism' in the productivity analysis. The micro-meso-macro transition in the TFP analysis has a prominent future in economic research. This research uses a two-stage methodology to estimate TFP at the establishment level in Mexico. The first stage compares different parametric approaches using the log-linear Cobb-Douglas production function specification in a subset of the Economic Census. The subset of data covers medium and large manufacturing establishments from 1993 to 2018. The parametric methodologies included in the first stage were the FE models, SF models (Battese & Coelli 1995, Karakaplan & Kutlu 2017), CFA models (Levinsohn & Petrin 2003, Wooldridge 2009) and the SYS-GMM model (Blundell & Bond 1998). The objective of the first stage of the methodology is to analyse whether there is a significant difference in the TFP estimates depending on the parametric approach selected. The main result is that there are no significant differences in TFP estimates across parametric approaches. Therefore there are no large implications for TFP estimates when one approach is preferred over another. The second stage of the methodology estimates a production function with the specification of Klette & Griliches (1996). This stage has two objectives (i) to correct the price bias in the production function by economic sector and (ii) to quantify the effect of TFP determinants in all the economic sectors of the Mexican economy. In this stage, the Wooldridge (2009) model is considered the preferred parametric approach. The reason for implementing the Wooldridge model is that this model overcomes endogeneity and functional dependence. The Wooldridge model overcomes the functional dependence of OP and LP models as those CFA models have a bias on the elasticity of the free variable (employment) due to the two-stage estimation (Ackerberg et al. 2015). In addition, the Wooldridge model provides plausible magnitudes for the elasticities compared to other methods, which can result from appropriate instruments used in the GMM estimator (Mollisi & Rovigatti 2017). Then, the production function with a mark-up correction estimated with the Wooldridge model overcomes three econometric issues pointed out in the literature: (i) endogeneity of inputs, (ii) omitted price bias, and (iii) functional dependence of CFA. The drawback in implementing the Wooldridge model is that this parametric approach does not cover the whole microdata due to limitations in the dynamic structure of the Economic Census. The assumption of this research to estimate TFP at the establishment level is that it is possible to calculate common output elasticities (average across industries) that account for common technology rather than individual elasticities at the economic sector level (Harris 2021). Then, common output elasticities can be applied across 18.8 million establishments with a common technology of reference from 1993 to 2018.

7.1.1 Main findings

In the introductory Chapter 1, the research questions and objectives were highlighted, and this concluding section answers the research questions. There are four research questions addressed in this research.

1. Why are some firms more productive than others?
2. To what extent is the TFP disparity across economic activities (e.g., sectors, subsectors) and geographical locations (e.g., states, municipalities)?
3. What is the contribution of the firm selection process to TFP growth?
4. Have the Mexican geographical locations had TFP convergence (i.e. 'catch-up')?

Consequently, this research provides four answers to the research questions.

(i) Some establishments in Mexico are more productive than others (i.e. TFP heterogeneity) due to supply-side attributes and context variables that determine TFP (i.e. X-efficiency factors).

TFP determinants are classified into two categories: Non-Spatial and Spatial. In the category of Non-Spatial TFP determinants, the results indicate that older establishments have higher TFP due to the learning-by-doing effect. The reduction of fixed costs increases TFP, which shows that managerial capabilities and efforts to reduce expenses positively impact efficiency. In addition, sectoral concentration measured by the HHI positively impacts TFP. This result can be explained because higher concentration incentivises investment in better production processes, and more competition does not necessarily mean higher productivity, as Schumpeterian models predict (Aghion et al. 2015). In the first stage of the methodology, additional TFP determinants were explored in large and medium manufacturing establishments, including formality, export activity and interest expenses. Large and medium manufacturing establishments in the formal sector have higher TFP than their counterparts in the informality. Conversely, export activity and interest expenses negatively affected TFP in large and medium manufacturing establishments. One reason for the negative effect of exporting is that the measurement of export activity could capture the negative shock that Mexican exporters had from international competition, mainly from China (Blyde & Fentanes 2019). There are two possible explanations for the negative relationship between interest expenses and TFP. The first explanation is that there is a reversal causality in which establishments with low TFP (and probably low profits) demand financial credit to survive in the market. The second explanation is that high interest expenses can reflect indebtedness and financial distress that affect productive capacity and ultimately decreases TFP at the firm level in Mexico (Dvouletỳ & Blažková 2021). In the category of Spatial TFP determinants, the results suggest that population density negatively affects TFP; as a result, it can be argued that there are congestion costs due to high population density. However, population density positively impacts TFP in the retail trade sector (NAICS 46). This effect is relevant because the retail trade is the largest sector, which accounted for 41.6% of establishments in 2018. The agglomeration index increases TFP due to MAR externalities. This result indicates that Mexican establishments get benefits from local specialisation. However, the diversification index affects TFP because the Jacobian externalities may generate urbanisation costs due to high prices and wages in large urban areas (Puga 2010). In summary, space is not neutral in determining efficiency because spatial factors determine the TFP of Mexican establishments. In particular, the first stage of the methodology strategy indicated that Porter's externalities (i.e., local competition) negatively affected TFP in medium and large manufacturing establishments. Finally, efficiency at the establishment level has decreased over time, mainly as a result of the global financial crisis of 2008-2009. This result is consistent with the negative TFP growth in the period 1998-2018.

(ii) There is a significant disparity in TFP across sectors and geographical locations. The sectoral dimension of TFP can be classified into three sectors with high TFP: (i) mining, quarrying, and oil and gas extraction (NAICS 21), (ii) wholesale and retail trade (NAICS 43 and 46, respectively), (iii) finance and insurance (NAICS 52). Overall, services and oil extraction had a high TFP during 2018, while manufacturing activities had a low TFP performance. These findings are related to the study of Padilla-Perez & Villarreal (2017), which argues that there has been a structural transformation in Mexico with a decrease of productivity. In addition, there is evidence to associate the highest TFP level during 2003 in Mexico with the high oil production records of the state-owned petroleum company PEMEX. The geographical dimension of TFP in Mexico indicates three main clusters of high TFP at the state level: (i) some northern states in Mexico, which has high TFP due to the comparative advantages of localisation economies and proximity to the U.S that create a spillover effect; (ii) Mexico City and Jalisco, including some contiguous states, these regions indicate that big cities are more productive than their counterparts due to agglomeration economies; (iii) the state of Campeche and Tabasco which are mainly dedicated to the oil industry, representing a natural geographical advantage.

(iii) TFP growth in Mexico was slightly positive, with a rate of 0.10% p.a. for the period 1998-2018. The TFP growth decomposition calculated with the Haltiwanger and Melitz-Polanec approaches estimates that surviving establishments pull TFP growth downwards while net entrants push TFP growth upwards. Then, unproductive establishments tend to survive in the Mexican economy. This result indicates a dysfunctional firm selection, allowing unproductive establishments to survive and contribute negatively to TFP growth in Mexico (Levy-Algazi 2018, Ros-Bosch 2019). Despite there are high entry and exit rates in Mexico, this fact has not improved TFP growth. Therefore, the Mexican economy is permissive and tolerant by allowing the survival of unproductive establishments. Consequently, there is an inefficient allocation of resources. This result is interesting in the context of emergent economies to analyse the causes of dysfunctional firm selection and its causes. There are reasons to believe that the inefficient business firm selection in Mexico can be related to the informal sector (Levy-Algazi 2018, Alvarez & Ruane 2019). The positive effect of firm selection on TFP growth is that opening businesses (establishments) in Mexico drives TFP growth. This result indicates that entrepreneurship increases productivity growth. However, whether entrepreneurship in Mexico comes from the formal or informal sector is not distinguished.

(iv) The results show no evidence of TFP convergence across states due to an aggregation bias. The use of disaggregated TFP at the municipality level overcomes the aggregation bias. The results indicate that the absolute convergence rate b is 0.21% using the weighted TFP at the municipality level, and it would take 323 years for half the weighted TFP gap to be eliminated (i.e. half-life period, v). In addition, the TFP disparity across municipalities (i.e., sigma-convergence) followed a decreasing trend from 1998 to 2018. Therefore, a long period of beta-convergence produces a reduction of sigma-convergence, as Sala-i Martin (1996) predicted.

7.1.2 Limitations and future work

There can be enumerated three limitations of this research related to data and methodology

1. A reduced number of TFP determinants were included in the production function with mark-up correction. The reason for using a reduced number of TFP determinants is to use a larger sample of the microdata of Mexico. The inclusion of other TFP determinants could reduce the estimation sample.

2. There is a limitation in the dynamic structure of the microdata of the Economic Census. The estimation of the Wooldridge model comes at the cost of reducing the microdata sample significantly for the estimation. This limitation comes from the large rates of entry and exit constraining the use of dynamic instruments in the Wooldridge model. Alternative parametric approaches can be implemented to cover a larger extent of the microdata. However, the results show that the estimations of different parametric approaches do not lead to a large difference in the parametrisation of the production function (Figure 3.1).

3. The appropriate method of aggregation in the weighted TFP to measure the sectoral and geographical dimension of productivity can be debated because there are different methods of TFP aggregation in the literature (Dias & Robalo 2021). The method of TFP aggregation follows the studies of Haltiwanger (1997), Melitz & Polanec (2015), which use output weights for the aggregation, but this research uses TFP in levels to compare TFP across sectors and geographical locations. On the other hand, studies like Harris & Moffat (2022) prefer a TFP aggregation by using weighted average ln TFP by geographic locations. The use of different TFP aggregations is due to the author´s preference to choose a metric which represents with veracity the productivity in Mexico and addresses the research questions. The use of the weighted average TFP provided a better representation of the geographical and sectoral dimension of TFP in Mexico, while the use of weighted average ln TFP provided a better representation of TFP growth decomposition in Mexico.

This research proposes five recommendations for future work to overcome the previously mentioned limitations and to extend the TFP analysis in different directions. Those five recommendations include (i) More inclusion of TFP determinants, (ii) TFP growth decomposition with data of shorter time gaps and different TFP growth measurements, (iii) Disaggregation of TFP growth decomposition by deciles, age and size, (iv) Variance decomposition in components of TFP dispersion, prices, aggregated demand and residuals, and (v) TFP analysis between frontier and non-frontier establishments. The description of each recommendation for future work is enumerated as follows:

(i) There can be complementary work to explore other TFP determinants using different samples of the Economic Census. Additional TFP determinants include R&D, subsidies and financial variables of profitability (Harris & Moffat 2015*a*, 2020, Blažková & Dvouletỳ 2018, Dvouletỳ & Blažková 2021). However, the analysis of additional TFP determinants comes with the cost of reducing the estimation sample because variables such as R&D, subsidies and financial variables are available for fewer observations than the TFP determinants analysed in this research. The inclusion of those variables can be analysed in depth in medium and large manufacturing establishments due to more information available in that sector. De Loecker & Syverson (2021) provide a comprehensive overview of the industrial organisation (IO) perspective on productivity. There are two emerging topics of research to analyse productivity from an IO perspective as De Loecker & Syverson (2021, p. 68-70) explain. The first topic accounts for distinguishing the role of managers and managers on productivity at the firm level. The second topic accounts for the role of unobservable input quality in determining productivity. For instance, the quality of inputs can include intangible capital, which can associate new technology, such as Artificial Intelligence (AI), with productivity. Therefore, a future line of research can analyse the effect on TFP from managers' skills and the incorporation of AI into the production process in emerging countries. Finally, future work can consider the two approaches to approximate the measurement of learning by exporting as De Loecker (2013) proposed.

(ii) It is necessary to study the contribution of firm selection to TFP growth more in-depth. There are two relevant aspects to extend the analysis of TFP growth in Mexico. The first relevant aspect consists of confirming the results about the contribution of the firm selection to TFP growth in Mexico by using microdata without a large gap in time as the database used in this thesis. The reason is that the 5-years gap in the microdata structure of the Economic Census can overestimate the number of entering and exiting establishments and underestimate the number of surviving establishments. The use of manufacturing surveys is an option for microdata without a large gap in time. Even though the manufacturing surveys have lower coverage of establishments, the lower gap in time in the panel dataset can reduce the bias to categorise establishments with entry, survival and exit in the market. The second relevant aspect consists of comparing the two metrics of TFP growth using logarithms and levels according to Jensen's inequality that Dias & Robalo (2021) pointed out. For that reason, an extension of this research consists of comparing the arithmetic and the geometric TFP growth using the decomposition of Halitwanger and Melitz-Polanec.

(iii) In addition, the analysis of TFP growth can be extended to measure the contribution of surviving, entering and exiting establishments by deciles, age and size. The extension of TFP growth decomposition by deciles can provide evidence about the magnitude of the contribution of firm selection by productivity levels. The TFP growth decomposition of firm selection by age can examine if older and surviving establishments contribute more to TFP growth in relation to younger and surviving establishments in Mexico. Finally, the disaggregation of TFP growth decomposition by size will provide evidence about the contribution to TFP growth of firm selection by employment size.

(iv) The evidence of the TFP dispersion (i.e. heterogeneity) of the Mexican establishments over time opens one question: what is the effect of TFP dispersion in other variables?. For instance, Carlsson et al. (2019, p. 19-20) used the aggregated demand of Klette & Griliches (1996) to decompose its components by the variance of prices, TFP, aggregated demand, and residuals. This research used the model Klette & Griliches (1996), and the main equation of departure to measure the variance decomposition can be equation C.1 in Appendix C. Prices at the establishment level can be inferred by estimating the parameters in equation C.1. Subsequently, the effect of TFP dispersion on price dispersion and aggregated demand can be measured. This analysis can be relevant to analyse the impact of TFP dispersion in cyclicality (aggregated demand) and distribution of prices across establishments.

(v) Another future line of research can incorporate the TFP distinction between frontier and non-frontier establishments in Mexico. This distinction can extend the productivity analysis to understand if there is a divergent productivity pattern between the frontier and non-frontier establishments in emergent economies over time. For instance, Aghion et al. (2015) explain the divergent pattern between productivity growth and level of competition when firms are classified into frontier and non-frontier, which confirms the findings of the U-shape model between productivity and competition in Aghion et al. (2005).

7.1.3 Policy implications

In recent years, leading economies have released industrial strategies as supply-side policies oriented to increasing productivity, facilitating economic growth, and promoting national industrial innovations that generate conditions for economic development. Lin (2011) considers the acceptance of industrial strategies in mainstream economics as the third wave of development thinking of industrial policies. After the financial crisis, the international economic discussion centred on the variety of market failures as a limitation for economic growth. For instance, there are pervasive externalities, imperfect capital markets, asymmetric information, and limited funding for new businesses, education and health. Then, the role of the government in promoting industrial policies is central to overcoming the limitations to economic growth (Lin 2011). Joseph Stiglitz argues that government interventions are not perfect. In strategic sectors, the social choice of the agent responsible for the resource allocation is not between perfect markets and imperfect governments; instead, the choice is between imperfect markets and imperfect governments. Then, industrial strategies are complementary to market functioning, and governments must find a balance between industrial strategies and market functioning by designing a system where they interact effectively (Lin 2011, p. 56-62).

The design and implementation of an industrial strategy were missing in Mexico for decades. It is expected that by the end of 2022, the Mexican government will release a new industrial strategy oriented toward supporting high technological firms with an emphasis on regional economies. In addition, there are reasons to assert that the government has recently implemented industrial strategies to develop macro infrastructure projects. However, the current industrial policy in Mexico (i.e., 'decalogo' of industrial policy) overemphasises actions that preserve high levels of productivity in leader regions and sectors and underestimate the implementation of actions oriented to compensate and rebalance Mexico's productivity structure. The policy implications related to the results of this thesis comprise three components: (i) horizontal, (ii) vertical, and (iii) regional industrial strategies. Horizontal industrial strategies are broad plans that benefit the business environment to promote productivity growth in the whole economy. Vertical industrial strategies are policies with a selective approach to increase productivity in specific sectors. Finally, regional industrial strategies can rebalance the geographical structure of productivity across regions. The following subsections provide suggestions for three complementary parts of industrial strategies in Mexico.

1. Horizontal industrial strategies. Implementing horizontal industrial strategies provides a more favourable environment to increase businesses' efficiency and investment. A priority is to design and implement horizontal industrial strategies related to firm-specific attributes of the supply-side. The following recommendations for industrial strategies consider the establishment's age and the fixed cost ratio as the central variables to increase TFP. In addition, there are considered recommendations to improve the firm selection (i.e. survival and net entry).

    - There is evidence to infer that there is a process of learning-by-doing in the production process in Mexican establishments. Learning-by-doing is not only a process in which production improves through repetition. Variables of endogenous growth, such as knowledge spillovers, human capital, R&D, and absorptive capacity, complement and reinforce the learning-by-doing process. Young (1991) argued that there are two characteristics of the learning-by-doing process: knowledge spillovers and diminishing returns to scale. The diminishing returns to scale imply that the adoption and development of new technologies transform knowledge into new products that initially increase the learing-by-doing process until this process is exhausted. This research proposes that government programs can provide training to upgrade working skills by including formal and informal education related to innovation applied to businesses (e.g., programming, robotics, artificial intelligence and data science). Training programs can be relevant in an economy such as Mexico because its structure relies on the intensive use of employment (according to the measurement of elasticities in the production function). In addition, promoting organisations and chambers (e.g. manufacturing, commerce, tourism) can facilitate knowledge spillovers across firms in the same sector. Updating skills and promoting knowledge spillovers can improve the learning-by-doing process and increase TFP.
    - The managerial capabilities and organisation efforts to reduce costs increase TFP. Training programs must be oriented toward cost minimisation to keep establishments in opera-

tion. In addition, government platforms can provide information on prices georeferenced (e.g. housing, land, price of fuel by supplier). Access to more information on prices allows producers to decide better and minimise costs. In addition, simplifying times and costs in bureaucratic procedures can reduce costs at the establishment level. For that reason, it is of public interest to measure and publish metrics of efficiency associated with public services (e.g. legal system). In addition, this research proposes that government programs can provide training to improve managerial skills by including formal and informal education (e.g., law, management, marketing, finances and accounting).

- In addition, local governments should create plans to attract new businesses and promote the opening of new businesses. The evidence provides that net entrants in the Mexican market contribute positively to TFP growth. The simplification of the institutional framework, efficiency improvement of institutions and public advisory via online (e.g. legal accounting, taxes) can incentive the openness of formal establishments.

2. Vertical industrial strategies. This research examined TFP at the sector and subsector levels, and there is evidence to propose that there is room for productivity improvement in key Mexican sectors. Implementing vertical industrial strategies can stimulate productivity improvements in three specific sectors: manufacturing, trade, and oil extraction. The following outcomes describe the policy implications in each of these industries.

   - Economic sectors 43 and 46 (wholesale and retail trade) are highly productive but also with a high dispersion within the sector (Dias et al. 2020). The high TFP disparity in the trade industry could be more evident in highly populated areas. Therefore, the challenge for industrial strategies is to design mechanisms for productivity improvements in laggard firms in the services sector (Monahan & Balawejder 2020, Dias et al. 2020). Monahan & Balawejder (2020) propose that successful economies can create a bridge between services and manufacturing to increase productivity. For instance, the reliance on manufacturing activities with programming services using artificial intelligence is action-oriented to increase aggregated productivity in both sectors.
   - It is crucial to improve the TFP of the manufacturing sector in Southern regions of Mexico that could pull the manufacturing productivity downwards.The manufacturing sector in the north of Mexico has had TFP benefits due to spillovers with the U.S. economy that can reflect supply-side and demand-side linkages between the south of the U.S. and the north of Mexico because both geographical locations share a border (Iacovone et al. 2022). The creation of economic linkages in other Mexican regions is important, particularly in the South of Mexico. More transport infrastructure oriented to reduce cost and increase absorptive capacity in the Southern Mexican regions can generate spillovers and TFP increases in the manufacturing sector of the South of Mexico.
   - Due to emerging technologies, the oil industry is expected to be less dominant in the energy sector in the coming years. Therefore, there will be less room for arbitrary

decisions to increase (or reduce) oil extraction deliberately, as PEMEX used to take when it was granted the government monopoly as it was during 2003 (Figure 5.6 and G.1). Mexico's oil extraction industry has lost dominance as a driver sector of TFP growth. The Mexican government must initiate a route for the energy transition so that TFP growth does not largely depend on oil extraction but also on emerging technologies. In addition, it is recommended that local governments in Campeche and Tabasco begin the energy transition because the TFP of that location depends largely on oil extraction.

3. Regional industrial strategies. The implementation of regional industrial strategies can be oriented toward solving one specific problem in a particular location (Mazzucato 2018). The current infrastructure project of the Mexican-Government (2019) can be catalogued as mission-oriented industrial policies oriented to leverage the economic performance of Southern Mexico and to reduce the economic gap between Southern regions and their counterparts. There are inferred two main objectives of the Mexican-Government (2019) in terms of regional industrial strategies: (i) to update and develop the infrastructure of the petrol industry and (ii) to develop regional mobility to facilitate tourism and commerce. Creating public infrastructure through public investment is probably the most ambitious industrial policy for the Mexican government. The creation of public infrastructure reinforces externalities and gets reflected in higher TFP levels by geographical locations. Therefore, the stimulation of externalities (i.e. specialisation) expands the nucleus of productive establishments in Mexico. There are considered two channels of transmission.

   - Agglomerations economies have a positive effect on TFP through MAR externalities. Thus, developing specialised industrial clusters via government programs and creating and upgrading specialised infrastructure that generates positive externalities to increase establishments' efficiency (e.g., universities and public goods).
   - Evidence suggests that congestion costs affect TFP at the establishment level due to population density and the negative effect of Jacobian externalities. Creation and updating infrastructure oriented to reduce congestion costs can increase TFP, particularly in highly populated areas (e.g. efficient transport, social housing, etc.). More transportation hubs (i.e. airports, trains, undergrounds, cable cars).

   There is crucial to design and implement regional industrial strategies that consider closing the TFP gaps from the bottom and preserving high TFP in leader regions to create conditions for integral regional economic development in Mexico. There are three additional considerations for the improvement of regional industrial strategies.

   - Implementing a national industrial strategy should include the economic integration of Mexico-U.S. as a crucial factor that generates productivity spillover. The economic integration of Mexico-U.S. benefits northern Mexican states that share a border with the U.S. but also to contiguous states. Contiguous states are characterised by attracting foreign firms of high technology (e.g. Aguascalientes, Queretaro). For that reason, it is convenient to continue promoting economic integration and better connectivity in the bilateral relation of Mexico-U.S. (e.g. more efficient transportation by land). The continuation of NAFTA (now USMCA) is a positive factor that benefits the productivity of particular regions in Mexico.

- This research argues that the TFP at different levels of geographical disaggregation is a crucial variable of guidance in implementing differentiated regional industrial strategies. One of the objectives of regional industrial strategies is to compensate for the asymmetric effects of externalities that generate TFP disparities across Mexican regions. For instance, the asymmetric geographic effect that generates the bilateral relation between Mexico and U.S.
- There is crucial that regional industrial strategies target groups of establishments in low-productive states to define LED actions. Particularly, it is more convenient to implement industrial strategies in a target group of low-productive establishments in Oaxaca than to target low-productive establishments spread in different geographical locations. Thus, implementing an industrial strategy implies 'closing the gaps' of regional productivity from the bottom with actions oriented toward raising the productivity of establishments in less productive states to accelerate the convergence process.

The transition towards an integrated industrial strategy in Mexico. Industrial strategies are instruments of economic policy to increase TFP in Mexico on its different dimensions (e.g. geographical and sectoral). This PhD thesis proposes that there is room for implementing industrial strategies as an economic policy to promote sustainable economic growth based on productivity growth. This research suggests that Mexico's economic policy must make the transition towards an integrated industrial strategy to include complementary horizontal, vertical and regional industrial strategies. Implementing an integrated industrial strategy in Mexico can work as leverage for economic and productivity recovery after the Covid-19 crisis.

The implementation of industrial strategies relies on public finances. Therefore, exploring and proposing funding options to implement industrial strategies is crucial. The funding options to implement industrial strategies are beyond this research, but the evaluation of tax reforms is necessary for the public debate. Ultimately, better public finances improve the government's position to implement industrial strategies to facilitate better infrastructure, update skills, and a better business environment. As a result, Mexican establishments can increase their TFP and ultimately improve aggregated economic growth. Industrial strategies are part of the institutional framework that contributes to incentive productivity from the micro (establishment level) to the macro (country level).

In conclusion, productivity is not a theoretical economic artifice. Instead, productivity should be a concept of public interest reflected as an objective of public policies. The evaluation of productivity should be a priority in public scrutiny because productivity is an engine of sustainable economic growth to produce more with less. After all, increasing TFP levels is necessary to improve living standards over time in Mexico.

Appendix A

Price indices

Table A.1: Price index of gross output from the KLEMS model, 1993-2018

NAICS 2-digits code	Economic Sector	1993	1998	2003	2008	2013	2018
11	Agriculture, Forestry, Fishing and Hunting	20.3	47.8	59.3	80	100	133
21	Mining, Quarrying, and Oil and Gas Extraction	9.8	22	32.8	83.5	100	123
22	Utilities	17.3	46.1	78.2	106.4	100	146.1
23	Construction	12.7	36.6	62.1	84.9	100	136.7
31	Manufacturing (food, beverage and tobacco, etc)	15.6	43	56.2	80.4	100	137.5
32	Manufacturing (wood, paper, printing, etc.)	15.6	43	56.2	80.4	100	137.5
33	Manufacturing (primary metals, machinery, etc.)	15.6	43	56.2	80.4	100	137.5
43	Wholesale	17.2	44.9	59.6	79.8	100	134.4
46	Retail trade	17.2	44.9	59.6	79.8	100	134.4
48	Transportation	13.6	39.1	58.6	77.6	100	122.4
49	Postal services and warehouse	13.6	39.1	58.6	77.6	100	122.4
51	Information	23.5	59.4	88.1	102.4	100	84.5
52	Finance and Insurance	42.2	58.3	91.9	106.3	100	109.5
53	Real estate, rental, and leasing	19.3	50.2	70.1	87	100	112.9
54	Professional, scientific, and technical services	10.7	34.6	67.8	85	100	118.6
55	Management of companies and enterprises	19.3	50.2	70.1	87	100	112.9
56	Administrative and support of waste management and remediation services	14.5	43	66.2	83.3	100	117
61	Educational services	10.5	28	53.3	75.4	100	125.4
62	Health care and social assistance	11.4	26.6	57.1	74.4	100	128.8
71	Arts, entertainment, and recreation	15	37.7	66.5	85	100	120.2
72	Accommodation and food services	15.1	38.5	66.8	81.3	100	126.9
81	Other services (except public administration)	17.9	42.7	67.1	83.3	100	119.9

Source: Own elaboration with information of INEGI

Table A.2: Price index of intermediate inputs from the KLEMS model, 1993-2018

NAICS 2-digits code	Economic Sector	1993	1998	2003	2008	2013	2018
11	Agriculture, Forestry, Fishing and Hunting	18.1	44.2	58	79.5	100	131.2
21	Mining, Quarrying, and Oil and Gas Extraction	11.8	25.3	45.1	67.4	100	131.9
22	Utilities	15.5	45	57.4	117.8	100	115.3
23	Construction	13.6	39.8	62	85	100	136
31	Manufacturing (food, beverage and tobacco, etc)	17.7	50	61.8	80.9	100	134.1
32	Manufacturing (wood, paper, printing, etc.)	17.7	50	61.8	80.9	100	134.1
33	Manufacturing (primary metals, machinery, etc.)	17.7	50	61.8	80.9	100	134.1
43	Wholesale	26.6	60.3	71.3	81.2	100	125.8
46	Retail trade	26.6	60.3	71.3	81.2	100	125.8
48	Transportation	14.5	40.8	62.7	77.1	100	118.9
49	Postal services and warehouse	14.5	40.8	62.7	77.1	100	118.9
51	Information	16.4	44.1	70.7	81.5	100	124.2
52	Finance and Insurance	18.9	49.7	70.1	86.5	100	124.1
53	Real estate, rental, and leasing	18.4	47.4	68.5	86.8	100	117.7
54	Professional, scientific, and technical services	15.6	44.5	71.1	83.4	100	121.6
55	Management of companies and enterprises	18.4	47.4	68.5	86.8	100	117.7
56	Administrative and support of waste management and remediation services	17	46.2	69.6	83.8	100	127
61	Educational services	16	39.8	63.5	85.5	100	121
62	Health care and social assistance	10.5	29.1	57.4	75.9	100	124.6
71	Arts, entertainment, and recreation	16	41.3	67.8	83.2	100	123.1
72	Accommodation and food services	14.7	39.2	61.1	81.1	100	127.1
81	Other services (except public administration)	17.9	43.8	67.7	81.7	100	121.8

Source: Own elaboration with information of INEGI

Table A.3: Price index of investment in fixed assets from the KLEMS model, 1993-2018

NAICS 2-digits code	Economic Sector	1993	1998	2003	2008	2013	2018
11	Agriculture, Forestry, Fishing and Hunting	10.8	33.7	60.8	83	100	141.7
21	Mining, Quarrying, and Oil and Gas Extraction	12.9	38.4	61.4	83.3	100	128.9
22	Utilities	13	35.6	60	84.1	100	137.3
23	Construction	17.6	48.5	64.2	82	100	141.6
31	Manufacturing (food, beverage and tobacco, etc)	16.8	49.8	67.2	83.3	100	143.2
32	Manufacturing (wood, paper, printing, etc.)	16.8	49.8	67.2	83.3	100	143.2
33	Manufacturing (primary metals, machinery, etc.)	16.8	49.8	67.2	83.3	100	143.2
43	Wholesale	15.9	46.1	66.7	80.9	100	132.1
46	Retail trade	15.9	46.1	66.7	80.9	100	132.1
48	Transportation	18.1	45.2	64.6	81.6	100	137.8
49	Postal services and warehouse	18.1	45.2	64.6	81.6	100	137.8
51	Information	19	59.4	69.3	85.2	100	137.7
52	Finance and Insurance	20	57	80.3	89	100	140.4
53	Real estate, rental and leasing	16	39.4	62.8	84.5	100	136.6
54	Professional, scientific, and technical services	17.2	46	66	86.9	100	138.4
55	Management of companies and enterprises	16	39.4	62.8	84.5	100	136.6
56	Administrative and support of waste management and remediation services	16.6	50	68.1	81.9	100	143.3
61	Educational services	12.3	36.9	64.2	84.3	100	138.7
62	Health care and social assistance	11.3	36.4	64.2	83.4	100	139.7
71	Arts, entertainment, and recreation	11	33.2	53.8	77.6	100	146.4
72	Accommodation and food services	12.8	40.5	63.4	84.9	100	141.9
81	Other services (except public administration)	13.2	41.8	67.3	82.3	100	145.8

Source: Own elaboration with information of INEGI

Appendix B

Specification of the SF models

This section provides the specification of the composite residual in the SF models of Battese & Coelli (1995) and Karakaplan & Kutlu (2017).

B.1 Battese and Coelli (1995) model

Equation B.1 presents the specification of a production function with the SF model.

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}'_{it}\beta_{\mathrm{x}} + \beta_T t - u_{it} + v_{it} \tag{B.1}$$

Either the technical efficiency term (u_{it}) and the random shocks to efficiency (v_{it}) have different distributions. Battese & Coelli (1995) assume that $u_{it} \sim \mathrm{N}^+\left(\mu_{\mathrm{1it}}, \sigma^2_{\mathrm{1it}}\right)$ and $v_{it} \sim \mathrm{N}\left(0, \sigma^2_{\mathrm{2it}}\right)$. Thus u_{it} has a one-sided (i.e. truncated) distribution with mean (μ_{1it}) and covariance (σ^2_{1it}) and v_{it} follows a normal distribution with mean zero and covariance (σ^2_{2it}). Equations B.2 and B.3 specify the parametrization of the mean (μ_{1it}) and variance (σ^2_{1it}) of the technical efficiency term (u_{it}) in the Battese & Coelli (1995) model.

$$\mu_{1it} = \mathrm{x}'_{1it}\delta \tag{B.2}$$

$$\sigma^2_{1it} = \exp\left(x'_{2it}\gamma\right) \tag{B.3}$$

In equation B.2 μ_{1it} is in the function of exogenous variables in the vector $x^{'}_{1it}$ that includes the index of agglomeration multiplied by the coefficient δ. The agglomeration index is included because it is assumed that MAR externalities can explain the average technical efficiency in medium and large manufacturing establishments from 2003 to 2018. In addition, equation B.3 expresses that σ^2_{1it} is in the function of exogenous variables in the vector $x^{'}_{2it}$ that only includes the constant term.

There was also parametrized the variance of the random shocks σ^2_{3it} as a function $\exp(\cdot)$ of the exogenous variables in x'_{3it} multiplied by the vector of coefficients ϑ as equation B.4 expresses.

$$\sigma^2_{2it} = \exp\left(\mathrm{x}'_{3it}\vartheta\right) \tag{B.4}$$

In the previous equation, the vector x'_{3it} only includes the constant term as an exogenous variable to the variance of the random shocks.

In the Battese & Coelli (1995) model, there was estimated a vector of parameters defined as $\phi_{BC95} = (\beta, \delta, \gamma, \vartheta)$. This vector comprises four elements, and each element is a vector of coefficients estimated simultaneously in a one-step approach with the ML estimation rather than the approach of two steps, which is less efficient (Wang & Schmidt 2002). The specification of Battese & Coelli (1995) model in Table 3.11 accounts that the vectors δ, γ and ϑ have a dimension of 1×1 in the first stage of the estimation strategy.

Table 3.11 in the column referring to the results of the Battese & Coelli (1995) model (BC95) describes that the parameters δ and γ are statistically significant. In particular, the parameter δ indicates that the agglomeration index affects the mean of the technical efficiency. Overall, the significance of the parameters δ and γ indicate that the parametrization of the technical efficiency is appropriate. In addition, Table 3.11 in column BC95 shows that the parameter ϑ is statistically significant, indicating that the parametrization of the variance of the random shocks is appropriate. The extended results of Table 3.11 confirm the validation to parameterize the variables (μ_{1it}, σ^2_{1it}, σ^2_{2it}) that determine the distribution of the technical efficiency and the random shocks in the Battese & Coelli (1995) model.

B.2 Karakaplan and Kutlu (2017) model

It is generally assumed that the random shock to productivity v_{it} in the SF is uncorrelated with the variables in the frontier function. However, it can be the case that the SF model presents a bias of endogeneity. Karakaplan & Kutlu (2017) developed an SF model that corrects the endogeneity of inputs. Equation B.5 and B.6 specifies the SF model of Karakaplan & Kutlu (2017) with endogeneity bias of capital k_{it} and this bias is corrected with the investment i_{it} as an instrumental variable.

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mathrm{x}'_{1it}\beta + \eta\varepsilon_{it} - u_{it} + \mathrm{w}_{it} \tag{B.5}$$

$$k_{it} = \rho_0 + \rho i_{it} + \varepsilon_{it} \tag{B.6}$$

According to Karakaplan & Kutlu (2017), an auxiliary regression is necessary to correct the endogeneity bias of inputs. Equation B.6 specifies the auxiliary function where the investment i_{it} is an instrument that corrects the bias of k_{it}, which is a similar expression that Olley & Pakes (1996) used to correct capital endogeneity. The parameters of correction estimated in the auxiliary function are the constant ρ_0 and ρ is the effect of correction of the instrumental variable i_{it} on the input k_{it}. The residual ε_{it} of the auxiliary regression is included in the SF model of equation B.6 where $\varepsilon_{it} = k_{it} - \rho_0 - \rho i_{it}$. If ρ_0 and ρ are statistically significant in B.6, then the instruments in the auxiliary function are valid. In addition, If the parameter η in equation B.5 is statistically significant, then the variable k_{it} is endogenous and corrected via equation B.6.

In equation B.5, the variable u_{it} is the idiosyncratic efficiency term with a distribution $u_{it} \sim \mathrm{N}^{+}\left(\mu_u, \sigma^2_{\mathrm{3it}}\right)$ while w_{it} is the variable that measures the random shocks to efficiency with a distribution $\mathrm{w}_{it} \sim \mathrm{N}\left(0, \sigma^2_{\mathrm{4it}}\right)$. Karakaplan & Kutlu (2017) specify that the variance σ^2_{3it} of u_{it} and the variance σ^2_{4it} of w_{it} can be parametrized using a function $\exp(\cdot)$ as equations B.7 and B.8 specify.

$$\sigma^2_{4it} = \exp\left(x'_{4it}\gamma\right) \tag{B.7}$$

$$\sigma^2_{5it} = \exp\left(x'_{5it}\tau\right) \tag{B.8}$$

Equations B.7 and B.8 are parametrized with the exogenous variables in x'_{4it} and x'_{5it}, both vectors only include the constant term. The statistical significance of the parameters γ and τ indicates if the constant terms in x'_{4it} and x'_{5it} are appropriate exogenous variables to parametrize the variance of the random shocks.

The application of the STATA routine developed by Karakaplan (2017) estimates the model of Karakaplan & Kutlu (2017). This routine obtains estimators by using ML. In addition, this routine tests for joint significance of the parameter(s) η for endogeneity with the eta test to confirm whether the correction for endogeneity in the model is necessary. The routine of Karakaplan (2017) estimates the vector of parameters as $\phi_{KK17} = (\beta, \eta, \rho, \gamma, \tau)$. Karakaplan and Kutlu (2017) do not refer to the parametrization of the mean of the technical efficiency μ_u as they assume that $\mu_u = 0$.

The results of the estimation of the Karakaplan & Kutlu (2017) model are presented in column KK17 of Table 3.11. Table 3.11 displays that the parameters ρ_0 and ρ are statistically significant. Therefore, the investment variable (i_{it}) is an appropriate instrument for the capital (k_{it}). However, the eta test indicates endogeneity in the SF. The persistence of endogeneity in the KK17 model is the result of simultaneous endogeneity, which indicates endogeneity in the rest inputs of the production function (i.e. intermediate inputs and employment). For that reason, the correction of endogeneity in only one input with the KK17 model is limited to consider the instrumental approach as valid.

Appendix C

Explanation of the mark-up model to estimate TFP

Klette & Griliches (1996, p. 351-353) initially derived the mark-up model. The mark-up model accounts for a CES demand system coupled with monopolistic competition (De Loecker 2011). Equation C.1 presents the demand-side function of the producer i in time t, in which the proportion of the producer's output Q_{it} in the industry's output Q_{st} depends inversely on the proportion of the producer's price P_{it} and the industry's price index P_{st}. The negative CES parameter $-\sigma$ represents the negative relationship between output and price and $\exp\left(u_{it}^{d}\right)$ are stochastic shocks to demand.

$$\frac{Q_{it}}{Q_{st}} = \left(\frac{P_{it}}{P_{st}}\right)^{-\sigma} \exp\left(u_{it}^{d}\right) \tag{C.1}$$

Equation C.2 presents the Cobb-Douglas supply-side function of the producer i in time t. In C.2, the output Q_{it} is expressed as a Cobb-Douglas production function that includes the capital K_{it}, the employment L_{it}, the intermediate inputs M_{it}, the TFP determinants X_{it}, a time trend T and supply shocks u_{it}^{s}.

$$Q_{it} = \alpha_i M_{it}^{\alpha_m} L_{it}^{\alpha_l} K_{it}^{\alpha_k} X_{it}^{\alpha_X} T^{\alpha_T} \exp\left(u_{it}^{S}\right) \tag{C.2}$$

Equation C.3 is the producer's revenue, which is equal to the price multiplied by the output (quantity).

$$R_{it} = P_{it} Q_{it} \tag{C.3}$$

In C.4 it is rearranged the demand function in C.1 to express the producer's price P_{it} as a function of the rest variables.

$$\left[\left(\frac{Q_{it}}{Q_{st}}\right)\left(\frac{1}{\exp\left(u_{it}^{d}\right)}\right)\right]^{-\frac{1}{\sigma}} P_{st} = P_{it} \tag{C.4}$$

Plugging C.4 in C.3, the producer's revenue is expressed as follows.

$$R_{it} = Q_{it}^{\frac{\sigma-1}{\sigma}} Q_{st}^{\frac{1}{\sigma}} \left[\exp\left(u_{it}^{d}\right)\right]^{\frac{1}{\sigma}} P_{st} \tag{C.5}$$

The real revenue is expressed as the producer's revenue deflated by the industrial price index.

$$\tilde{R}_{it} = \frac{R_{it}}{P_{st}} = \frac{P_{it}Q_{it}}{P_{st}} \tag{C.6}$$

Plugging C.6 in C.5, the producer's real revenue is simplified to the expression in C.7

$$\tilde{R}_{it} = Q_{it}^{\frac{\sigma-1}{\sigma}} Q_{st}^{\frac{1}{\sigma}} \left[\exp\left(u_{it}^{d}\right)\right]^{\frac{1}{\sigma}} \tag{C.7}$$

Equation C.8 expresses the industrial output is equal to the industrial revenue divided by the industrial price index.

$$Q_{st} = \frac{R_{st}}{P_{st}} \tag{C.8}$$

Plugging C.8 in C.7 then:

$$\tilde{R}_{it} = Q_{it}^{\frac{\sigma-1}{\sigma}} \left[\frac{R_{st}}{P_{st}}\right]^{\frac{1}{\sigma}} \left[\exp\left(u_{it}^{d}\right)\right]^{\frac{1}{\sigma}} \tag{C.9}$$

Replacing the production function in C.9, the final expression of the producer's real revenue is in C.10:

$$\tilde{R}_{it} = \left[\alpha_i M_{it}^{\alpha_m} L_{it}^{\alpha_l} K_{it}^{\alpha_k} X_{it}^{\alpha_X} T^{\alpha_T} \exp\left(u_{it}^{s}\right)\right]^{\frac{\sigma-1}{\sigma}} \left[\frac{R_{st}}{P_{st}}\right]^{\frac{1}{\sigma}} \left[\exp\left(u_{it}^{d}\right)\right]^{\frac{1}{\sigma}} \tag{C.10}$$

Equation C.11 applies natural logarithms to C.10.

$$\tilde{r}_{it} = \frac{\sigma-1}{\sigma}\left[\alpha_i + \alpha_m m_{it} + \alpha_l l_{it} + \alpha_k k_{it} + \mathrm{x}_{it}'\alpha_{\mathrm{x}} + \alpha_T t\right] + \frac{1}{\sigma}\left[r_{st} - p_{st}\right] + \frac{\sigma-1}{\sigma}u_{it}^{s} + \frac{1}{\sigma}u_{it}^{d} \tag{C.11}$$

If it is considered that the u_{it} constitutes the demand and supply shocks, expressed as follows

$$u_{it} = \frac{\sigma-1}{\sigma}u_{it}^{s} + \frac{1}{\sigma}u_{it}^{d} \tag{C.12}$$

Then equation C.11 is expressed as the production function to estimate in the second stage of the estimation strategy.

$$\tilde{r}_{it} = \frac{\sigma-1}{\sigma}\left[\alpha_i + \alpha_m m_{it} + \alpha_l l_{it} + \alpha_k k_{it} + \mathrm{x}_{it}'\alpha_{\mathrm{x}} + \alpha_T t\right] + \frac{1}{\sigma}\left[r_{st} - p_{st}\right] + u_{it} \tag{C.13}$$

The issue estimating a production with the producer's real revenues leads to a bias because the industrial price index as a deflator does not clear the price transmission on producer's output. The mark-up model advantage is overcoming the omitted price bias by using a CES demand system to infer the producer's price. The firms' real revenue uses a log Cobb-Douglas multiplied by a mark-up factor and the industrial output multiplied by the inverse of the demand elasticity (output-price).

Appendix D

Estimation of the mark-up model with the SYS-GMM model

Table D.1: Parameters estimated in the production function with mark-up correction using the SYS-GMM model by economic sector (NAICS,2 digits) in Mexico, 1993-2018. Economic sectors (31-33)[a/]

Parameter	NAICS (2 digits) Dependent: ln gross output	31 Manufacturing (food, beverage, tobacco, etc.)	32 Manufacturing (wood, paper, printing, etc.)	33 Manufacturing (machinery, computers, electronics, electrical equipment, etc.)
α_m	ln intermediate inputs	0.756***	0.833***	0.740***
		(0.002)	(0.002)	(0.023)
α_l	ln employment	0.168***	0.161***	0.211***
		(0.003)	(0.003)	(0.038)
α_k	ln capital	0.023***	0.027***	0.148***
		(0.001)	(0.001)	(0.019)
α_{x}	ln age	0.025***	0.013***	0.016***
		(0.000)	(0.001)	(0.002)
	ln fixed costs ratio	-0.002***	-0.004***	-0.003***
		(0.000)	(0.000)	(0.000)
	ln HHI	0.016***	0.012***	-0.050***
		(0.004)	(0.004)	(0.005)
	ln population density	-0.048***	-0.036***	0.027***
		(0.009)	(0.011)	(0.009)
	ln agglomeration index	0.028***	0.042***	0.038***
		(0.002)	(0.002)	(0.004)
	ln diversification index	-0.074***	-0.083***	-0.080***
		(0.004)	(0.007)	(0.009)
α_T	time-trend	0.023*	0.004	-0.051***
		(0.013)	(0.002)	(0.015)
$1/\sigma$	Inverse of the elasticity of demand	-0.338**	-0.008	0.208***
		(0.144)	(0.015)	(0.062)
$\sigma/(\sigma-1)$	Mark-up correction	0.747***	0.993***	1.263***
		(0.001)	(0.002)	(0.002)
α_0 (Constant)	ln intermediate inputs	1.408	-0.158	-1.525***
		(1.000)	(0.109)	(0.564)
N	Observations	1,016,501	385,726	567,170
	Number of id˙tot	601,945	249,264	350,241
	AR(1) z-statistics	-110.4	-63.89	-45.39
	AR(1) p-value	0	0	0
	AR(2) z-statistics	2.040	-1.224	1.830
	AR(2) p-value	0	0	0
	Hansen test	402	203.4	78.82
	Hansen p-value	0	0	0

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a/] The SYS-GMM model does not present autocorrelation of second-order AR(2) and does not present overidentification of instruments (Hansen test)
Source: Own calculation using microdata of the Economic Census of Mexico

Table D.2: Parameters estimated in the production function with mark-up correction using the SYS-GMM model by economic sector (NAICS, 2 digits) in Mexico, 1993-2018. Economic sectors (49,53,55,61)[a/]

Parameter	NAICS (2 digits) Dependent: ln gross output	49 Postal service and warehousing	53 Real Estate and Rental and Leasing	55 Management of Companies and Enterprises	61 Educational Services
α_m	ln intermediate inputs	0.583***	0.683***	0.622***	0.429***
		(0.023)	(0.004)	(0.104)	(0.005)
α_l	ln employment	0.306***	0.188***	0.040	0.494***
		(0.029)	(0.006)	(0.116)	(0.007)
α_k	ln capital	0.041***	0.043***	0.327***	0.047***
		(0.015)	(0.002)	(0.114)	(0.002)
α_x	ln age	0.050***	0.031***	-0.093	0.073***
		(0.007)	(0.002)	(0.091)	(0.002)
	ln fixed costs ratio	0.012**	-0.002***	-0.079***	-0.000
		(0.005)	(0.000)	(0.026)	(0.001)
	ln HHI	-0.059***	0.007***	0.064	0.046***
		(0.012)	(0.002)	(0.155)	(0.005)
	ln population density	0.132***	0.031	0.321	0.024
		(0.046)	(0.033)	(0.282)	(0.019)
	ln agglomeration index	0.074***	0.058***	0.256**	0.129***
		(0.020)	(0.006)	(0.109)	(0.009)
	ln diversification index	0.123**	-0.127***	-1.771	-0.104***
		(0.061)	(0.020)	(1.545)	(0.018)
α_T	time-trend	0.011	-0.001	0.133	-0.102***
		(0.017)	(0.004)	(0.234)	(0.008)
$1/\sigma$	Inverse of the elasticity of demand	-0.119	0.153***	-0.072	0.254***
		(0.151)	(0.023)	(0.549)	(0.089)
$\sigma/(\sigma-1)$	Mark-up correction	0.894***	1.181***	0.933***	1.341***
		(0.002)	(0.005)	(0.005)	(0.004)
α_0 (Constant)	ln intermediate inputs	-3.004***	-2.194***	5.813	-4.913***
		(0.529)	(0.212)	(7.980)	(0.391)
N	Observations	10,615	228,860	925	190,770
	Number of id_tot	8,301	158,499	743	116,341
	AR(1) z-statistics	-6.165	-43.06	0.386	-50.36
	AR(1) p-value	7.05e-10	0	0.699	0
	AR(2) z-statistics	1.625	-0.943	-0.578	-1.614
	AR(2) p-value	0	0	1	0
	Hansen test	27.79	493.7	5.995	354.7
	Hansen p-value	0.00348	0	0.424	0

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a/] The SYS-GMM model does not present autocorrelation of second-order AR(2) and does not present overidentification of instruments (Hansen test)
Source: Own calculation using microdata of the Economic Census of Mexico

Appendix E

Alternative metrics of TFP aggregation from micro to macro

E.1 Description of alternative metrics of TFP aggregation

The TFP aggregation by regions/sectors presented in Chapter 5 has the particularity that the sum of the weights equals one $\sum_i^{N_t^j} \theta_{it}^j = \Sigma_i^{N_t^j} Y_{it}/Y_{jt} = 1$ (i.e. normalised weights). In this case, Y_{it}/Y_{jt} reflects the relative output importance of each firm in the region/sector j, which reflects imperfect competition. However, one disadvantage occurs when these weights are applied in the TFP aggregation. The disadvantage is that the weights within each subsample region/sector change the weighted TFP distribution.

TFP in the sample N_t^j is distributed with the function f_P represented as $TFP_{it} \sim f_P\left(\mu_P, \sigma_P^2\right)$. The weights follow their distribution f_W in the sample N_t^j represented as $\theta_{it}^j \sim f_W\left(\mu_W, \sigma_W^2\right)$. In the case of the weighted TFP in the sample N_t^j, the product of the weights and TFP distributions results in the weighted TFP distribution represented as $f_W f_P = f_{WP}$ and weighted TFP is distributed $\theta_{it}^j TFP_{it} \sim f_{WP}\left(\mu_{WP}, \sigma_{WP}^2\right)$. The weights' distribution modifies, to a low or larger degree, the weighted TFP distribution, which is explained by the two following arguments.

- High concentration in the weights' distribution f_W. The only condition in which the distribution of the weights does not modify the weighted TFP distributions is when the weights are equal in the sample (N_t^j). The latter means that $\theta_{it}^j = Y_{it}/Y_{jt} = 1/N_t^j$ (i.e. uniform distribution). If a region/sector has a large proportion of firms with low weights and a small proportion with high weights, the TFP distributions (f_P) will be largely modified by the weights' distribution (f_W). The high concentration in the weight distribution implies that the weighted mean TFP can reflect regional/sectoral output concentration and lead to a mismeasurement of aggregated productivity.[1]

- TFP does not reflect the establishment's output importance. A high value of TFP reflects efficiency when a firm produces a high output in relation to its inputs. There can be the case in which a small firm dedicated to R&D is highly efficient, but its output is not that large to have high relative importance in the output of the region/sector j.[2] For that reason, efficiency does not reflect the establishment's output importance, and there can be a pronounced dissimilarity in the weights' distribution (f_W) and the TFP distributions (f_P). The high dissimilarity of weight and TFP distribution causes the weighted TFP to be underestimated in some firms while overestimated in others.

Overall, the disadvantage of implementing the output's weights is that they modify weighted TFP to a low or large extent, which can lead to mismeasurement in the aggregated productivity. Therefore, this Appendix extends the measurement of TFP aggregation from micro to macro. This Appendix aims to provide additional evidence of the geographical and sectoral dimensions of TFP by using alternative aggregation metrics.

The immediate and most straightforward TFP aggregation uses average TFP across different subsamples in regions/sectors. For instance, the arithmetic mean can be calculated as follows.

$$\overline{TFP}_{jt} = \frac{1}{N_t^j} \sum_{i=1}^{N_t^j} (TFP_{it}) \tag{E.1}$$

The sum of the weight in each aggregation over regions/sectors j is equal to one because $\sum_i^{N_t^j} 1/N_t^j = 1$. Therefore, equation E.1 fulfils the condition for the solution to calculate normalised weights. The mean TFP within the aggregation j reflects the central tendency of the TFP distribution in j (i.e. region, sector). Furthermore, the average TFP in natural logarithm (ln) can be applied as equation E.2 displays.

$$\overline{\dot{TFP}}_{jt} = \frac{1}{N_t^j} \sum_{i=1}^{N_t^j} \ln (TFP_{it}) \tag{E.2}$$

Equation E.2 measures the central tendency of the TFP distribution in ln. This metric is equivalent to the geometric average of TFP. Harris (2021) and Harris & Moffat (2022) used this TFP aggregation by geographical locations to provide evidence of the spatial productivity differences between regions in New Zealand and Great Britain, respectively. However, the disadvantage of the use of averages from equations E.1 and E.2 is that the weights $1/(N_t^j)$ are similar across observations

[1] There can be two explanations for a high concentration of f_W. From the economic perspective, high concentration comes from the market structure and industrial organization. From a statistical perspective, a small sample of N_t^j can generate that the weights θ_{it}^j have a large variance σ_W^2, which implies a high concentration in the region/sector.

[2] In the inverse case, there can be large firms with high relative importance in the output of the region/sector j but inefficient (with low TFP).

(establishments) within the aggregation j, which does not account for imperfect competition.

This document proposes a criterion of plausibility to determine whether the average of the TFP in levels or ln provides a better representation of the productivity in Mexico on its different subsamples. The criterion of plausibility consists of using the metric in equation E.1 or E.2, which has a higher correlation with labour productivity on the different subsamples (i.e. regional and sectoral). The justification for applying a plausibility criterion is that the literature accounts that TFP and labour productivity are positively correlated.[3]

Table E.1 presents the correlation of labour productivity with the average TFP in levels and ln from equations E.1 and E.2 in different subsamples.

Table E.1: Correlation of labour productivity with average TFP in levels and ln in different subsamples

Subsample	Labour productivity vs Average TFP	Labour productivity vs Average TFP (ln)
National	0.68	0.51
Sectors	0.22	0.38
Subsectors	0.33	0.36
States	0.29	0.2
Municipalities	0.37	-0.2
Average correlation	**0.36**	**0.22**

Source: Own estimation using microdata of the Economic Census of Mexico

The results from Table E.1 indicate that the average TFP in levels reflects a better criterion of plausibility to represent productivity in Mexico. TFP in levels results higher correlated with labour productivity because this metric reduces the long tails in the distribution compared to the TFP in ln. The following subsections present the results of TFP aggregation using average TFP on its geographical and sectoral dimensions.

E.2 Average TFP at the national level in Mexico

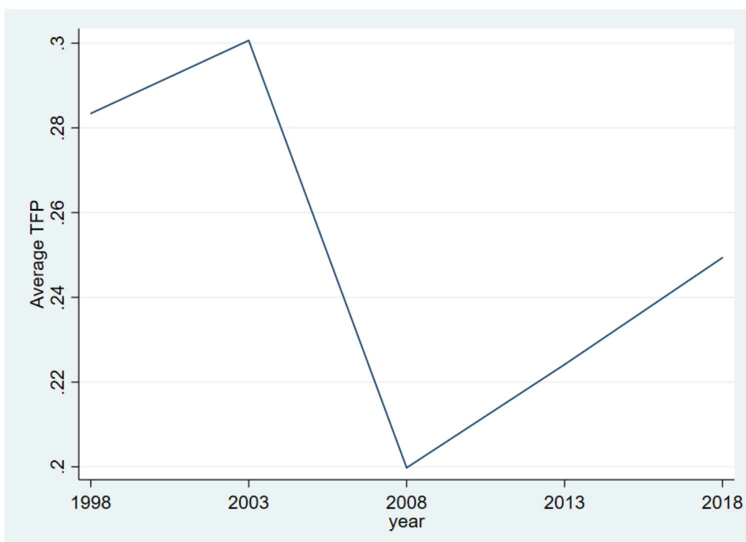
Equation E.3 displays the calculation of average TFP at the national level across observations (establishments) in each year N_t.

[3] For instance, if there is considered a production function with added value orientation and constant returns to scale $Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{(1-\alpha)}$, labour productivity is a positive function of TFP because $Y_{it}/L_{it} = A_{it} \left(K_{it}/L_{it}\right)^{\alpha}$.

$$\overline{TFP}_{jt} = \frac{1}{N_t} \sum_{i=1}^{N_t} (TFP_{it}) \tag{E.3}$$

Figure E.1 displays the average TFP in Mexico from 1998 to 2018, with a 5-year interval. The TFP aggregation using this metric follows a similar pattern over time to the TFP aggregation presented in Figure 5.1. The main feature in the TFP aggregation at the national level using average and weighted TFP is that productivity falls during a period of crisis, such as the global financial crisis in 2008. Following the crisis, TFP in Mexico recovered (Figure 5.1 and E.1). However, the average TFP has not reached the pre-crisis levels of 1998 and 2003. Similar to the arguments of Chapter 5, the high average TFP in 2003 is primarily explained by the productivity increase of oil extraction activities. The third subsection of this Appendix provides more evidence that supports this argument. Overall, the result in Figure E.1 confirms the procyclical productivity pattern in Mexico at the macroeconomic level (Kydland & Prescott 1982).

Figure E.1: Time-series of average TFP in Mexico, 1998-2018



Source: Own elaboration using microdata of the Economic Census of Mexico (INEGI)

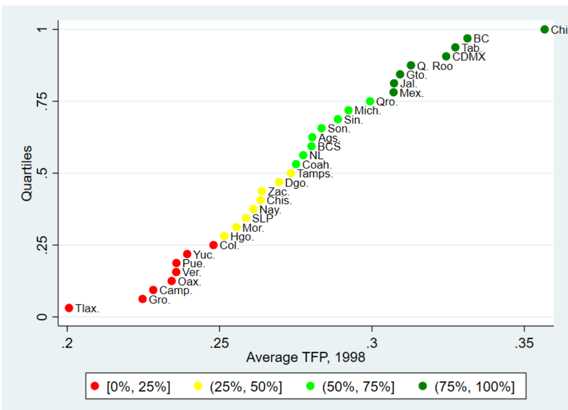
E.3 Average TFP across geographical locations in Mexico

E.3.1 State level

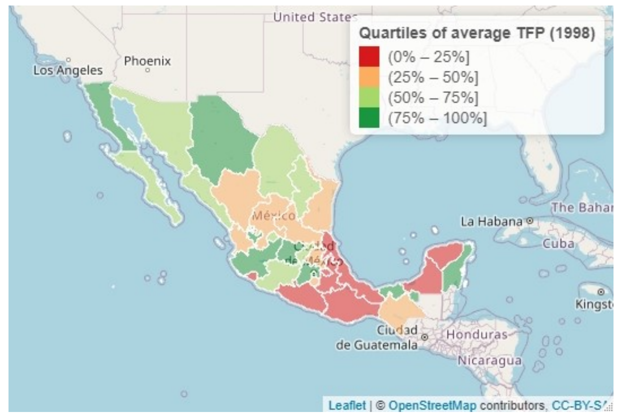
This subsection uses the aggregation of equation E.1 that measures the average TFP across establishments N in the geographical location j and the year t, represented as N_t^j. Figures E.2 (a) and (b) display the average TFP at the state level and its spatial distribution during 1998, while Figures E.2 (c) and (d) present the same metrics during 2018.

Figure E.2: The cumulative function of average TFP at the state level, categorised by quartiles and its spatial distribution during (a, b) 1998 and (c, d) 2018.[a/]

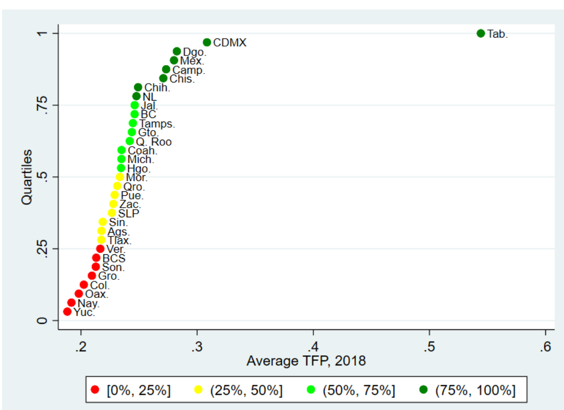
(a)



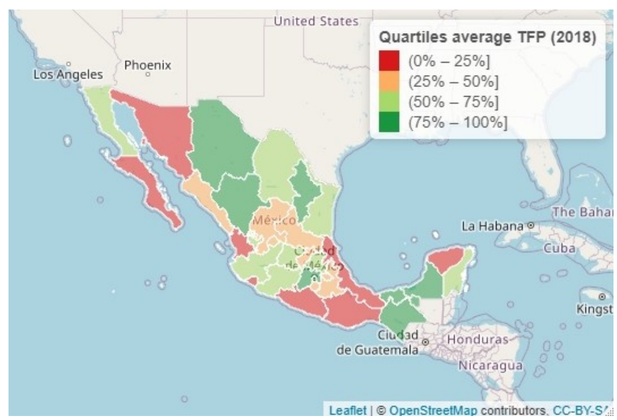
(b)



(c)



(d)



[a/] Link to the interactive map E2.b E2.d

Source: Own estimation using microdata of the Economic Census of Mexico.

The main results in Figure E.2 display three high-productivity clusters, including (i) the northern states of Mexico that share a border with the U.S., (ii) states in central Mexico with high population that comprises Mexico City, Jalisco and states in the vicinity, and (iii) states in the Southeast mainly dedicated to activities related to oil extraction and tourism. Chapter 5 explains why these regions have high TFP levels using references from the literature review.

The main difference in the geographical dimension of productivity between the results using the average TFP (in this Appendix) and the weighted TFP (Chapters 5 and 6) is that the weighted TFP lead to hgiher TFP levels in the South of Mexico, including Guerrero and Oaxaca. The latter Mexican states have high levels of poverty and low labour productivity (Figure 1.6 in Chapter 1). Therefore, the results in Figure 2E showing that Oaxaca and Guerrero have low TFP are reasonable considering the performance of other economic indices. In addition, the results presented in Figure E.2 are consistent with Iacovone et al. (2022, p. 31), showing that Oaxaca and Guerrero had low TFP levels in 2018.

Figures E.2 (b) and (d) compare the spatial distribution of average TFP across Mexican states between 1998 and 2018. The results show changes in the spatial distribution of average TFP across states over 25 years. For instance, Sonora (Son), in the north of Mexico, had a high average TFP in 1998, but its TFP decreased significantly in 2018. On the contrary, states in the South of Mexico, including Chiapas, Tabasco and Quintana Roo, increased their average TFP from 1998 to 2018. The increase in average TFP in southern states can reflect higher productivity primarily from oil extraction activities but also from touristic services. Using the average TFP as the analysis metric, the change in the geographic dimension of TFP in Mexico is that the country is shaping three regions that agglomerate establishments with high TFP levels in the North, Center and South of Mexico. Overall, Figure E.2 (b) and (d) show that there has been a rebalance of TFP between northern and southern Mexican states over the period 1998-2018.

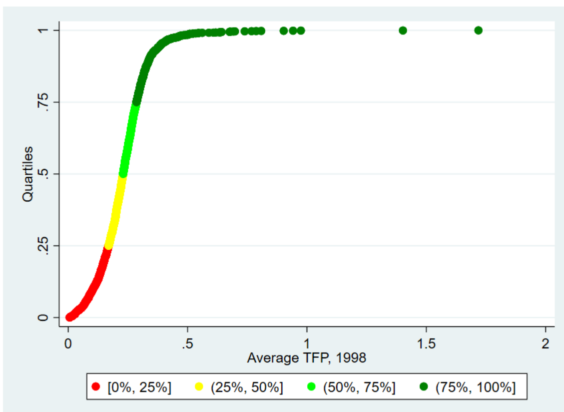
The presence of outliers in the sample is the main issue that explains the low correlation between labour productivity and average TFP at the state level in Table E.1. For instance, if the state of Campeche (1998-2018) were excluded from the sample, the correlation between average TFP and labour productivity at the state level would increase from 0.29 (Table E.1) to 0.89. The high labour productivity levels in Campeche are explained because this state has economic activities of oil extraction, which are capital-intensive and labour-saving. Then, labour productivity can lead to an overestimation of productivity in Campeche. In summary, Figure E.2 provides an appropriate geographical dimension of TFP in Mexico, extending the discussion and evidence of weighted TFP in Chapters 5 and 6.

E.3.2 Municipality level

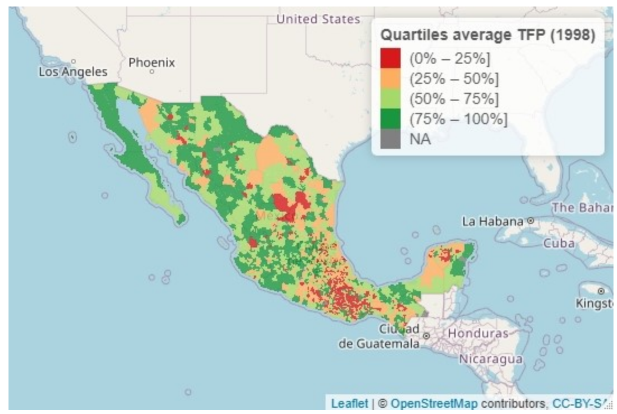
This subsection applies equation E.1 to calculate the average TFP at the municipality level. Figure E.3 (a) and (b) displays the average TFP at the municipality level and its spatial distribution during 1998, while Figure E.3 (c) and (d) present the same metrics during 2018.

Figure E.3: The cumulative function of average TFP at the municipality level, categorised by quartiles and its spatial distribution during (a, b) 1998 and (c, d) 2018.[a/]

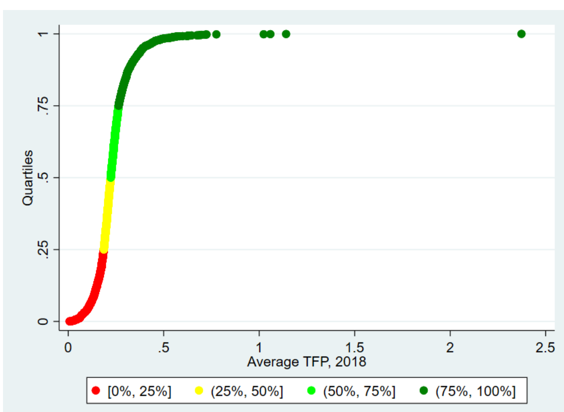
(a)



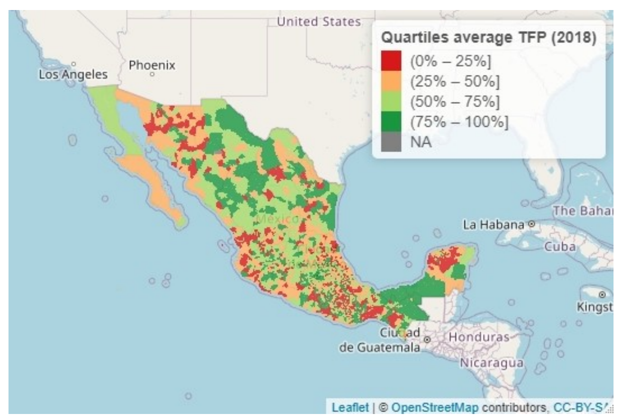
(b)



(c)



(d)



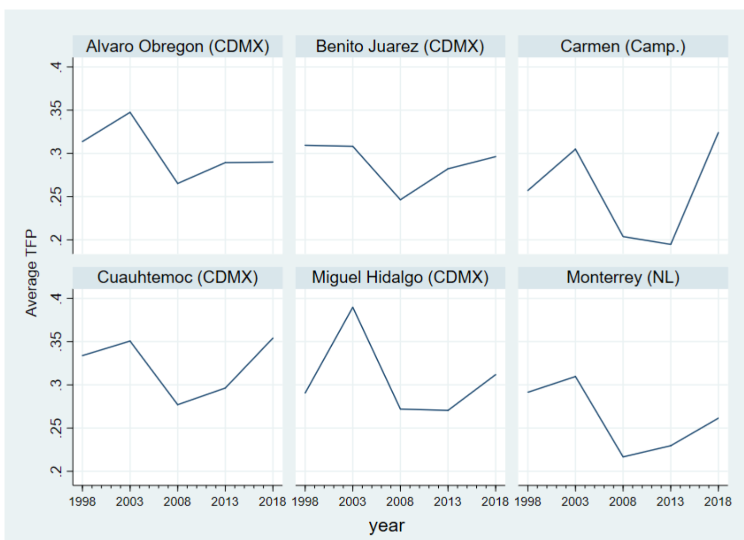
[a/] Link to the interactive map E3.b E3.d
Source: Own estimation using microdata of the Economic Census of Mexico.

Figure E.3 depicts a more granular geographical dimension of TFP in Mexico than Figure E.2. Although northern states have a high average TFP in Figure E.2, the results in Figure E.3 show a wide heterogeneity of productivity within states because there is a significant proportion of municipalities in northern states with low average TFP. In addition, Figures E.3 (a) and (b) show a large proportion of municipalities with low TFP in the South of Mexico during 1998. Mainly, those municipalities were concentrated in the states of Oaxaca and Guerrero. In 2018, Figures E.3 (c) and (d) show a decrease in locations with low average TFP in the South of Mexico. However, most municipalities with low average TFP in Mexico remained concentrated in the South between 1998 and 2018.

Figure E.3 shows that there has been a rebalance of average TFP across municipalities in Mexico between 1998 and 2018. For instance, many municipalities increased their TFP in states like Chiapas, Tabasco, Campeche and Quintana Roo. On the contrary, municipalities in Sonora and the vicinity of Jalisco and Mexico City decreased their average TFP between 1998 and 2018. The results of the geographical dimension of TFP in Mexico show that there are three clusters of high average TFP at the state level, but particular municipalities lead the high productivity of those clusters (Figure E.3). In addition, the productivity advantage of some states is explained because those states concentrate a larger number of municipalities with high average TFP within those states.

Figure E.4 presents the time-series of average TFP in the municipalities with the highest production levels in Mexico (See discussion for selecting these municipalities in subsection 5.2.1, Figure 5.4). Figure E.4 shows that the time-series of average TFP at the municipality level is highly correlated with the average TFP at the national level. Therefore, there was a high level of average TFP in 2003, and during the financial crisis in 2008, the average TFP dropped in the municipalities of Figure E.4. Therefore, the average TFP at the municipality level has a procyclical component.

Figure E.4: Time-series of average TFP in selected municipalities, 1998-2018



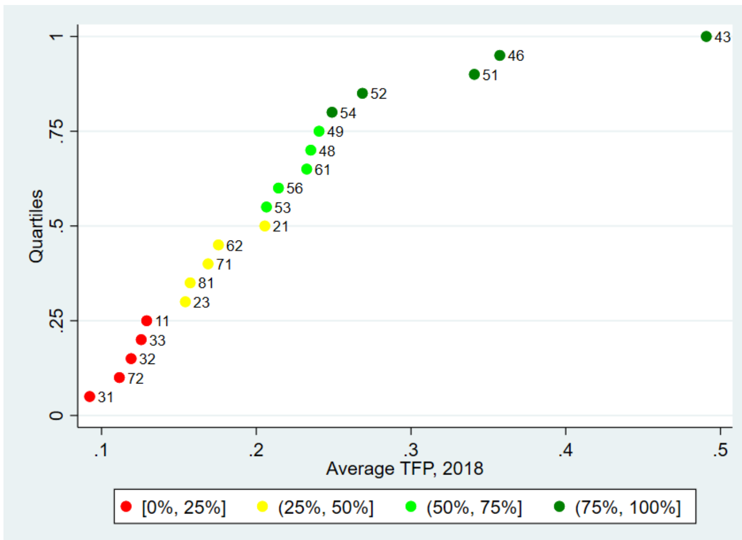
Source: Own elaboration using microdata of the Economic Census of Mexico (INEGI)

E.4 Average TFP across economic activities in Mexico

E.4.1 Sector level

This subsection also uses the aggregation of equation E.1 that measures the average TFP across establishments N in the sector j and the year t, represented as N_t^j. Figure E.5 (a) and (b) displays the average TFP at the sector level during 1998 and 2018, respectively.

Figure E.5: Average TFP at sector level by quartiles, 2018



Source: Own elaboration using microdata of the Economic Census of Mexico (INEGI)

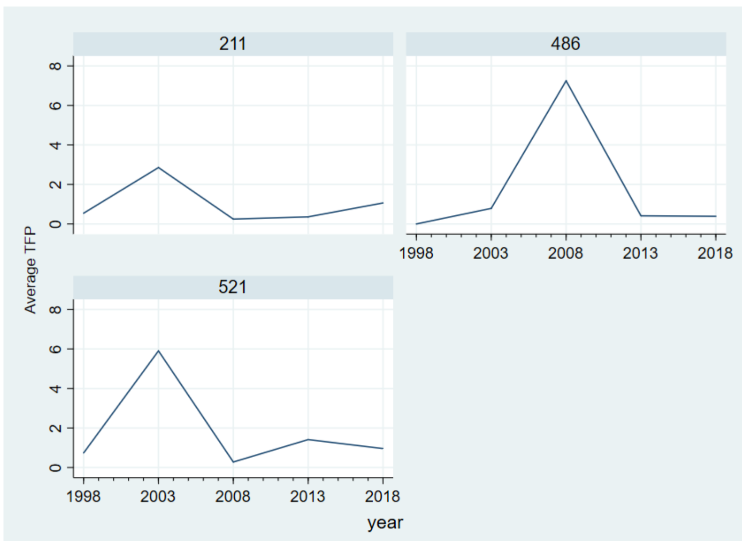
Sectors of Wholesale (NAICS 43), Retail trade (NAICS 46), Information (NAICS 51), Finance and Insurance (NAICS 52), and Professional, scientific, and technical services (NAICS 54) had the highest average TFP during 2018. On the contrary, the economic activities of the Manufacturing sector (NAICS 31-33) had a low average TFP in 2018. The low average TFP in the manufacturing sector can be explained with two arguments. The first argument is related to the view of Loría et al. (2019), which argues that stagnant productivity and low productivity growth explain the slow economic growth of the Mexican economy. The second argument is that TFP in the manufacturing sector is underestimated because economic activities that produce intangible products must be included in the manufacturing sector. The current NAICS consider that the production of intangible assets such as professional, technical services and R&D are included in the tertiary sector (i.e. services). Then, some proponents consider that the manufacturing sector should incorporate activities of intangible products (Coyle 2016, Mullen et al. 2019, Hauge & O'Sullivan 2019).

One of the significant differences between weighted and average TFP is the sector of mining, quarrying, and oil and gas extraction (NAICS 21). In Figure 5.5, the sector with NAICS 22 had the highest weighted TFP, while in Figure E.5, the average TFP of that sector was in the third quartile of average TFP. This difference is because the distribution of weights θ_{it}^{j} within the sector NAICS 22 affect the TFP distribution and thus the weighted TFP aggregation during 2018.

E.4.2 Subsector level

This subsection applies equation E.1 to calculate the average TFP at the subsector level. Figure E.6 displays selected subsectors with the highest average TFP for the whole period of 1998-2018. These subsectors are identified with the NAICS code 211 (Oil and Gas Extraction), subsector 436 (Wholesale of vehicles and parts), and 533 (Services of Nonfinancial Intangible Assets).

Figure E.6: Selected subsectors with the highest average TFP, 1998-2018



Source: Own elaboration using microdata of the Economic Census of Mexico (INEGI)

Similar to results in Chapter 5, Figure E.6 shows that oil and gas extraction activities had a high average TFP during 2003 and did not recover after the financial crisis of 2008. The time-series of the average TFP in the oil and gas extraction subsector is highly correlated with the average TFP at the national level (Figure E.1). Therefore, this Appendix supports the argument of Chapter 5 in which the large increase of average TFP in Mexico during 2003 was caused by the subsector of oil and gas extraction via PEMEX production and ultimately due to the rise of oil extraction in Cantarell (See Appendix G). Particularly, the time-series of average TFP in the municipality Carmen (Campeche) in Figure E.4 is connected and highly correlated with the time-series of average TFP in oil and gas extraction in Figure E.6. The reason is that the oil field Cantarell and the state-owned company PEMEX are located in Carmen (Campeche). In addition, the subsectors 436 and 533 also followed the pattern of high average TFP during 2003, low average TFP during the financial crisis in 2008 and subsequent recovery without reaching the average TFP level pre-crisis. Therefore, there could be a spillover effect of productivity from oil and gas extraction to other subsectors.

Appendix F

Rates of entry, survival and exit by economic sectors and states in Mexico

Table F.1: Number of establishments in the market by periods in the Mexican manufacturing sector, 1993-2018

Number of periods in the market	1993	1998	2003	2008	2013	2018	Total by periods
One period	144,806						144,806
		143,680					143,680
			108,794				108,794
				132,668			132,668
					105,242		105,242
						271,471	271,471
Two periods	48,903	48,903					97,806
		34,416	34,416				68,832
			21,713	21,713			43,426
				47,226	47,226		94,452
					124,179	124,179	248,358
Three periods	22,508	22,508	22,508				67,524
		12,130	12,130	12,130			36,390
			12,875	12,875	12,875		38,625
				93,894	93,894	93,894	281,682
Four periods	10,196	10,196	10,196	10,196			40,784
		8,121	8,121	8,121	8,121		32,484
			35,318	35,318	35,318	35,318	141,272
Five periods	7,756	7,756	7,756	7,756	7,756		38,780
		25,703	25,703	25,703	25,703	25,703	128,515
Six periods	29,263	29,263	29,263	29,263	29,263	29,263	175,578
Total by years	**263,432**	**342,676**	**328,793**	**436,863**	**489,577**	**579,828**	**2,441,169**

Source: Own calculation using microdata of the Economic Census of Mexico.

Table F.2: Number of establishments in the Mexican manufacturing sector by groups: exiting, surviving and entering, 1993-2018

Group of firm selection	1993	1998	2003	2008	2013	2018	Total by periods
Exiting establishments	144,806	192,583	165,718	176,707	181,220		**861,019**
Surviving establishments	118,626	150,093	163,075	260,156	308,357		**1,000,322**
Total by years	**263,432**	**342,676**	**328,793**	**436,863**	**489,577**		**1,861,341**
Group of firm selection	**1993**	**1998**	**2003**	**2008**	**2013**	**2018**	**Total by periods**
Entering establishments		224,050	178,700	273,788	229,421	271,471	**1,177,415**
Surviving establishments		118,626	150,093	163,075	260,156	308,357	**1,000,322**
Total by years		**342,676**	**328,793**	**436,863**	**489,577**	**579,828**	**2,177,737**

Source: Own calculation using microdata of the Economic Census of Mexico

Table F.3: Percentage of establishments in the Mexican manufacturing sector by groups: exiting, surviving and entering, 1998-2018

Group of firms' selection	1993	1998	2003	2008	2013	2018	Total by group
Exiting establishments	54.97%	56.20%	50.40%	40.45%	37.02%		**46.26%**
Surviving establishments	45.03%	43.80%	49.60%	59.55%	62.98%		**53.74%**
Total by years	**100%**	**100%**	**100%**	**100%**	**100%**		**100%**
Group of firms' selection	**1998**	**1998**	**2003**	**2008**	**2013**	**2018**	**Total by group**
Entering establishments		65.38%	54.35%	62.67%	46.86%	46.82%	**54.07%**
Surviving establishments		34.62%	45.65%	37.33%	53.14%	53.18%	**45.93%**
Total by years		**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Source: Own calculation using microdata of the Economic Census of Mexico

Table F.4: Average percentage rate of entering, surviving and exiting establishments by sector, 1998-2018

NAICS code	Sector	Average (1998-2013)		Average (2003-2018)	
		Entering	**Surviving**	**Exiting**	**Surviving**
11	Agriculture, Forestry, Fishing and Hunting	39.97	60.03	37.23	62.77
21	Mining, Quarrying, and Oil and Gas Extraction	43.73	56.27	40.8	59.2
46	Retail trade	47.11	52.89	36.5	63.5
62	Health Care and Social Assistance	48.5	51.5	35.23	64.77
81	Other Services (except Public Administration)	50.45	49.55	36.76	63.24
43	Wholesale	50.95	49.05	43.62	56.38
61	Educational Services	51.28	48.72	41.15	58.85
33	Manufacturing (primary metals, machinery, etc.)	51.46	48.54	44	56
32	Manufacturing (wood, paper, etc.)	51.47	48.53	43.66	56.34
31	Manufacturing (food, beverage etc.)	52.44	47.56	37.42	62.58
48	Transport	54.71	45.29	85	15
54	Professional, Scientific, and Technical Services	55.36	44.64	47.16	52.84
23	Construction	59.38	40.62	53.73	46.27
53	Real Estate and Rental and Leasing	61.78	38.22	47.19	52.81
72	Accommodation and Food Services	62.51	37.49	41.73	58.27
71	Arts, Entertainment, and Recreation	63.31	36.69	51.72	48.28
51	Information	65.54	34.46	62.59	37.41
52	Finance and Insurance	65.9	34.1	37.81	62.19
56	Administrative and Support and Waste Management and Remediation Services	67.87	32.13	46.88	53.12
49	Postal service and warehousing	69.15	30.85	91.67	8.33

Source: Own elaboration with information from the Economic Census (INEGI)

Table F.5: Average percentage rate of entering, surviving and exiting establishments by states, 1998-2018

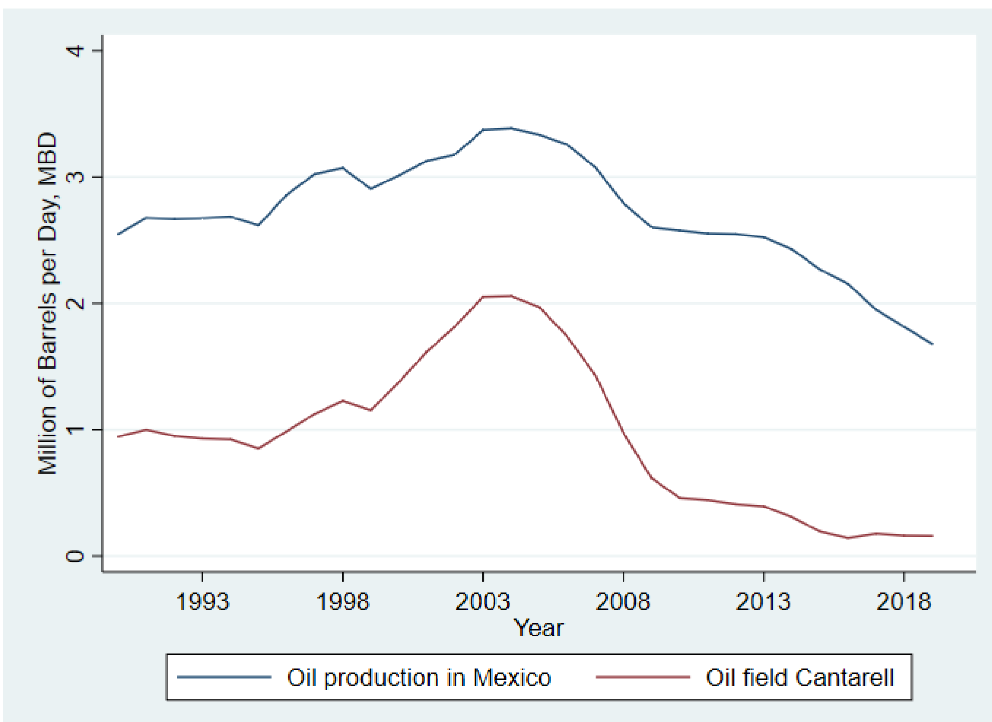
State	Acronym	Average (1998-2013)		Average (2003-2018)	
		Entering	Surviving	Exiting	Surviving
Mexico City	CDMX	45.87	54.13	40.89	59.11
Zacatecas	Zac.	46.38	53.62	36.63	63.37
Michoacan	Mich.	48.89	51.11	35.44	64.56
San Luis Potosi	SLP	49.11	50.89	37.64	62.36
Jalisco	Jal.	49.21	50.79	38.25	61.75
Durango	Dgo.	49.35	50.65	39.47	60.53
Guanajuato	Gto.	49.48	50.52	37.35	62.65
Sinaloa	Sin.	49.89	50.11	36.91	63.09
Veracruz	Ver.	50.13	49.87	39.88	60.12
Chihuahua	Chih.	50.37	49.63	43.19	56.81
Tamaulipas	Tamps.	50.44	49.56	43.73	56.27
Yucatan	Yuc.	50.47	49.53	34.99	65.01
Nayarit	Nay.	50.58	49.42	34.95	65.05
Guerrero	Gro.	50.64	49.36	37.97	62.03
Morelos	Mor.	50.82	49.18	38.04	61.96
Aguascalientes	Ags.	50.9	49.1	37.92	62.08
Sonora	Son.	50.98	49.02	41.24	58.76
Coahuila	Coah.	51.09	48.91	42.23	57.77
Puebla	Pue.	51.22	48.78	37.4	62.6
Campeche	Camp.	51.35	48.65	38.88	61.12
Nuevo Leon	NL	52.01	47.99	43.91	56.09
State of Mexico	Mex.	52.47	47.53	38.25	61.75
Tlaxcala	Tlax.	52.91	47.09	37.49	62.51
Hidalgo	Hgo.	53	47	36.49	63.51
Oaxaca	Oax.	53.06	46.94	37.07	62.93
Queretaro	Qro.	53.21	46.79	35.85	64.15
Chiapas	Chis.	53.54	46.46	37.01	62.99
Colima	Col.	53.86	46.14	40.4	59.6
Tabasco	Tab.	54.15	45.85	40.14	59.86
Baja California	BC	55.35	44.65	43.02	56.98
Baja California Sur	BCS	55.96	44.04	40.71	59.29
Quintana Roo	Q. Roo	60.27	39.73	44.22	55.78

Source: Own elaboration with information from the Economic Census (INEGI)

Appendix G

Stylized facts that support the TFP evolution at the sectoral level

Figure G.1: Oil production in Mexico and Cantarell, the most important Mexican oil field (MBD), 1990-2019.[a/]



[a/] Adjustments to the oil production of the period 2017-2019 according to the PEMEX's financial reports.

Source: National Commission of Hydrocarbons (CNH in Spanish) and PEMEX financial reports.

Appendix H

Selection of the spatial convergence model

Table H.1: Parametrical comparison of spatial convergence models using weighted TFP at the state level, 1998-2018 [a/]

Parameters	Variables	(1) Spatial convergence model ($W1$ matrix)	(2) Spatial convergence model ($W2$ matrix)	(3) Spatial convergence model ($W3$ matrix)	(4) Spatial convergence model ($W4$ matrix)
β	Initial weighted TFP (1998)	-0.009	-0.009	-0.007	-0.015
		(0.013)	(0.013)	(0.015)	(0.014)
ρ	W weighted TFP growth (1998-2018)	0.011	-0.011	-0.001	0.043
		(0.028)	(0.034)	(0.018)	(0.057)
γ	W Initial weighted TFP (1998)	-0.747**	-0.228	0.366	-0.530
		(0.346)	(1.326)	(0.885)	(1.101)
λ	W Error	0.589**	0.059	-0.467	-0.551
		(0.265)	(1.216)	(1.119)	(1.125)
α	Constant	0.012	-0.004	-0.001	0.030
		(0.024)	(0.016)	(0.010)	(0.034)
Observations		32	32	32	32
R-squared pseudo		0.0412	0.0310	0.0287	0.0419
AIC		-117.2	-116.3	-116.1	-117.9
BIC		-108.4	-107.5	-107.3	-109.1

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

[a/] $W1$ matrix: first-order queen. $W2$ matrix: first and second-order queen. $W3$ matrix: rook. $W4$ matrix: inverse distance matrix

Source: Own elaboration with microdata of the Economic Census (INEGI)

Appendix I

An extension of the regional TFP convergence

I.1 Regional convergence using average TFP

Appendix E concluded that average TFP is an alternative metric of analysis that provides a plausible representation of the geographic and sectoral dimension of TFP in Mexico. This Appendix aims to extend the examination of regional TFP convergence in Mexico using the average TFP as the research metric. Then, this Appendix is complementary to the regional TFP convergence of Chapter 6.

This subsection estimates the models of TFP convergence and the estimation strategy presented in section 6.2 using the average TFP at the state and municipality levels. Like Chapter 6, the objective is to test whether there was a TFP convergence across Mexican states and municipalities between 1998 and 2018 using the average TFP as the research metric. The following summarises the estimation strategy to examine beta-convergence and sigma-convergence.

1. The initial estimation is the neoclassical convergence model from 1998 to 2018 using the average TFP ($\overline{TFP}_{jt}$) in the state or municipality j.

$$\left[\ln\left(\overline{TFP}_{jt}\right) - \ln\left(\overline{TFP}_{j1}\right)\right]/T = \alpha + \beta \ln\left(\overline{TFP}_{j1}\right) + \varepsilon_j \tag{I.1}$$

2. The neoclassical model of TFP convergence is estimated by census period of 5-years interval from 1998 to 2018 to analyse TFP convergence in the short-term.

3. Subsequently, there is estimated whether spatial autocorrelation exists in any of the variables of the neoclassical model.

4. If any variables have spatial autocorrelation, the Manski model for spatial convergence is estimated from 1998 to 2018.

$$\begin{aligned} \left[\ln\left(\overline{TFP}_{jt}\right) - \ln\left(\overline{TFP}_{j1}\right)\right]/T &= \alpha + \beta \ln\left(\overline{TFP}_{j1}\right) \\ +\rho W\left[\ln\left(\overline{TFP}_{jt}\right) - \ln\left(\overline{TFP}_{j1}\right)\right]/T &+ \gamma \ln\left(\overline{TFP}_{j1}\right) + \lambda W \varepsilon_j + \varepsilon_j \end{aligned} \tag{I.2}$$

5. If any of the variables in the Manski model is not statistically significant, that (those) variable(s) is (are) excluded until reaching the final Saptial convergence model. The Spatial convergence model includes different specifications of a W matrix, and the model with the lowest information criterion is the selected model over the rest.

6. There is calculated sigma-convergence using average TFP to evaluate the evolution of average TFP disparities over time.

The specification of the variables in the models of TFP convergence in equations I.1 and I.2 is similar to the explanation in section 6.1 but using average TFP. In addition, sigma convergence is calculated with S.D. across the average TFP of states and municipalities per year.

I.2 Analysis of average TFP convergence at the state level

I.2.1 Beta-convergence

Table I.1 estimates the neoclassical convergence model from equation I.1 using the average TFP at the state level from 1998 to 2018.

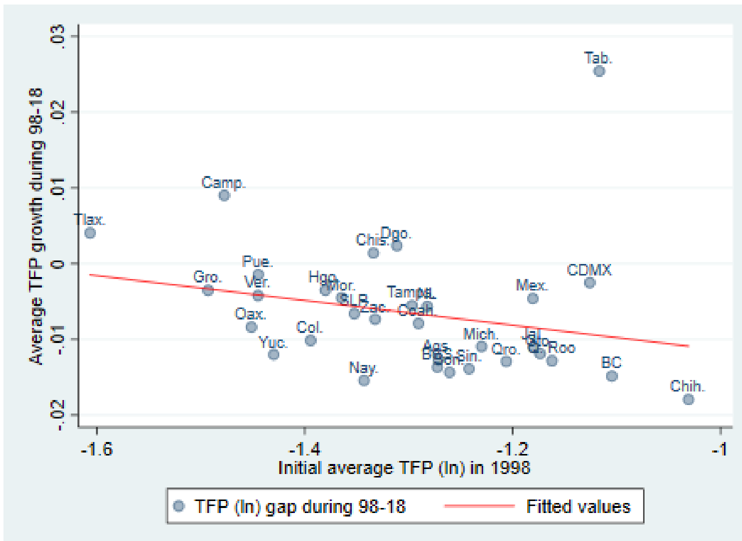
Table I.1: Neoclassical model of regional convergence (regression) using average TFP at the state level, 1998-2018

Parameters	Variables	Dependent average TFP growth (1998-2018)
β	Initial average TFP (1998)	-0.016
		(0.015)
α	Constant	-0.028
		(0.020)
Observations		32

Robust standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1
Source: Own estimation using microdata of the Economic Census of Mexico

None of the parameters in Table I.1 is statistically significant, which indicates that the parameter β is statistically zero. Therefore, the evidence suggests no beta-convergence in average TFP across Mexican states from 1998 to 2018. This result is similar to Chapter 6, which indicated no convergence across states using weighted TFP as the analysis metric. Figure I.1 displays the neoclassical TFP convergence model results from a graphic perspective.

Figure I.1: Neoclassical model (regression) of regional TFP convergence using average TFP at the state level, 1998-2018



Source: Own estimation using microdata of the Economic Census of Mexico

The fitted values in Figure I.1 (i.e. red line) indicate a negative relationship between initial average TFP in 1998 and average TFP growth (1998-2018). However, the state of Tabasco (Tab) is a significant outlier in the sample due to its large average TFP growth. This outlier causes that parameter β is not statistically significant due to the large dispersion in the sample. The large average TFP growth in Tabasco results from higher productivity in oil extraction and production activities.

The lack of beta-convergence using average TFP can result from an aggregation bias when the average TFP is used at the state level, similar to the results presented in Chapter 6 when weighted TFP was examined. It is important to note that convergence analysis is susceptible when a small sample is analysed. In this case, a high TFP growth in a state can represent a large outlier that generates non-statistically significance in the beta-convergence parameter. However, Chapter 6 identified three outliers in the sample of the neoclassical convergence model using weighted TFP, while this Appendix only identified one outlier using the average TFP. For that reason, there can be inferred that weighted TFP can be more sensitive to an aggregation bias due to using the weights (See the discussion about the use of weights in Appendix E).

Table I.2 estimated beta-convergence by census periods (5-year interval) from 1998 to 2018. The estimation from Table I.2 aims to investigate whether the lack of average TFP convergence in Table I.1 applies to the whole period (1998-2018) or only there was a lack of convergence in particular periods.

Table I.2: The neoclassical model of regional TFP convergence by periods using average TFP at the state level, 1998-2018

Parameters	Variables	1998-2003	2003-2008	2008-2013	2013-2018
β	Initial average TFP (1998)	-0.103***	-0.009	-0.072*	0.048
		(0.016)	(0.031)	(0.040)	(0.088)
α	Constant	-0.123***	-0.092**	-0.098	0.098
		(0.022)	(0.040)	(0.068)	(0.139)
Observations		32	32	32	32

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1
Source: Own estimation using microdata of the Economic Census of Mexico

The results from Table I.2 indicate a period of average TFP convergence in 1998-2003. During 1998-2003, there was a high average TFP due to the intensification of trade activity generated by NAFTA and reached a high average TFP due to the boom in oil prices and oil production in Mexico (Figure I.1 and Appendix E). Then, high levels of average TFP at the national level are associated with beta-convergence across states.

Table I.3 examines whether there is spatial autocorrelation in any of the variables estimated in the neoclassical convergence model from equation I.1 using Moran's index.

Table I.3: Evaluation of spatial dependence in the variables of the convergence model using average TFP at the state level, 1998-2018[a/]

Dependent Variable	$\left[\ln\left(\overline{TFP}_{jt}\right) - \ln\left(\overline{TFP}_{j1}\right)\right]/T$	$\ln\left(\overline{TFP}_{j1}\right)$	ε_j
Moran's I	0.102	0.012	0.070
E(I)	-0.032	-0.032	-0.032
SE(I)	0.030	0.033	0.028
Z(I)	4.419	1.342	3.657
P-value(I)	0.000	0.180	0.000
Number of observations	32	32	32

[a/] In the first column, E(I), SE(I), Z(I) refer to the expected value, standard error, and Z-statistics of Moran's Index, respectively.
Source: Own calculation using microdata of the Economic Census of Mexico

The results in Table I.3 indicate spatial autocorrelation in the initial levels of average TFP across states during 1998. For that reason, evidence suggests that the parameter β from the neoclassical model can be biased as the spatial component was omitted in the average TFP convergence across states. There is a proposed estimation strategy with the specification of the Manski model to estimate a spatial convergence model using average TFP at the state level (See discussion in subsection 6.2.1).

Table I.4 estimated a spatial convergence model using four specifications of W matrices that measure spatial connectivity across states, including the first-order queen ($W1$ matrix), first and second-order queen ($W2$ matrix), rook ($W3$ matrix) and inverse distance ($W4$ matrix). The main parameter of interest is β. The results show no beta-convergence as any model has $\beta < 0$ and is statistically significant at 95% confidence. The model that includes the $W2$ matrix is preferred over the rest as the selected spatial model according to the criterion of better fitness due to the lowest AIC and BIC (Column (2) in Table I.4). However, the spatial model with the $W2$ matrix can present specification issues because the parameter λ does not present spatial stationarity as this parameter is larger than the unity (Beenstock & Felsenstein 2019).[1] The exclusion of spatial variables not statistically significant can improve the magnitude and significance of the spatial parameters, but the parameter of analysis β is not subject to significant changes. In conclusion, there is not beta-convergence across states using average TFP.

Table I.4: Spatial model of regional convergence using average TFP at the state level, 1998-2018.[a/]

Parameters	Variables	(1) Spatial convergence model ($W1$ matrix)	(2) Spatial convergence model ($W2$ matrix)	(3) Spatial convergence model ($W3$ matrix)	(4) Spatial convergence model ($W4$ matrix)
β	Initial average TFP (1998)	-0.010	-0.007	-0.009	-0.013
		(0.010)	(0.010)	(0.011)	(0.010)
ρ	W average TFP growth (1998-2018)	-0.020	-0.045*	-0.003	-0.156**
		(0.020)	(0.026)	(0.003)	(0.069)
γ	W Initial average TFP (1998)	0.381	0.612**	0.431	0.349
		(0.281)	(0.274)	(0.376)	(0.549)
λ	W Error	0.154	-1.293**	0.280	-0.123
		(0.386)	(0.621)	(0.455)	(0.853)
α	Constant	-0.042	-0.070**	-0.019	-0.225**
		(0.031)	(0.034)	(0.014)	(0.092)
Observations		32	32	32	32
R-squared pseudo		0.242	0.307	0.103	0.258
AIC		-213	-217	-209.2	-212.2
BIC		-204.2	-208.2	-200.4	-203.4

Standard errors in parentheses

*** p¡0.01, ** p¡0.05, * p¡0.1

[a/] W1 matrix: first-order queen. W2 matrix: first and second-order queen. W3 matrix: rook. W4 matrix: inverse distance matrix

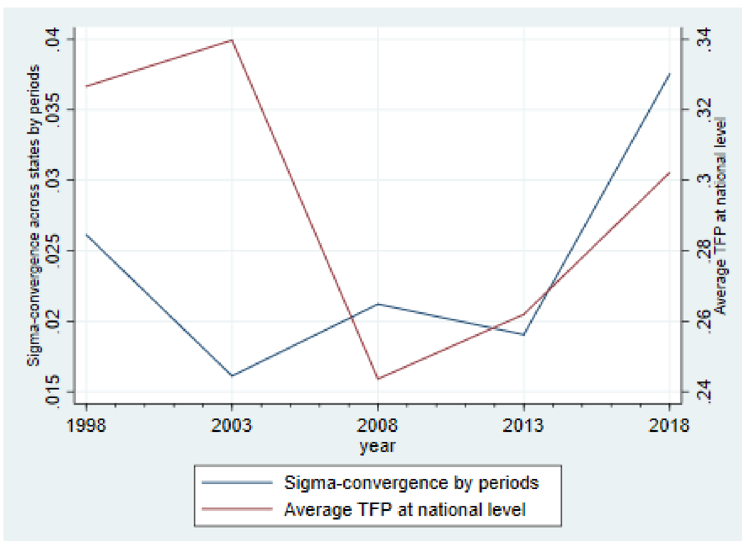
Source: Own elaboration with microdata of the Economic Census (INEGI)

[1] Beenstock & Felsenstein (2019) argue that when the spatial parameters tend to the unity, there is no spatial stationarity, which implies that spatial impulses do not decrease with distance. In the case of spatial non-stationarity, the spatial parameters will be nonsense and spurious.

I.2.2 Sigma convergence

Figure I.2 presents the calculation of sigma-convergence compared with the average TFP at the national level. The results indicate that periods of a high average TFP are associated with large values of sigma convergence that indicate higher disparities of average TFP across states (1998 and 2018). On the contrary, periods of decreasing or low average TFP at the national level (during the global crisis of 2008 and 2013) cause the sigma-convergence to fall; as a result, the disparities across states decrease. The evolution of sigma-convergnece can suggest that in periods of average TFP increase, only a few states concentrate a significant TFP growth (outliers), which generates a higher dispersion of average TFP across states. As a result, the increase in average TFP in Mexico does not reflect a reduction of disparities when the average TFP is examined across states.

Figure I.2: Sigma-convergence using average TFP at the state level and average TFP at the national level, 1998-2018



Source: Own estimation using microdata of the Economic Census of Mexico

I.3 Analysis of average TFP convergence at the municipality level

I.3.1 Beta convergence

Table I.5 estimates the neoclassical convergence model from equation I.1 using the average TFP at the municipality level from 1998 to 2018.

Table I.5: Neoclassical model of regional convergence (regression) using average TFP at the municipality level, 1998-2018

Parameters	Variable	Neoclassical model (Regression)
β	Initial average TFP (1998)	-0.040***
		(0.001)
α	Constant	-0.061***
		(0.001)
Observations		2,424

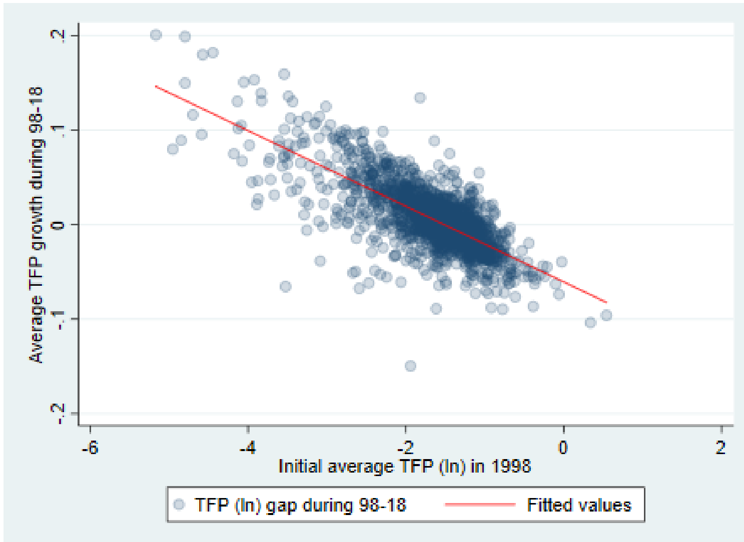
Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1
Source: Own estimation using microdata of the Economic Census of Mexico

The parameters α and β in Table I.5 are statistically significant, indicating beta-convergence across municipalities using average TFP as the research metric. This result is similar to Chapter 6 (Table 6.6), which indicated convergence across municipalities using weighted TFP as the analysis metric. The convergence rate b of average TFP across municipalities is estimated at 0.2%, and it would take around 340 years (v) for half the average TFP gap across municipalities to be eliminated (See calculation of the half-life period in subsection 6.4.2).

Figure I.3 displays the results of the neoclassical TFP convergence model from a graphic perspective. The fitted value (red line) represents beta-convergence. Compared to the convergence of average TFP at the state level, the sample of average TFP at the municipality level displays less dispersion (and better fitness). The explanation for the finding that beta-convergence exists across municipalities but not across states is that the average TFP at the state level has an aggregation bias. The calculation of average TFP across states generates large outliers in the sample (Figure I.1). For that reason, when the average TFP is estimated at a lower disaggregation (i.e. municipality level), the outliers get fragmented, and the dispersion in the sample reduces. The explanation about the aggregation and TFP convergence at different geographical levels due to the aggregation bias is the same argument presented in subsection 6.4.2.

The neoclassical model was estimated to test whether there was average TFP convergence in every census period (5-year interval) from 1998 to 2018. The results in Table I.6 indicate that the parameter β is negative and statistically significant in every period but with variations in magnitude.

Figure I.3: Neoclassical model (regression) of regional convergence using average TFP at the municipality level, 1998-2018



Source: Own estimation using microdata of the Economic Census of Mexico

Therefore, there was continuous beta-convergence of average TFP across municipalities but with variations of rate convergence. This result indicates that low-productive municipalities caught-up but at a different rate between 1998 and 2018.

The period 2003-2008 had the most intense period of beta-convergence, which is associated with the lowest average TFP at the national level due to the global crisis in 2008 (Figure E.1 in Appendix E). The evidence of Table I.6 indicates that beta-convergence of average TFP across Mexican municipalities becomes more intense for incorrect economic reasons. The explanation is that in a period of low economic growth (2003-2008), the most productive municipalities have low levels of TFP and the low-productive municipalities catch up faster. A correct functioning will imply that a high average TFP at the national level is accompanied by intense periods of beta-convergence. On the contrary, the evidence of Table I.6 shows that there was convergence in the period of high average TFP at the national level (1998-2003) but at a slower pace.

Table I.7 evaluates spatial autocorrelation in the variables of the neoclassical model of TFP convergence at the municipality level from equation I.1. The results indicate that the expected value of Moran's index (E(I)) is zero in the three columns of Table I.7, and there is no spatial autocorrelation in any of the variables of the neoclassical model of average TFP convergence. As a result, the use of techniques of Spatial Econometrics does not improve the results from the estimation of the neoclassical model in Table I.5.

Table I.6: The neoclassical model of regional convergence by periods using average TFP at the municipality level, 1998-2018

Parameters	Variables	1998-2003	2003-2008	2008-2013	2013-2018
β	Initial average TFP (1998)	-0.115***	-0.124***	-0.121***	-0.116***
		(0.006)	(0.007)	(0.006)	(0.006)
α	Constant	-0.147***	-0.262***	-0.194***	-0.164***
		(0.008)	(0.010)	(0.011)	(0.010)
Observations		2,424	2,424	2,424	2,424

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1
Source: Own estimation using microdata of the Economic Census of Mexico

Table I.7: Evaluation of spatial dependence in the variables of the convergence model using average TFP at the municipality level, 1998-2018[a/]

Dependent Variable	$\left[\ln\left(\overline{TFP}_{jt}\right) - \ln\left(\overline{TFP}_{j1}\right)\right]/T$	$\ln\left(\overline{TFP}_{j1}\right)$	ε_j
Moran's I	0.087	0.149	0.040
E(I)	0.000	0.000	0.000
SE(I)	0.001	0.001	0.001
Z(I)	94.172	161.364	43.589
P-value(I)	0.000	0.000	0.000
Number of observations	2,424	2,424	2,424

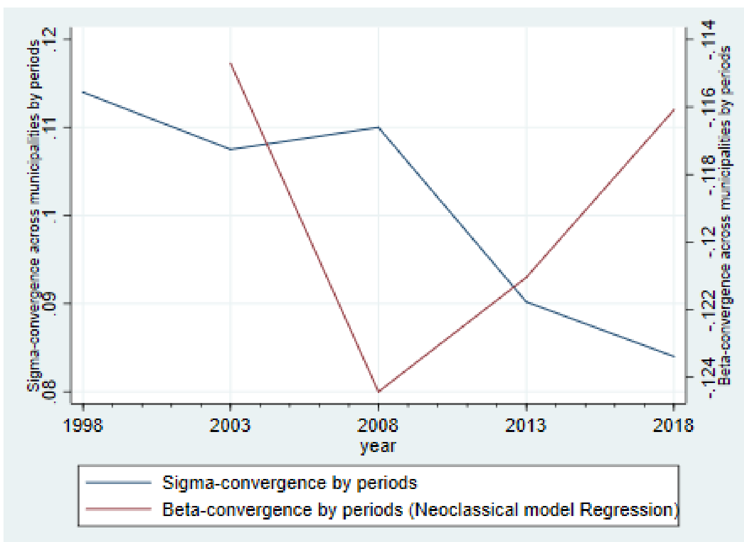
[a/] In the first column, E(I), SE(I), Z(I) refer to the expected value, standard error, and Z-statistics of Moran's Index, respectively.
Source: Own calculation using microdata of the Economic Census of Mexico

I.3.2 Sigma convergence

This subsection calculates sigma-convergence using average TFP at the municipality level. This metric investigates the evolution of average TFP disparities across municipalities over time. Figure I.4 compares the time-series of sigma convergence and beta-convergence using the results of Table I.6. The results indicate that in periods of intense beta-convergence., there is a decrease in sigma-convergence (lower disparities). On the contrary, with low intense beta-convergence (in the global financial crisis), there is also an increase of sigma convergence (larger disparities).

Overall, sigma-convergence has displayed a decreasing trend from 1998 to 2018 (Figure I.4). This result can indicate that the average TFP disparities across municipalities have reduced due to a continuous beta-convergence, as Sala-i Martin (1996) proposes. This result is similar to when sigma-convergence was analysed using weighted TFP in subsection 6.4.2.

Figure I.4: Sigma-convergence and beta-convergence using average TFP at the municipality level, 1998-2018



Source: Own estimation using microdata of the Economic Census of Mexico

Bibliography

1. Acemoglu, D., Johnson, S. & Robinson, J. A. (2002), 'Reversal of fortune: Geography and institutions in the making of the modern world income distribution', *The Quarterly journal of economics* **117**(4), 1231–1294.

2. Acemoglu, D., Johnson, S. & Robinson, J. A. (2005), 'Institutions as a fundamental cause of long-run growth', *Handbook of economic growth* **1**, 385–472.

3. Ackerberg, D. A., Caves, K. & Frazer, G. (2015), 'Identification properties of recent production function estimators', *Econometrica* **83**(6), 2411–2451.

4. Aghion, P., Akcigit, U. & Howitt, P. (2015), 'The Schumpeterian growth paradigm', *economics* **7**(1), 557–575.

5. Aghion, P., Bloom, N., Blundell, R., Griffith, R. & Howitt, P. (2005), 'Competition and innovation: An inverted-u relationship', *The quarterly journal of economics* **120**(2), 701–728.

6. Aghion, P., Harris, C., Howitt, P. & Vickers, J. (2001), 'Competition, imitation and growth with step-by-step innovation', *The Review of Economic Studies* **68**(3), 467–492.

7. Aghion, P. & Howitt, P. (1990), 'A model of growth through creative destruction'.

8. Akerlof, G. A. & Yellen, J. L. (1985), 'A near-rational model of the business cycle, with wage and price inertia', *The Quarterly Journal of Economics* **100**(Supplement), 823–838.

9. Alvarez, J. & Ruane, M. C. (2019), *Informality and aggregate productivity: The case of Mexico*, International Monetary Fund.

10. Amiti, M. & Konings, J. (2007), 'Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia', *American Economic Review* **97**(5), 1611–1638.

11. Anderton, R., Di Lupidio, B. & Jarmulska, B. (2019), 'Product market regulation, business churning and productivity: Evidence from the European Union countries', *Business Churning and Productivity: Evidence from the European Union Countries (November, 2019)* .

12. Angeles-Castro, G., Salazar-Rivera, M. P. & Sandoval-Contreras, L. (2019), 'Federalismo fiscal y su efecto en el crecimiento y la distribución de ingresos. Evidencia para México', *Gestión y política pública* **28**(1), 107–139.

13. Anselin, L. (1988), *Spatial econometrics: methods and models*, Vol. 4, Springer Science & Business Media.

14. Anselin, L. (2003), 'Spatial externalities, spatial multipliers, and spatial econometrics', *International regional science review* **26**(2), 153–166.

15. Arellano, M. & Bond, S. (1991), 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations', *The review of economic studies* **58**(2), 277–297.

16. Arrow, K. (1962), Economic welfare and the allocation of resources for invention, *in* 'The rate and direction of inventive activity: Economic and social factors', Princeton University Press, pp. 609–626.

17. Arrow, K. J., Chenery, H. B., Minhas, B. S. & Solow, R. M. (1961), 'Capital-labor substitution and economic efficiency', *The review of Economics and Statistics* pp. 225–250.

18. Asker, J., Collard-Wexler, A. & De Loecker, J. (2014), 'Dynamic inputs and resource (mis) allocation', *Journal of Political Economy* **122**(5), 1013–1063.

19. Aw, B. Y., Roberts, M. J. & Xu, D. Y. (2011), 'R&d investment, exporting, and productivity dynamics', *American Economic Review* **101**(4), 1312–1344.

20. Baptista, R. & Swann, G. (1999), 'A comparison of clustering dynamics in the US and UK computer industries', *Journal of evolutionary economics* **9**(3), 373–399.

21. Baqaee, D. & Farhi, E. (2019), A short note on aggregating productivity, Technical report, National Bureau of Economic Research.

22. Barnett, A., Chiu, A., Franklin, J. & Sebastia-Barriel, M. (2014), 'The productivity puzzle: a firm-level investigation into employment behaviour and resource allocation over the crisis'.

23. Barro, R. J. (1996), 'Determinants of economic growth: A cross-country empirical study'.

24. Barro, R. J. & Sala-i Martin, X. (1992), 'Convergence', *Journal of political Economy* **100**(2), 223–251.

25. Bartelsman, E. J. & Doms, M. (2000), 'Understanding productivity: Lessons from longitudinal microdata', *Journal of Economic literature* **38**(3), 569–594.

26. Bartelsman, E. J. & Wolf, Z. (2017), 'Measuring productivity dispersion'.

27. Bartik, T. (2002), 'Instrumental variable estimates of the labor market spillover effects of welfare reform', *WE Upjohn Institute Staff Working Paper* (02-78).

28. Batisse, C. (2002), 'Dynamic externalities and local growth: A panel data analysis applied to Chinese provinces', *China Economic Review* **13**(2-3), 231–251.

29. Battese, G. E. & Broca, S. S. (1997), 'Functional forms of stochastic frontier production functions and models for technical inefficiency effects: a comparative study for wheat farmers in Pakistan', *Journal of productivity analysis* **8**(4), 395–414.

30. Battese, G. E. & Coelli, T. J. (1988), 'Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data', *Journal of econometrics* **38**(3), 387–399.

31. Battese, G. E. & Coelli, T. J. (1992), 'Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India', *Journal of productivity analysis* **3**(1), 153–169.

32. Battese, G. E. & Coelli, T. J. (1995), 'A model for technical inefficiency effects in a stochastic frontier production function for panel data', *Empirical economics* **20**(2), 325–332.

33. Baum, C. F., Schaffer, M. E. & Stillman, S. (2003), 'Instrumental variables and GMM: Estimation and testing', *The Stata Journal* **3**(1), 1–31.

34. Beenstock, M. & Felsenstein, D. (2019), *The econometric analysis of non-stationary spatial panel data*, Springer.

35. Belotti, F., Daidone, S., Ilardi, G. & Atella, V. (2013), 'Stochastic frontier analysis using Stata', *The Stata Journal* **13**(4), 719–758.

36. Berlingieri, G. (2014), 'Outsourcing and the Rise in Services (CEP Discussion Paper 1199)', *Recuperado de http://eprints. lse. ac. uk/51532/1/dp1199. pdf* .

37. Bernard, A. B. & Jensen, J. B. (1999), 'Exceptional exporter performance: cause, effect, or both?', *Journal of international economics* **47**(1), 1–25.

38. Bils, M., Klenow, P. J. & Ruane, C. (2021), 'Misallocation or mismeasurement?', *Journal of Monetary Economics* **124**, S39–S56.

39. Blanchard, O. (2006), 'Macroeconomía,(4ta edición) ed'.

40. Blažková, I. & Dvouletỳ, O. (2018), 'Investigating the differences in entrepreneurial success through the firm-specific factors: Microeconomic evidence from the Czech food industry', *Journal of Entrepreneurship in Emerging Economies* .

41. Bloom, N., Iacovone, L., Pereira-Lopez, M. & Van Reenen, J. (2022), Management and misallocation in Mexico, Technical report, National Bureau of Economic Research.

42. Blundell, R. & Bond, S. (1998), 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of econometrics* **87**(1), 115–143.

43. Blyde, J. S. & Fentanes, O. (2019), The heterogeneous impacts of import competition on Mexican manufacturing plants, Technical report, IDB Working Paper Series.

44. Borrayo López, R., Mendoza González, M. Á. & Castañeda Arriaga, J. M. (2019), 'Productividad y eficiencia técnica de la industria manufacturera regional de México, 1960-2013: un enfoque panel de frontera estocástica', *Estudios Económicos (México, DF)* **34**(1), 25–60.

45. Borrayo, R. & Quintana, L. (2018), 'Creatividad, eficiencia y concentración espacial en México', *Problemas del desarrollo* **49**(193), 33–66.

46. Brulhart, M. (1998), 'Economic geography, industry location and trade: the evidence', *The World Economy* **21**(6), 775–801.

47. Brunow, S. & Hirte, G. (2009), 'The age pattern of human capital and regional productivity: a spatial econometric study on German regions', *Papers in Regional Science* **88**(4), 799–823.

48. Burda, M. C. & Severgnini, B. (2018), 'Total factor productivity convergence in German states since reunification: Evidence and explanations', *Journal of Comparative Economics* **46**(1), 192–211.

49. Busso, M., Fazio, M. & Algazi, S. (2012), '(In) formal and (un) productive: The productivity costs of excessive informality in Mexico'.

50. Busso, M., Fentanes Téllez, O. E. & Levy Algazi, S. (2019), 'Vinculación longitudinal de los Censos Económicos 1994-2014 de México', *Realidad, datos y espacio. Revista internacional de estadística y geografía* **10**(2).

51. Busso, M., Levy, S. & Torres, J. (2019), 'Establishment dynamics and the persistence of resource misallocation in Mexico: An analysis of longitudinal data for 1998-2013.'.

52. Byrne, J. P., Fazio, G. & Piacentino, D. (2009), 'Total Factor Productivity convergence among Italian Regions: Some evidence from panel unit root tests', *Regional Studies* **43**(1), 63–76.

53. Cabral, R., López Cabrera, J. A. & Padilla, R. (2020), 'Absolute convergence in manufacturing labour productivity in Mexico, 1993–2018: A spatial econometrics analysis at the state and municipal level'.

54. Cainelli, G., Leoncini, R. & Montini, A. (2007), 'Spatial knowledge spillovers and regional productivity growth in Europe', *Revue d'économie régionale et urbaine* (2), 201–221.

55. Cameron, A. C. & Trivedi, P. K. (2005), *Microeconometrics: methods and applications*, Cambridge university press.

56. Carlin, W. & Soskice, D. (2005), 'The 3-equation New Keynesian Model—a graphical exposition', *Contributions in Macroeconomics* **5**(1).

57. Carlsson, M., Clymo, A. & Joslin, K.-E. (2019), 'Dispersion over the business cycle: Productivity versus demand'.
URL: *https://economicdynamics.org/meetpapers/2019/paper˙1125.pdf*

58. Caselli, F. (2005), 'Accounting for cross-country income differences', *Handbook of economic growth* **1**, 679–741.

59. Castellanos-Sosa, F. A. (2020), 'Labor Productivity Convergence in Mexico', *International Journal of Political Economy* **49**(3), 243–260.

60. Chen, E. K. (1997), 'The total factor productivity debate: determinants of economic growth in East Asia', *Asian-Pacific Economic Literature* **11**(1), 18–38.

61. Chen, M. & Guariglia, A. (2013), 'Internal financial constraints and firm productivity in China: Do liquidity and export behavior make a difference?', *Journal of Comparative Economics* **41**(4), 1123–1140.

62. Christensen, L. R. (1971), 'Conjugate duality and the transcendental logarithmic prodcution function', *Econometrica* **39**, 255–256.

63. Christensen, L. R., Jorgenson, D. W. & Lau, L. J. (1973), 'Transcendental logarithmic production frontiers', *The review of economics and statistics* pp. 28–45.

64. Cobb, C. W. & Douglas, P. H. (1928), 'A theory of production'.

65. Coelli, T. J., Rao, D. S. P., O'Donnell, C. J. & Battese, G. E. (2005), *An introduction to efficiency and productivity analysis*, springer science & business media.

66. Combes, P.-P. (2000), 'Economic structure and local growth: France, 1984–1993', *Journal of urban economics* **47**(3), 329–355.

67. Combes, P.-P., Duranton, G., Gobillon, L., Puga, D. & Roux, S. (2012), 'The productivity advantages of large cities: Distinguishing agglomeration from firm selection', *Econometrica* **80**(6), 2543–2594.

68. Comin, D. (2010), Total factor productivity, *in* 'Economic growth', Springer, pp. 260–263.

69. Cooley, T. F. (1997), 'Calibrated models', *Oxford Review of Economic Policy* **13**(3), 55–69.

70. Coricelli, F., Driffield, N., Pal, S. & Roland, I. (2012), 'When does leverage hurt productivity growth? A firm-level analysis', *Journal of international Money and Finance* **31**(6), 1674–1694.

71. Coyle, D. (2016), ‘The sharing economy in the UK’, *Report for Sharing Economy UK and AirBnB* **25**.

72. Dai, M., Maitra, M. & Yu, M. (2016), ‘Unexceptional exporter performance in China: The role of processing trade’, *Journal of Development Economics* **121**, 177–189.

73. Daude, C. & Fernández-Arias, E. (2010), ‘On the role of productivity and factor accumulation in economic development in Latin America and the Caribbean’.

74. De la Fuente, A. (2000), ‘Convergence across countries and regions: theory and empirics’, *Available at SSRN 231963* .

75. De Loecker, J. (2011), ‘Product differentiation, multiproduct firms, and estimating the impact of trade liberalization on productivity’, *Econometrica* **79**(5), 1407–1451.

76. De Loecker, J. (2013), ‘Detecting learning by exporting’, *American Economic Journal: Microeconomics* **5**(3), 1–21.

77. De Loecker, J. & Syverson, C. (2021), An industrial organization perspective on productivity, *in* ‘Handbook of industrial organization’, Vol. 4, Elsevier, pp. 141–223.

78. Dekle, R. & Eaton, J. (1999), ‘Agglomeration and land rents: evidence from the prefectures’, *Journal of Urban Economics* **46**(2), 200–214.

79. Del Gatto, M., Di Liberto, A. & Petraglia, C. (2011), ‘Measuring productivity’, *Journal of Economic Surveys* **25**(5), 952–1008.

80. Dias, D. A. & Robalo, C. (2021), ‘From micro to macro: a note on the analysis of aggregate productivity dynamics using firm-level data’, *Journal of Productivity Analysis* **56**(1), 1–14.

81. Dias, D. A., Robalo Marques, C. & Richmond, C. (2020), ‘A tale of two sectors: Why is misallocation higher in services than in manufacturing’, *Review of Income and Wealth* **66**(2), 361–393.

82. Díaz Bautista, A. (2017), ‘Total factor productivity (tfp) in manufacturing and economic growth in mexico’, *Análisis Económico* **32**(79), 7–24.

83. Díaz-Dapena, A., Fernández-Vázquez, E., Garduño-Rivera, R. & Rubiera-Morollon, F. (2019), ‘Economic integration and regional convergence: effects of NAFTA on local convergence in Mexico, 1980–2008’, *Applied Economics* **51**(50), 5515–5527.

84. Diewert, W. E. (1992), ‘Fisher ideal output, input, and productivity indexes revisited’, *Journal of Productivity Analysis* **3**(3), 211–248.

85. Ding, S., Guariglia, A. & Harris, R. (2016), ‘The determinants of productivity in Chinese large and medium-sized industrial firms, 1998–2007’, *Journal of Productivity Analysis* **45**(2), 131–155.

86. Duranton, G. & Puga, D. (2000), ‘Diversity and specialisation in cities: why, where and when does it matter?’, *Urban studies* **37**(3), 533–555.

87. Duranton, G. & Puga, D. (2001), ‘Nursery cities: urban diversity, process innovation, and the life cycle of products’, *American Economic Review* **91**(5), 1454–1477.

88. Duranton, G. & Puga, D. (2004), Micro-foundations of urban agglomeration economies, *in* ‘Handbook of regional and urban economics’, Vol. 4, Elsevier, pp. 2063–2117.

89. Durlauf, S. N., Johnson, P. A. & Temple, J. R. (2009), ‘The econometrics of convergence’, *Palgrave handbook of econometrics* pp. 1087–1118.

90. Dvouletỳ, O. & Blažková, I. (2021), ‘Exploring firm-level and sectoral variation in total factor productivity (TFP)’, *International Journal of Entrepreneurial Behavior and Research* .

91. Ehrl, P. (2013), ‘Agglomeration economies with consistent productivity estimates’, *Regional Science and Urban Economics* **43**(5), 751–763.

92. Elhorst, J. P. (2010), ‘Applied spatial econometrics: raising the bar’, *Spatial economic analysis* **5**(1), 9–28.

93. Escribá-Pérez, F. J. & Murgui-García, M. J. (2018), ‘Technology catching-up and regulation in European regions’, *Journal of Productivity Analysis* **49**(1), 95–109.

94. Esquivel, G. (1999), ‘Convergencia regional en México, 1940-1995’, *El trimestre económico* pp. 725–761.

95. Esquivel, G. (2003), *México: En pos del crecimiento*, Centro de Estudios Económicos, El Colegio de México.

96. Esquivel, G. (2010), ‘De la inestabilidad macroeconómica al estancamiento estabilizador: el papel del diseño y la conducción de la política económica’, *Crecimiento económico y equidad, México, El Colegio de México* pp. 35–78.

97. Ezcurra, R. & Rodríguez-Pose, A. (2014), ‘Government quality and spatial inequality: A cross-country analysis’, *Environment and Planning A* **46**(7), 1732–1753.

98. Farber, S., Páez, A. & Volz, E. (2009), ‘Topology and dependency tests in spatial and network autoregressive models’, *Geographical Analysis* **41**(2), 158–180.

99. Fare, R., Färe, R., Fèare, R., Grosskopf, S. & Lovell, C. K. (1994), *Production frontiers*, Cambridge university press.

100. Farrell, M. J. (1957), ‘The measurement of productive efficiency’, *Journal of the Royal Statistical Society: Series A (General)* **120**(3), 253–281.

101. Feenstra, R. C., Inklaar, R. & Timmer, M. P. (2015), 'The next generation of the Penn World Table', *American economic review* **105**(10), 3150–82.

102. Festré, A. & Nasica, E. (2009), 'Schumpeter on money, banking and finance: an institutionalist perspective', *The European Journal of the History of Economic Thought* **16**(2), 325–356.

103. Foster, L., Grim, C., Haltiwanger, J. & Wolf, Z. (2016), 'Firm-level dispersion in productivity: is the devil in the details', *American Economic Review* **106**(5), 95–98.

104. Foster, L., Haltiwanger, J. C. & Krizan, C. J. (2001), Aggregate productivity growth: Lessons from microeconomic evidence, *in* 'New developments in productivity analysis', University of Chicago Press, pp. 303–372.

105. Foster, L., Haltiwanger, J. & Syverson, C. (2008), 'Reallocation, firm turnover, and efficiency: Selection on productivity or profitability', *American Economic Review* **98**(1), 394–425.

106. Frank, M. Z. & Goyal, V. K. (2009), 'Capital structure decisions: which factors are reliably important?', *Financial management* **38**(1), 1–37.

107. Frankema, E. (2010), 'The colonial roots of land inequality: geography, factor endowments, or institutions?', *The Economic History Review* **63**(2), 418–451.

108. Fried, H. O., Lovell, C. K., Schmidt, S. S. & Schmidt, S. S. (2008), *The measurement of productive efficiency and productivity growth*, Oxford University Press.

109. Fuentes, N. A. & Fuentes, C. M. (2002), 'Regional economic growth in mexico: An analysis of total factor productivity', *Revista Mexicana de Economía y Finanzas Nueva Época REMEF (The Mexican Journal of Economics and Finance)* **1**(2).

110. Fujita, M. (2010), 'The evolution of spatial economics: from Thünen to the new economic geography', *The Japanese Economic Review* **61**(1), 1–32.

111. Galor, O. (1996), 'Convergence: Inferences from theoretical models', *The economic journal* **106**(437), 1056–1069.

112. Gandhi, A., Navarro, S. & Rivers, D. A. (2020), 'On the identification of gross output production functions', *Journal of Political Economy* **128**(8), 2973–3016.

113. Gardiner, B., Martin, R., Sunley, P. & Tyler, P. (2013), 'Spatially unbalanced growth in the British economy', *Journal of Economic Geography* **13**(6), 889–928.

114. Garduño Rivera, R. (2014), 'La apertura comercial y su efecto en la distribución regional de México', *El trimestre económico* **81**(322), 413–439.

115. Garibaldi, P., Martins, J. O. & van Ours, J. (2010), *Ageing, health, and productivity: The economics of increased life expectancy*, OUP Oxford.

116. Georgantzís, N. & Attanasi, G. (2016), Non-competitive markets, *in* 'Experimental economics', Springer, pp. 21–36.

117. Glaeser, E. (2011), 'Engines of innovation', *Scientific American* **305**(3), 50–55.

118. Glaeser, E. L. (1999), 'Learning in cities', *Journal of urban Economics* **46**(2), 254–277.

119. Glaeser, E. L., Kallal, H. D., Scheinkman, J. A. & Shleifer, A. (1992), 'Growth in cities', *Journal of political economy* **100**(6), 1126–1152.

120. Greenaway, D. & Kneller, R. (2007), 'Firm heterogeneity, exporting and foreign direct investment', *The Economic Journal* **117**(517), F134–F161.

121. Griffith, R., Redding, S. & Reenen, J. V. (2004), 'Mapping the two faces of R&D: Productivity growth in a panel of OECD industries', *Review of economics and statistics* **86**(4), 883–895.

122. Griffith, R., Redding, S. & Van Reenen, J. (2003), 'R&D and absorptive capacity: theory and empirical evidence', *Scandinavian journal of Economics* **105**(1), 99–118.

123. Griliches, Z. (1981), 'Market value, R&D, and patents', *Economics letters* **7**(2), 183–187.

124. Grossman, G. M. & Helpman, E. (1991), 'Trade, knowledge spillovers, and growth', *European economic review* **35**(2-3), 517–526.

125. Gual, J. & Jódar-Rosell, S. (2006), 'Vertical industrial policy in the EU: an empirical analysis of the effectiveness of state aid', *laCaixa Economic Paper* (01).

126. Haltiwanger, J. (1997), 'Measuring and Analysing Aggregate Fluctuations: The Importance of Building from Microeconomic Evidence", Federal Reserve Bank of St. Louis Economic Review, January/February'.
URL: *https://files.stlouisfed.org/files/htdocs/publications/review/97/05/9705jh.pdf*

127. Haltiwanger, J., Kulick, R. & Syverson, C. (2018), Misallocation measures: The distortion that ate the residual, Technical report, National Bureau of Economic Research.

128. Hanson, G. H. (1997), 'Increasing returns, trade and the regional structure of wages', *The economic journal* **107**(440), 113–133.

129. Hanson, G. H. (2010), 'Why isn't Mexico rich?', *Journal of Economic Literature* **48**(4), 987–1004.

130. Harris, R. (2011), 'Models of regional growth: past, present and future', *Journal of economic surveys* **25**(5), 913–951.

131. Harris, R. I. (2021), 'The importance of spatial differences in total factor productivity: New Zealand, 2001–16', *Regional Studies* **55**(7), 1209–1227.

132. Harris, R. & Li, S. (2019), ‘Government assistance and total factor productivity: firm-level evidence from China’, *Journal of Productivity Analysis* **52**(1), 1–27.

133. Harris, R. & Moffat, J. (2015*a*), ‘Plant-level determinants of Total Factor Productivity in Great Britain, 1997–2008’, *Journal of Productivity Analysis* **44**(1), 1–20.

134. Harris, R. & Moffat, J. (2015*b*), ‘Total Factor Productivity growth in local enterprise partnership regions in Britain, 1997–2008’, *Regional Studies* **49**(6), 1019–1041.

135. Harris, R. & Moffat, J. (2017), ‘The UK productivity puzzle, 2008–2012: evidence using plant-level estimates of total factor productivity’, *Oxford Economic Papers* **69**(3), 529–549.

136. Harris, R. & Moffat, J. (2019), ‘The decline of British manufacturing, 1973–2012: the role of total factor productivity’, *National Institute Economic Review* **247**, R19–R31.

137. Harris, R. & Moffat, J. (2020), ‘The impact of product subsidies on plant-level total factor productivity in Britain, 1997–2014’, *Scottish Journal of Political Economy* **67**(4), 387–403.

138. Harris, R. & Moffat, J. (2022), ‘The geographical dimension of productivity in Great Britain, 2011–18: the sources of the London productivity advantage’, *Regional Studies* **56**(10), 1713–1728.

139. Harris, R., Moffat, J. & Kravtsova, V. (2011), ‘In search of ‘W’’, *Spatial Economic Analysis* **6**(3), 249–270.

140. Hauge, J. & O’Sullivan, E. (2019), ‘Inside the black box of manufacturing: Conceptualising and counting manufacturing in the economy’.

141. Heathfield, D. F. & Wibe, S. (1987), *An introduction to cost and production functions*, Macmillan International Higher Education.

142. Henderson, J. V. (1986), ‘Efficiency of resource usage and city size’, *Journal of Urban economics* **19**(1), 47–70.

143. Henderson, J. V. (1991), ‘Urban development: Theory, fact, and illusion’, *OUP Catalogue* .

144. Henderson, V., Kuncoro, A. & Turner, M. (1995), ‘Industrial development in cities’, *Journal of political economy* **103**(5), 1067–1090.

145. Hermalin, B. E. (1992), ‘The effects of competition on executive behavior’, *The RAND Journal of Economics* pp. 350–365.

146. Hicks, D. (2011), ‘Structural change and industrial classification’, *Structural Change and Economic Dynamics* **22**(2), 93–105.

147. Hopenhayn, H. A. (1992), ‘Entry, exit, and firm dynamics in long run equilibrium’, *Econometrica: Journal of the Econometric Society* pp. 1127–1150.

148. Hopenhayn, H. A. (2014), 'Firms, misallocation, and aggregate productivity: A review', *Annu. Rev. Econ.* **6**(1), 735–770.

149. Howells, P. (2009), Money and banking in a realistic macro model, *in* 'Macroeconomic Theory and Macroeconomic Pedagogy', Springer, pp. 169–187.

150. Hsieh, C.-T. & Klenow, P. J. (2009), 'Misallocation and manufacturing TFP in China and India', *The Quarterly journal of economics* **124**(4), 1403–1448.

151. Hsieh, C.-T. & Klenow, P. J. (2014), 'The life cycle of plants in India and Mexico', *The Quarterly Journal of Economics* **129**(3), 1035–1084.

152. Hunt, D. (1989), 'Economic theories of development: an analysis of competing paradigms'.

153. Iacovone, L. (2012), 'The better you are the stronger it makes you: Evidence on the asymmetric impact of liberalization', *Journal of Development Economics* **99**(2), 474–485.

154. Iacovone, L., Munoz Moreno, R., Olaberria, E. & Pereira Lopez, M. D. L. P. (2022), 'Productivity growth in mexico'.

155. Imbs, J., Mumtaz, H., Ravn, M. & Rey, H. (2005), '" Aggregation Bias" DOES explain the PPP puzzle'.

156. INEGI, CONAPO, S. (2018), *Delimitación de zonas metropolitanas.*
URL: *https://www.gob.mx/sedatu/documentos/delimitacion-de-las-zonas-metropolitanas-de-mexico-2015-149891*

157. Jacobs, J. (1970), 'The Economy of Cities (10 uppl.)', *London: Jonathan Cape Ltd* .

158. Jacobs, J. (1986), 'Cities and The Wealth of Nations: Principles of Economic Life. Vintage'.

159. Jadhav, V. & Viswanathan, B. (2022), 'Conditional convergence and spatial convergence across 103 sub-state indian regions: Using spatial econometrics for panel data', *Indian Public Policy Review* **3**(5 (Sep-Oct)), 49–86.

160. Ji, Y.-b. & Lee, C. (2010), 'Data envelopment analysis', *The Stata Journal* **10**(2), 267–280.

161. Johansen, L. (1972), *Production functions: An integration of micro and macro, short run and long run aspects*, Vol. 75, North-Holland.

162. Johnson, C. (1984), 'The industrial policy debate re-examined', *California Management Review (pre-1986)* **27**(000001), 71.

163. Jondrow, J., Lovell, C. K., Materov, I. S. & Schmidt, P. (1982), 'On the estimation of technical inefficiency in the stochastic frontier production function model', *Journal of econometrics* **19**(2-3), 233–238.

164. Jorgenson, D. W., Stiroh, K. J., Gordon, R. J. & Sichel, D. E. (2000), 'Raising the speed limit: US economic growth in the information age', *Brookings papers on economic activity* **2000**(1), 125–235.

165. Jovanovic, B. (1982), 'Selection and the Evolution of Industry', *Econometrica: Journal of the econometric society* pp. 649–670.

166. Kaldor, N. (1984), *Causes of growth and stagnation in the world economy*, Cambridge University Press Cambridge.

167. Kanbur, R. & Zhang, X. (2005), 'Fifty years of regional inequality in China: a journey through central planning, reform, and openness', *Review of development Economics* **9**(1), 87–106.

168. Karakaplan, M. U. (2017), 'Fitting endogenous stochastic frontier models in Stata', *The Stata Journal* **17**(1), 39–55.

169. Karakaplan, M. U. & Kutlu, L. (2017), 'Endogeneity in panel stochastic frontier models: an application to the Japanese cotton spinning industry', *Applied Economics* **49**(59), 5935–5939.

170. Kehrig, M. (2011), 'The cyclicality of productivity dispersion', *US Census Bureau Center for Economic Studies Paper No. CES-WP-11-15* .

171. Kim, S. (2008), 'Spatial inequality and economic development: Theories, facts, and policies', *Urbanization and growth* pp. 133–166.

172. Klenow, P. J. & Rodriguez-Clare, A. (1997), 'The neoclassical revival in growth economics: Has it gone too far?', *NBER macroeconomics annual* **12**, 73–103.

173. Klette, T. J. & Griliches, Z. (1996), 'The inconsistency of common scale estimators when output prices are unobserved and endogenous', *Journal of applied econometrics* **11**(4), 343–361.

174. Kondo, K. (2018), 'Testing for global spatial autocorrelation in Stata'.
URL: *http://fmwww.bc.edu/RePEc/bocode/m/moransi.pdf*

175. Konings, J. & Vanormelingen, S. (2015), 'The impact of training on productivity and wages: firm-level evidence', *Review of Economics and Statistics* **97**(2), 485–497.

176. Krugman, P. (1991), 'Increasing returns and economic geography', *Journal of political economy* **99**(3), 483–499.

177. Krugman, P. R. (1979), 'Increasing returns, monopolistic competition, and international trade', *Journal of international Economics* **9**(4), 469–479.

178. Krugman, P. R. (1997), *The age of diminished expectations: US economic policy in the 1990s*, MIT press.

179. Kumbhakar, S. C. & Lovell, C. K. (2003), *Stochastic frontier analysis*, Cambridge university press.

180. Kydland, F. E. & Prescott, E. C. (1982), 'Time to build and aggregate fluctuations', *Econometrica: Journal of the Econometric Society* pp. 1345–1370.

181. Lee, K.-R., Leem, B., Lee, C. W. & Lee, C. (2011), 'Malmquist productivity index using DEA frontier in stata', *Stata Journal* **2**(2), 1–9.

182. Leibenstein, H. (1957), 'The theory of underemployment in backward economies', *Journal of Political Economy* **65**(2), 91–103.

183. Levine, R. (1997), 'Financial development and economic growth: views and agenda', *Journal of economic literature* **35**(2), 688–726.

184. Levinsohn, J. & Petrin, A. (2003), 'Estimating production functions using inputs to control for unobservables', *The review of economic studies* **70**(2), 317–341.

185. Levy-Algazi, S. (2018), *Under-rewarded efforts: The elusive quest for prosperity in Mexico*, Inter-American Development Bank.

186. Levy-Algazi, S. (2019), 'Réplica a la Reseña de Jaime Ros sobre 'Esfuerzos mal recompensados'.', *Economía UNAM* **16**(46), 284–303.

187. Lewis, W. A. (1954), 'Economic development with unlimited supplies of labour'.

188. Lin, J. Y. (2011), 'New structural economics: A framework for rethinking development', *The World Bank Research Observer* **26**(2), 193–221.

189. López, J. J. (2017), 'Financial frictions and productivity: Evidence from Mexico', *The Quarterly Review of Economics and Finance* **66**, 294–301.

190. Lopez-Martin, B. (2017), 'From firm productivity dynamics to aggregate efficiency', *The World Bank Economic Review* **30**(Supplement_1), S57–S66.

191. López-Noria, G. (2021), The impact of trade liberalization on the Mexican automobile industry: Evidence from the first 20 years of NAFTA, Technical report, Working Papers.

192. Loría, E., Moreno-Brid, J. C., Salas, E. & Sánchez-Juárez, I. (2019), 'Kaldorian Explanation of Low Economic Growth in Mexico', *Problemas del desarrollo* **50**(196), 3–26.

193. Lucas, R. E. (1988), 'On the mechanics of economic development', *Journal of monetary economics* **22**(1), 3–42.

194. Manjón, M. & Manez, J. (2016), 'Production function estimation in Stata using the Ackerberg–Caves–Frazer method', *The Stata Journal* **16**(4), 900–916.

195. Mankiw, N. G., Romer, D. & Weil, D. N. (1992), 'A contribution to the empirics of economic growth', *The quarterly journal of economics* **107**(2), 407–437.

196. Manski, C. F. (1993), 'Identification of endogenous social effects: The reflection problem', *The review of economic studies* **60**(3), 531–542.

197. Marshall, A. (1890), 'Principles of Economics, 8th edn (1920)', *London, Mcmillan* .

198. Martin, R. (2008), *Productivity dispersion, competition and productivity measurement*, number 692, Centre for Economic Performance, London School of Economics and Political ....

199. Martínez-Alanís, P. J. (2011), *Distorsiones regionales en la asignación de recursos y productividad de las manufacturas en México*, El Colegio de México.

200. Mazzucato, M. (2018), 'Mission-oriented innovation policies: challenges and opportunities', *Industrial and Corporate Change* **27**(5), 803–815.

201. McMillen, D. P. (2010), 'Issues in spatial data analysis', *Journal of Regional Science* **50**(1), 119–141.

202. Melitz, M. J. (2003), 'The impact of trade on intra-industry reallocations and aggregate industry productivity', *econometrica* **71**(6), 1695–1725.

203. Melitz, M. J. & Ottaviano, G. I. (2008), 'Market size, trade, and productivity', *The review of economic studies* **75**(1), 295–316.

204. Melitz, M. J. & Polanec, S. (2015), 'Dynamic Olley-Pakes productivity decomposition with entry and exit', *The Rand journal of economics* **46**(2), 362–375.

205. Melo, P. C., Graham, D. J. & Noland, R. B. (2009), 'A meta-analysis of estimates of urban agglomeration economies', *Regional science and urban Economics* **39**(3), 332–342.

206. Mendoza-Velázquez, A., German-Soto, V., Monfort, M. & Ordóñez, J. (2020), 'Club convergence and inter-regional inequality in Mexico, 1940-2015', *Applied Economics* **52**(6), 598–608.

207. Mexican-Government (2013), *Plan Nacional de Desarrollo 2013-2018*.
URL: *https://observatorioplanificacion.cepal.org/es/planes/plan-nacional-de-desarrollo-2013-2018-de-mexico*

208. Mexican-Government (2019), *Plan Nacional de Desarrollo 2019-2024*.
URL: *https://presidente.gob.mx/plan-nacional-de-desarrollo-2019-2024/*

209. Midrigan, V. & Xu, D. Y. (2014), ‘Finance and misallocation: Evidence from plant-level data’, *American economic review* **104**(2), 422–458.

210. Misch, F. & Saborowski, C. (2018), *Resource misallocation and productivity: Evidence from Mexico*, International Monetary Fund.

211. Mollisi, V. & Rovigatti, G. (2017), ‘Theory and practice of TFP estimation: The control function approach using Stata’.

212. Monahan, E. & Balawejder, F. (2020), ‘The sectoral landscape: An evidence review’.

213. Monfort, P. (2008), *Convergence of EU regions: Measures and evolution*, European Commission, Regional Policy Brussels.

214. Mullen, H., Barr, M. & Mason, C. (2019), ‘Data provision in the games industry in Scotland’.

215. Mundlak, Y. & Hoch, I. (1965), ‘Consequences of alternative specifications in estimation of Cobb-Douglas production functions’, *Econometrica: Journal of the Econometric Society* pp. 814–828.

216. Nakamura, R. (1985), ‘Agglomeration economies in urban manufacturing industries: a case of Japanese cities’, *Journal of Urban economics* **17**(1), 108–124.

217. Nelson, R. R. & Phelps, E. S. (1966), ‘Investment in humans, technological diffusion, and economic growth’, *The American economic review* **56**(1/2), 69–75.

218. Nickell, S. J. (1996), ‘Competition and corporate performance’, *Journal of political economy* **104**(4), 724–746.

219. Nishimizu, M. & Page, J. M. (1982), ‘Total factor productivity growth, technological progress and technical efficiency change: dimensions of productivity change in Yugoslavia, 1965-78’, *The Economic Journal* **92**(368), 920–936.

220. Nordhaus, W. D. (2004), ‘Retrospective on the Postwar Productivity Slowdown’, *Available at SSRN 625182* .

221. North, D. C. (1991), ‘Institutions’, *Journal of economic perspectives* **5**(1), 97–112.

222. OECD (2015), *The Future of Productivity.*
URL: *https://www.oecd-ilibrary.org/content/publication/9789264248533-en*

223. OECD (2018), *Perspectives on Global Development 2019.*
URL: *https://www.oecd-ilibrary.org/content/publication/persp˙glob˙dev-2019-en*

224. OECD. (2020), *Latin American Economic Outlook 2020 Digital Transformation for Building Back Better*, OECD.

225. Olley, G. S. & Pakes, A. (1996), 'The Dynamics of Productivity in the Telecommunications Equipment', *Econometrica* **64**(6), 1263–1297.

226. Otsuka, A. & Goto, M. (2016), 'Total factor productivity and the convergence of disparities in Japanese regions', *The Annals of Regional Science* **56**(2), 419–432.

227. Overman, H. G., Rice, P. & Venables, A. J. (2010), 'Economic linkages across space', *Regional Studies* **44**(1), 17–33.

228. Padilla-Perez, R. & Villarreal, F. G. (2017), 'Structural change and productivity growth in Mexico, 1990–2014', *Structural change and economic dynamics* **41**, 53–63.

229. Petrin, A., Poi, B. P. & Levinsohn, J. (2004), 'Production function estimation in Stata using inputs to control for unobservables', *The Stata Journal* **4**(2), 113–123.

230. Pitelis, C. & Antonakis, N. (2003), 'Manufacturing and competitiveness: the case of Greece', *Journal of economic studies* .

231. Pitt, M. M. & Lee, L.-F. (1981), 'The measurement and sources of technical inefficiency in the Indonesian weaving industry', *Journal of development economics* **9**(1), 43–64.

232. Porter, M. E. (1990), 'The competitive advantage of nations The Free Press', *New York* **564**.

233. Pritchett, L. (1997), 'Divergence, big time', *Journal of Economic perspectives* **11**(3), 3–17.

234. Puga, D. (2010), 'The magnitude and causes of agglomeration economies', *Journal of regional science* **50**(1), 203–219.

235. Puggioni, D. (2019), Productivity, markups, and trade: Evidence from Mexican manufacturing industries, Technical report, Working Papers.

236. Quah, D. (1993), 'Galton's fallacy and tests of the convergence hypothesis', *The Scandinavian Journal of Economics* pp. 427–443.

237. Ram, R. (2018), 'Comparison of cross-country measures of sigma-convergence in per-capita income, 1960–2010', *Applied Economics Letters* **25**(14), 1010–1014.

238. Restuccia, D. & Rogerson, R. (2013), 'Misallocation and productivity'.

239. Restuccia, D. & Rogerson, R. (2017), 'The causes and costs of misallocation', *Journal of Economic Perspectives* **31**(3), 151–74.

240. Rey, S. J. & Gallo, J. L. (2009), 'Spatial analysis of economic convergence', *Palgrave handbook of econometrics* pp. 1251–1290.

241. Rey, S. J. & Montouri, B. D. (1999), 'US regional income convergence: a spatial econometric perspective', *Regional studies* **33**(2), 143–156.

242. Rigg, J., Bebbington, A., Gough, K. V., Bryceson, D. F., Agergaard, J., Fold, N. & Tacoli, C. (2009), 'The World Development Report 2009'reshapes economic geography': geographical reflections', *Transactions of the Institute of British Geographers* **34**(2), 128–136.

243. Riley, R., Rincon-Aznar, A. & Samek, L. (2018), 'Below the aggregate: a sectoral account of the UK productivity puzzle', *ESCoE Discussion Papers* **6**.

244. Ringstad, V. (1967), 'Econometric analyses based on a production function with neutrally variable scale-elasticity', *The Swedish Journal of Economics* pp. 115–133.

245. Rodríguez-Castelán, C., Lopez-Calva, L.-F. & Cabanillas, O. B. (2020), 'The Effects of Local Market Concentration and International Competition on Firm Productivity: Evidence from Mexico', *World Bank Policy Research Working Paper* (9210).

246. Rodrik, D. (2008), 'Normalizing industrial policy'.
URL: *https://drodrik.scholar.harvard.edu/files/dani-rodrik/files/normalizing-industrial-policy.pdf*

247. Romer, D. (2018), *Advanced Macroeconomics.*, McGraw Hill.

248. Romer, P. M. (1986), 'Increasing returns and long-run growth', *Journal of political economy* **94**(5), 1002–1037.

249. Romo, D. (2015), 'El campo petrolero Cantarell y la economía mexicana', *Problemas del desarrollo* **46**(183), 141–164.

250. Roodman, D. (2009), 'How to do xtabond2: An introduction to difference and system GMM in Stata', *The stata journal* **9**(1), 86–136.

251. Ros-Bosch, J. (2013), *Algunas tesis equivocadas sobre el estancamiento económico de México*, El Colegio de México AC.

252. Ros-Bosch, J. (2019), 'Dinámica empresarial disfuncional y productividad estancada: una reseña del nuevo libro de Santiago Levy', *Economía UNAM* **16**(46), 270–283.

253. Rosenstein-Rodan, P. N. (1943), 'Problems of industrialisation of eastern and south-eastern Europe', *The economic journal* **53**(210/211), 202–211.

254. Rostow, W. (1956), 'The take-off into self-sustained growth', *The Economic Journal* **66**(261), 25–48.

255. Sala-i Martin, X. (1996), 'Regional cohesion: evidence and theories of regional growth and convergence', *European Economic Review* **40**(6), 1325–1352.

256. Sargent, T. C. & Rodriguez, E. R. (2001), *Labour or total factor productivity: Do we need to choose?*, Department of Finance Ottawa, ON, Canada.

257. Schmidt, P. & Sickles, R. C. (1984), 'Production frontiers and panel data', *Journal of Business & Economic Statistics* **2**(4), 367–374.

258. Schreyer, P. & Pilat, D. (2001), 'Measuring productivity', *OECD Economic studies* **33**(2), 127–170.

259. Solow, R. M. (1956), 'A contribution to the theory of economic growth', *The quarterly journal of economics* **70**(1), 65–94.

260. Stakhovych, S. & Bijmolt, T. H. (2009), 'Specification of spatial models: A simulation study on weights matrices', *Papers in Regional Science* **88**(2), 389–408.

261. Syverson, C. (2011), 'What determines productivity?', *Journal of Economic literature* **49**(2), 326–365.

262. Tobler, W. R. (1970), 'A computer movie simulating urban growth in the Detroit region', *Economic geography* **46**(sup1), 234–240.

263. Tran, V. T. (2013), 'The middle-income trap: Issues for members of the Association of Southeast Asian Nations'.

264. Tsvetkova, A., Ahrend, R., Martins, J. O., Lembcke, A. C., Knutsson, P., Jong, D. & Terzidis, N. (2020), 'The spatial dimension of productivity: Connecting the dots across industries, firms and places'.

265. Van Beveren, I. (2012), 'Total factor productivity estimation: A practical review', *Journal of economic surveys* **26**(1), 98–128.

266. Wang, H.-J. & Schmidt, P. (2002), 'One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels', *journal of Productivity Analysis* **18**(2), 129–144.

267. Wen, M. (2004), 'Relocation and agglomeration of Chinese industry', *Journal of development economics* **73**(1), 329–347.

268. Wooldridge, J. M. (2009), 'On estimating firm-level production functions using proxy variables to control for unobservables', *Economics letters* **104**(3), 112–114.

269. Yasar, M., Raciborski, R. & Poi, B. (2008), 'Production function estimation in Stata using the Olley and Pakes method', *The Stata Journal* **8**(2), 221–231.

270. Young, A. (1991), 'Learning by doing and the dynamic effects of international trade', *The quarterly journal of economics* **106**(2), 369–405.

271. Young, A. T., Higgins, M. J. & Levy, D. (2008), 'Sigma convergence versus beta convergence: Evidence from US county-level data', *Journal of Money, Credit and Banking* **40**(5), 1083–1093.

272. Yu, M. (2015), 'Processing trade, tariff reductions and firm productivity: Evidence from chinese firms', *The Economic Journal* **125**(585), 943–988.