Energy Demand and Efficiency: Explore the Potential of SFA and DEA as Tools for the Determination of the Efficiency of Energy in Mexico Transport and Industrial Sectors

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Declaration

The work developed in this thesis is based on research carried out at Durham University. This work has not previously been submitted in any other institution to obtain a similar degree or qualification. The present document is my own work unless referenced to the contrary in the text.

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"No solo no hubiéramos sido nada sin ustedes, sino con toda la gente que estuvo a nuestro alrededor desde el comienzo; algunos siguen hasta hoy. ¡Gracias totales!"

– Gustavo Adrian Cerati.

CVU: 865034

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Dedication

Para toda mi familia y amigos.

Mamá, papá y hermano. Los quiero mucho.

[This is for all of my friends and family.

My Mum, Dad, and brother, I love you very much.]

Abstract

This research presents the process of research of the energy efficiency and demand in the transport and industrial sectors of Mexico. To do this, two types of methodologies were used: a parametric one Stochastic Frontier Analysis (SFA) and a non-parametric Data Envelopment Analysis (DEA). Both estimate the energy efficiency and are commonly used in the field. Once the data was collected and the research was carried out, three types of models were created. The first one for the SFA and the other ones for DEA, where one model was used for the transport sector and the other for the industrial sector. The results indicate the levels of efficiency in the sectors selected. For the SFA, the data showed statistical significance and the results expected, due to the economic theory of the price and income elasticities for the energy demand. In addition, the inefficiency component was significant and estimated for the 17 sectors analysed. While DEA results were estimated separately for each sector and therefore, different variables were used. The findings for the transport sector indicate that only one sector is efficient and in the industrial sector 10 of 13 are efficient. In both sets of results, the transport sector seems to be more efficient than the industrial sector. The purpose of estimating the levels of efficiency was to reach a conclusion on which sector could improve its productivity. Furthermore, this research could be developed into a doctoral thesis, where it would be necessary to use a more complex model of the aforementioned model and carry out more research into the impact of the productivity and energy policies.

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CHAPTER 1: INTRODUCTION

In this section, a brief introduction to the concept of energy efficiency is going to be discussed. In addition, the next sections of this chapter will discuss the rationale for this research, by analysing the research questions, as well as the objectives of this project and the scopes and limitations of this research.

The remainder of this thesis includes more information related to the methodologies selected; here is where those concepts will be explored in depth , as well as a literature review section which will discuss the literature relevant to the development of this area of research. Furthermore, there will be a section on methodology and results, where the models for the demand of energy and energy efficiency will be presented for both the transport and the industrial sector in Mexico. Finally, conclusions will be made on the research and there will be a discussion of the results in order to suggest further research in this area.

1.1 Introduction to energy efficiency in Mexico

Energy efficiency is a concept studied within a lot of different disciplines, including engineering, physics, and economics,; the aim of the studies vary from discipline to discipline, but the interest in reducing the amount of energy used is one of the most important shared goals. Ordinarily, energy efficiency is associated with the reduction of energy use in the production process. An example of this is a factory that invests in new machinery that requires less electricity to produce the same quantity of products compared with the old machinery. The concept of energy is both simple and complex and can enroll lots of disciplines and variables that make it difficult to define the meaning. However, this thesis will approach the concept from the engineering and economic points of view. The literature review will explore the perspectives of different experts.

Currently, the study of the efficient use of energy has become relevant for a lot of actors, especially public ones. The importance of energy efficiency is now so high that this is part of the agenda for a lot of actors because this field is linked to commercial, industrial, energy security and environmental benefits countries (Patterson, 1996).

In addition, the energy efficiency could be studied in three main sectors: industrial, residential and transport. Normally, there are a lot of studies in these sectors because of the use of the required technology, sustainability goals, and policy requirements (Filippini & Hunt, 2015; Patterson, 1996; Series, 1995). Table 1.1 shows the percentage of energy use in four sectors in Mexico. The transport sector demands almost 50% of the energy used in Mexico, followed by the industrial sector with more than 30%. Therefore, as both of these sectors represent 80% of the total energy consumption, these sectors will form the basis of this work.

YEAR	INDUSTRIAL	AGRICULTURAL	RESIDENTIAL	TRANSPORT
1965	35%	4%	32%	29%
1975	37%	4%	24%	35%
1985	38%	3%	22%	37%
1995	31%	3%	24%	42%
2005	32%	3%	20%	45%
2015	31%	4%	19%	46%

Table 1.1: Proportion of each sector per energy consumed in selected years

The energy efficiency indicators used for the development of policies or decision making can be commonly dived into four different types according to Patterson: thermodynamic, physical-thermodynamic, economic-thermodynamic and economic (Patterson, 1996). The thermodynamic type is purely related to a measure of the efficiency in terms of this subject and could be estimated by simple ratios or complex formulas. While the economic way is concerned with money. In addition, the other two groups of indicators used to measure efficiency are a combination of the previous concepts, plus other related concepts. This work could be catalogued in the study of the economic indicator and the thermodynamic-economic indicator.

Energy Intensity (EI) is commonly used as a measurement of energy efficiency and it was developed by the Energy Information Administration (EIA) in 1995 (Series, 1995). According to EIA, countries with a high-intensity level have high industrial outputs as a proportion of GDP. However, countries with a low-intensity level are rich in labour. It could

be summarised by saying that countries with more capital (K) are more intensive in their energy use, and those that have a low level have more labour (L) and are less intensive in their energy use. The energy intensity indicator shows important inferences of how energy efficient a country or sector is on a monetary scale.

Energy intensity is defined in equation 1, where EI is the name of the variable of energy intensity and is equal to the energy consumption divided by the production or GDP. The interpretation is usually quite simple; some quantity of energy is needed to produce one unit of money. Also, this is not only measured with the GDP of a country, but it could also be obtained by using other variables such as population or areas (Series, 1995). Examples of this will be given specifically in the results section, but a quick analysis of the concept will be defined to ensure understanding of this concept.

$$EI = \frac{EC}{Y}$$

Equation 1: Energy intensity

Figure 1 shows the energy intensity in Mexico, by taking the ratio between the energy used and GDP. Since 2009, the energy intensity has decreased continuously, but in 2016 experienced a slight increase. Analysing the last six years (2010-2016) from Figure 1 as an example, it is inferred that the country lost capital (K) by a decrease in the intensity. However, this assumption is not enough to establish if the energy is used efficiently or not, and which is the abundant factor of production (capital or labour).

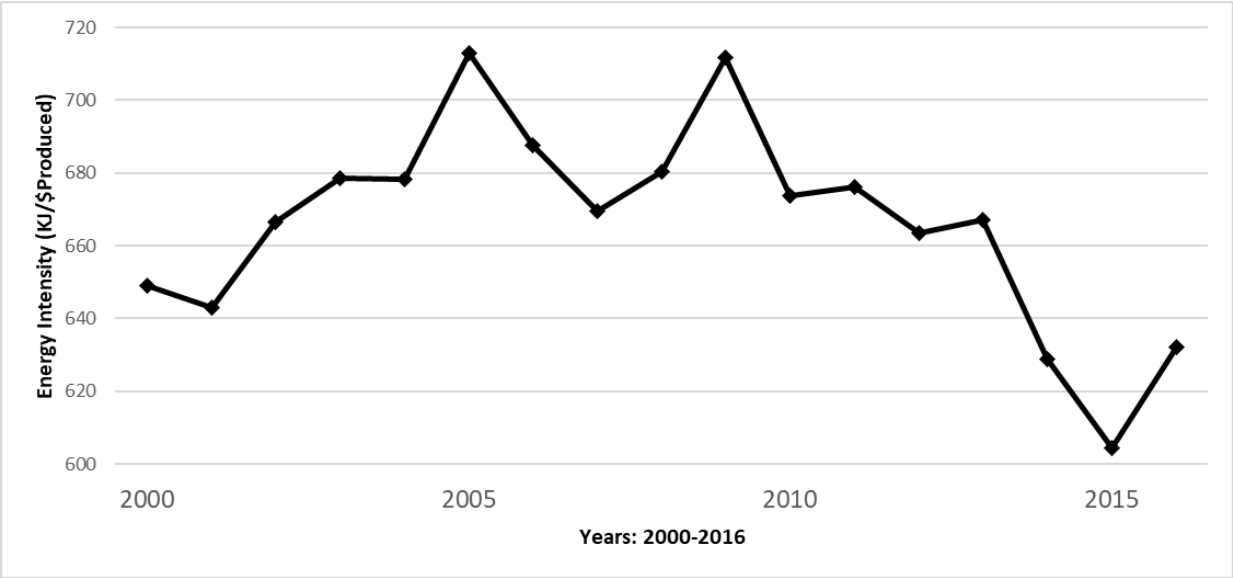

Figure 1: Energy intensity in Mexico

This work explores the use of two alternatives ways to measure energy efficiency. The first is a parametric approach named Stochastic Frontier Analysis (SFA). The second is a non-parametric approach named Data Envelopment Analysis (DEA). Both concepts will be explored in the next chapter of this work entitled "literature review" but are mentioned here by way of introduction and to explain their relevance to developing this study. This work is based on the use of those techniques to estimate the energy efficiency levels in the transport and industrial sectors of Mexico.

The stochastic frontier analysis is a methodology used mainly by economists to measure frontiers in a production or cost function. Currently, this technique is used to estimate the energy efficiency. The other method used to estimate energy efficiency is Data Envelopment Analysis (DEA), which is simpler than SFA and is mainly used by engineers.

1.2 Rationale

These days, there are numerous debates in the energy field regarding the best way to measure the levels of efficiency among the aforementioned sectors, which has led to the development of the following question:

- How can energy efficiency be appropriately defined and measured? (S. Zhang, 2016)

The use of energy intensity as an indicator of energy efficiency is limited since the change in the intensity is also a function of several factors in the structure of the economy (Filippini & Hunt, 2011, 2015). As part of the rationale, this work uses the methodologies commonly used in the field such as Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). However, at this stage, it is not clear whether SFA or DEA is the best for measuring energy efficiency; further research is needed to determine that. The transport and industrial sectors were selected for further analysis because both sectors represent almost 80% of the total energy consumption in Mexico for the period selected (1997-2016).

The methodologies (SFA and DEA) mentioned to estimate the energy efficiency have not been used in previous work related to Mexico. While plenty of works have studied the transport and industrial sectors or energy sector in different countries, regions and even continents; only a few studies are country-specific and after reviewing the existing literature, there is no literature which is specific to Mexico (Filippini & Hunt, 2016; Filippini & Zhang, 2016; Lundgren, Marklund, & Zhang, 2016; Lutz, Massier, Sommerfeld, & Löschel, 2017; S. Zhang, 2016; Zheng, 2015; G. Zhou, Chung, & Zhang, 2014).

1.3 Objectives

This thesis seeks to answer the following questions:

- How can energy efficiency be measured? What is the potential for improving energy efficiency in Mexico's transport and industrial sectors?
- Are the transport and industrial sectors energy efficient?
- Which factors influence energy efficiency? How can energy efficiency be stimulated?

The main aim of this work is to provide a comprehensive overview of energy efficiency in Mexico. This work uses tools that are currently used to measure energy efficiency. Also, drivers and other factors will be analysed to recommend the creation of policies that could enhance energy efficiency.

Therefore, this thesis focuses on the measured energy efficiency levels by using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). The reasons for this will

be explained in the next chapter, in the “literature review”. Furthermore, this work covers some research objectives. The focus areas and objectives of this work are:

- To explore the energy efficiency concept and how to measure it.
- To explore some of the driving forces that could affect energy efficiency in Mexico.
- To estimate an energy demand and analyse their elasticities.
- To stimulate future works in related fields and case studies.

CHAPTER 2: LITERATURE REVIEW

To address the objectives raised in the introduction, this chapter will explore some possible answers to the questions established. Firstly, this chapter covers how energy efficiency could be measured and pays particular attention to SFA and DEA methods. Secondly, this section explores related case studies that were applied to the sector and area studied. Finally, it explores which factor can affect and stimulate energy efficiency according to experts in the field.

This literature review aims to answer the following questions:

- DEA and SFA
    - What is DEA and SFA?
        - Why are they relevant to this thesis?
- Which factors could influence energy efficiency?
- What do the studies in the transport sector say about energy efficiency?
- What do the studies in the industrial sector say about energy efficiency?
- What are the policy and energy implications for a country?

2.1 Energy efficiency measurement

In the previous section, the concept of energy efficiency and energy intensity was mentioned. Energy intensity should not be considered the only way to measure energy efficiency because there are two methods currently used to estimate energy efficiency (Filippini & Hunt, 2011). The ways to measure it will be addressed in this current section, where the methods will be explained in accordance with the relevant literature.

The two approaches currently used in energy efficiency literature are Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). The first approach uses econometric models that measure the efficiency and the outputs could contribute to answering the research questions developed in the previous section. The alternative approach is commonly used by engineers to measure efficiency due to the use of non-parametric variables; this could be explored as an alternative to SFA (S. Zhang, 2016). Both concepts will be explained in detail in the next sections.

2.1.1 Stochastic Frontier Analysis (SFA)

The origins of SFA in economics are related to producer theory, where this type of methodology was used to measure the possibilities of production; it has interesting characteristics that make it a good tool for measuring efficiency in a lot of cases, such as the energy studies (Aigner, Lovell, & Schmidt, 1977; Filippini & Hunt, 2011). In this methodology, it is assumed that the producers seek to obtain optimum outputs (Aigner et al., 1977). Then, when the optimum result could not be obtained, a frontier is created to describe which is an optimum result and the efficiency is described by the distance between the frontier and the observed result (Aigner et al., 1977; M. Zhang, 2012). Besides the origins of the SFA, the concept can be used in other fields such as energy, where a frontier could be constructed to know how far away it is from the optimum result.

One of the advantages of using SFA as a method to measure energy efficiency is that it includes statistical noise, which could be useful to better understand what the drivers are that affect the efficiency (Filippini & Hunt, 2011; S. Zhang, 2016). Generally, the statistical noise is assumed to follow a normal distribution, but it depends on the type of model used (S.

Zhang, 2016). However, the inefficiency component assumes a non-negative distribution. Furthermore, another distinctive characteristic of SFA is that it is a parametrical methodology that is mostly based on an econometric base and producer theory (Filippini & Hunt, 2015).As a result, SFA is one of the most accepted techniques currently used in the energy efficiency field as an alternative to the energy intensity indicator (Filippini & Hunt, 2011).

"The normal process of obtaining efficiency is this: first, the function is defined, either as production function or cost function, with Cobb-Douglas or translog functional form; second, using regression approaches to estimate the parameters describing the structure of the function; third, obtain the inefficient error term; thus, the efficiency is worked out" (M. Zhang, 2012).

Furthermore, the extensions and use of this method started to be applied in energy efficiency in the 2000s. The work created by Filippi and Hunt is the first of its kind to use SFA in an energy demand function (Filippini & Hunt, 2011, 2012, 2015, 2016; Filippini, Hunt, & Zorić, 2014). In their work, a panel frontier was used to measure the energy demand function of 29 OECD countries (Filippini & Hunt, 2011). Also, the economic perspective in a theoretical framework was explained to establish an empirical method for measuring energy efficiency by using SFA (Filippini & Hunt, 2015). The studies developed by Filippi and Hunt were later essential in starting to use SFA in the demand of energy in different sectors, such as the residential, industrial and transport sectors (Filippini & Orea Sánchez, 2014; Filippini & Zhang, 2016; Llorca, Baños, Somoza, & Arbués, 2017; Llorca & Jamasb, 2017; Lundgren et al., 2016; Lutz et al., 2017; Orea, Llorca, & Filippini, 2015; Weyman-Jones, Boucinha, & Inácio, 2015; Zheng, 2015).

The use of SFA is relevant to this research because it is linked to our research questions. By using this method, the energy demand and efficiency can be estimated for the transport and industrial sectors in Mexico. Some of the available literature worked with this methodology, see table 2.1 for more information about it. Therefore, a successful SFA can be applied for the creation of new policies.

Table 2.1: SFA literature review findings

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
AMJADI ET AL (2018) [3]	In this study, the rebound effect for fuel and electricity was measured for the four most energy-intensive sectors in Sweden: pulp and paper, basic iron and steel, chemical, and mining. The authors used a firm-level panel data set from 2000 to 2008 and applied SFA to measure the rebound effect.	The results highlight the importance of implications regarding the environmental and energy security policies. The CO2 emission saving is almost four times larger than the iron and steel sector, pulp and paper sector, and more than twice as large as the other three energy-intensive sectors combined.	Industry
FILIPPINI AND HUNT (2011) [10]	This study used SFA to estimate the energy demand function of 29 countries from 1978 to 2006. The energy efficiency of each country is also modelled and represents a measurement which underlies the efficiency for each of the 29 OECD countries over time.	The main findings from this research, for this thesis, is that energy intensity might give a reasonable indication of efficiency improvements in some cases.	Countries
FILIPPINI AND HUNT (2012) [11]	This paper estimates a US frontier residential aggregate energy demand function by using SFA using 48 US states from 1995 to 2007. Utilising an econometric energy demand model, the efficiency and inefficiency of each state is modelled, and it is argued that this represents a measure of the inefficient use of residential energy for each state.	The estimates for the underlying residential energy efficiency using this approach show that, although for a number of states the change in the simple measures of energy intensity might give a reasonable indication of their relative energy efficiency, this is not always the case, as is the case in the Florida, Minnesota and Louisiana examples discussed.	Residential

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
FILIPPINI, HUNT, ZORIC (2014) [14]	This research combines the approaches taken in energy demand modelling and frontier analysis in order to econometrically estimate the level of energy efficiency for the residential sector in the EU-27 member states from 1996 to 2009. The estimates for the energy efficiency confirm that the EU residential sector indeed holds a relatively high potential for energy savings via a reduction in inefficiency.	The results suggest that the rankings of member states based on energy intensity and energy efficiency levels may differ substantially. The results imply that improved energy efficiency can be linked to the introduced financial incentives and energy performance standards, while informative measures such as labelling and educational campaigns are not shown to have a significant effect in fostering energy efficiency improvements.	Residential
FILIPPINI AND ZHANG (2016) [16]	This research presents empirical analysis of the energy efficiency in Chinese provinces by employing a log-log aggregate energy demand frontier model. The model is estimated by using data from 29 provinces from 2003 to 2012. Several econometric model specifications for panel data are used, such as the random effects model and the true random effects model.	The results in this research indicate that exogenous factors of energy efficiency indicators obtained from parametric or non-parametric methods seem to be an interesting approach to promote the efficient use of energy. From an energy policy point of view, this study suggests that the energy-saving targets defined by the central government based on energy intensity indicators could be integrated as targets based on energy efficiency indicators obtained from parametric or nonparametric methods and benchmarking indicators on the level of energy efficiency could be used to allocate resources.	Country: China

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
HOKKANEN (2014) [18]	This thesis utilises frontier estimation techniques to estimate technical efficiency for various industrial sectors in Finland. Production frontiers are estimated in a parametrical and non-parametrical way. The two main approaches to frontier estimation utilised in the thesis are Stochastic Frontier Analysis (SFA) and Stochastic Nonparametric Envelopment of Data (StoNED). Technical efficiencies are estimated with both cross-sectional and panel data methods.	For the majority of the SFA models used in this thesis, the hypothesis of constant returns to scale production is rejected, with only a few sectors satisfying this hypothesis. The main finding was that the Finnish industrial sector is partially efficient in their use of energy. Most sectors are operating on average with a reasonably high degree of efficiency, maintained even during adverse market conditions. The high level of expertise in the past made the mining, forestry and metal refining and fabrication sectors the most efficient.	Industry
KOKKINOUP (2012) [28]	This thesis explores the implication of the interrelationship and the complementarities between value added, capital, labour, technical change, and other factors that contribute to the technical efficiency. By using both DEA and SFA methodologies, this work uses a database from the European Union from 1980 to 2005.	The results indicate that inefficiency was present in production and several relevant explanatory variables vastly contributed to it, such as investment and the freedom in the economy. This research found that the investment and the freedom in the economy are both positively associated with technical efficiency in European Union manufacturing. The empirical evidence reported in this thesis supports this hypothesis and shows that investment and freedom in the economy have a positive impact on technical efficiency for the industries studied, playing a significant role in determining the contribution of innovation in efficiency, productivity and, consequently, economic growth.	Industry

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
LIN AND LONG (2014) [29]	This research uses SFA to study the average energy efficiency and energy saving potential of the chemical industry based on a trans-log production function for China's chemical industry.	The average energy efficiency in China was 0.6897 and the average energy conservation potential was 89.42. Shanghai has the highest energy efficiency, while Shanxi has the lowest energy efficiency and the largest energy conservation potential. The energy efficiency of the eastern region is the highest while that of the western region is the lowest. The energy efficiency gap between the eastern and the western regions is still widening.	Industry
LLORCA ET AL (2017) [31]	In this paper, a stochastic frontier analysis approach is applied to estimate energy demand functions in the transport sector. This approach is to obtain energy efficiency measures on a country level. A transitive multilateral price index is constructed for aggregating the diverse energy components employed in the sector. The random parameters model is used to obtain the income and price elasticities for each country. The estimated model is compared with alternative approaches such as latent class, true fixed effects, or true random effects models. The procedure is applied to Latin America and the Caribbean countries.	The results indicate that the specification that best fits is a random parameter model. By using the efficiencies obtained through SFA, the findings show that efficiency is relatively high, there is room for energy savings and the reduction of greenhouse gas emissions.	Transport

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
LLORCA ET AL (2017) [32]	This paper analyses the energy efficiency and rebound effects for road freight transport in 15 European countries from 1992 to 2012. The authors estimate an energy demand function using a stochastic frontier analysis approach and examine the influence of key features of the rebound effect in the road freight transport sector.	The results show an average fuel efficiency of 88.8% and a rebound effect of 3.8% for the countries in the sample during the period. The results imply that extra benefits can be derived from policies encouraging fuel efficiency in the countries studied which are relatively fuel inefficient, not only because of the fuel efficiency improvement, but also because of their lower rebound effect.	Transport
LUNDGREN ET AL (2016) [33]	This paper estimates firm level energy demand and energy efficiency for 14 sectors in Swedish manufacturing using SFA. The energy demand frontier is estimated.	The results indicate that the European trading system has a moderate effect on energy efficiency, possibly due to the price being too low during the period studied. The estimation indicates positive signs of the effect of EU ETS on energy efficiency, but negatives in fuel. Specifically, for the pulp and paper industry, the results show that fuel efficiency is positively but insignificantly affected by EU ETS, and electricity efficiency is significantly negatively affected.	Industry
LUTZ (2017) [34]	This research studies the determinants of energy efficiency in the German manufacturing sector based on firm-level. An SFA is used to estimate the cost-minimising energy demand function at the two-digit industry level using firm-level heterogeneity. Apart from the SFE, the potential drivers of energy efficiency were studied.	Energy-intensive industries in the German manufacturing sector (pulp and paper, chemicals, and basic metal industries) seem to have a potential to increase their energy efficiency in comparison with less energy-intensive industries. The changes in energy demand and efficiency in energy-intensive industries have larger impacts on the overall objectives of the research than those in industries with low energy intensities.	Industry

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
MARROQUÍN (2014) [36]	This paper analyses the relationship between energy consumption (fuel and electricity), industrial production and employment levels in Mexico from 2003 to 2012. To determine this, a panel cointegration methodology is employed. The study is applied for a short and long term.	A relationship was established in the long run for energy consumption, industrial production, and employment. The author suggests that it is important for Mexico to invest in the production of energy and preferably, renewable energies.	Industry
OREA ET AL (2015) [39]	This paper applies works regarding the energy demand frontier model introduced by Filippini and Hunt (2011, 2012). The authors added the rebound effect in their research.	The average energy efficiency ranges from 91% to 94%. The rebound effect decreases with more income. Energy price shows a positive relationship with the rebound effect, which implies that more inefficient states have more elastic demands with respect to changes in energy price. Energy inefficient states tend to have small rebound effects compared with energy efficient states.	Country
WEYMAN-JONES ET AL (2015) [45]	The paper describes the application of the energy demand model proposed by Filippini and Hunt (2011, 2012) to Portuguese households as a new approach to evaluating energy efficiency.	The results obtained facilitate the identification of priority regions and consumer brands to reduce inefficiency in electricity consumption. The time-series data set shows that the expected electricity savings from the efficiency were fully realised.	Households

2.1.2 Data Envelopment Analysis (DEA)

DEA is a concept that uses linear programming techniques to measure the efficiency of a set of Decision-Making Units (DMUs). An advantage of this is that it is not required to have a particular functional form for the technology frontier (S. Zhang, 2016). The DEA approach is a non-parametric method, so statistical noise is not included. In comparison with SFA, this methodology is not affected by any distributional assumptions. The properties mentioned show some advantages of using DEA to measure energy efficiency, but also show some of the weaknesses of DEA, in comparison with SFA (S. Zhang, 2016).

Efficiency measures are calculated by using linear programming techniques and estimating a hypothetical frontier as for the SFA (Coelli, Rao, O'Donnell, & Battese, 2005). DEA estimates a frontier based on what is the best practice in production by using factors such as capital, labour, raw materials, etc. (Schuschny, 2007). The objective is simple; find the ideal combination of outputs to achieve the inputs calculated (Schuschny, 2007). In addition, if the purpose is evaluating the changes in the efficiency levels, a Malmquist Index should be used. To do so, this index requires at least two observations in time for inputs and outputs. Once the observations are obtained, the analysis can be ordered in terms of efficiency (Martínez-Damiàn, Brambila-Paz, & García-Mata, 2013). The Malmquist Index is partially similar to SFA because both analyse information throughout the years. Therefore, this technique is used in this research to evaluate efficiency in specific sectors throughout the years.

Plenty of studies used DEA as a method for estimating energy efficiency. An example of this is the study carried out by Zhou and Ang, which uses DEA analysis to estimate energy efficiency (P. Zhou, Ang, & Zhou, 2012). In their study, the energy efficiency of 21 OCDE countries was measured using non-parametric variables, such as energy inputs, GDP, CO_2 emissions etc. (P. Zhou et al., 2012). Other examples related to this field will be addressed in the next section, where DEA is used in specific sectors, particularly in the industrial sector (S. Zhang, 2016). As DEA presents a method of measuring energy efficiency in a non-parametric way, it presents an alternative methodology to SFA, which has also been used by other experts (M. Zhang, 2012; S. Zhang, 2016; P. Zhou et al., 2012).

The use of DEA is relevant for this research because it makes the estimation of the energy efficiency possible by using a different approach. Since this type of approach is a non-parametric one, understanding and estimating the results should be easier. Fortunately, there is a variety of literature in this field and this made it easier to find a model that could be adapted to the data available for the case study, see table 2.2 for more information.

Table 2.2: DEA literature review findings

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
AL-RAIFE (2016) [2]	This research evaluates the energy efficiency and productivity growth in the industrial sector from 1999 to 2013 using data envelopment analysis (DEA). Two cases are analysed; in the first case (GVA), the output is the gross value added, whereas two outputs are considered in the second case (GCO), CO2 emission and GVA. Five key input factors are considered in both cases. From DEA window analysis, the technical inefficiency (TIE) values are zeros in windows (2001–2005) to (2003–2007), (2007–2011), and (2008–2012), whereas the pure technical inefficiency (PTIE) values are zeros in windows (1999–2003) to (2003–2007). Finally, the scale inefficiency (SIE) values are zeros in windows (2001–2005) to (2003–2007).	Five input factors are identified, including the energy consumption, number of employees, number of establishments, compensation of employees, and intermediate consumption. Correlation analysis is carried out to examine the factor relations. Furthermore, increasing returns to scale is observed in 19 out of 55 data lines, which indicates that the size of the operational scale (number of employees and establishments) should be increased to optimise scale. Finally, the results of the Malmquist Index showed that the geometric average is larger than 1 for the first (1999–2003) and second (2004–2008) plans, whereas it is less than 1 for the third plan (2009–2013). This result indicates the need for introducing technology, rather than increasing efficiency, in order to achieve the productivity growth.	Industry
CUI AND LEI (2014) [9]	In this paper, transportation energy efficiency is newly defined and its inputs and outputs are obtained through the literature review. Labour input, capital input and energy input are selected as the inputs, passenger turnover volume and freight turnover volume are defined as the outputs. A new model—three-stage virtual frontier DEA (three-stage virtual frontier Data Envelopment Analysis) is proposed to evaluate transportation energy efficiencies. The case of thirty Chinese PARs (provincial administrative regions) from 2003 to 2012 is applied to verify its rationality.	The results show that transport structure and management measures have important impacts on transportation energy efficiency.	Country level: China

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
LIU AND LIN (2018) [30]	This study shows the new energy efficiency model that integrates output growth and energy conservation to measure provincial energy efficiency in China's transport sector. A censored model and truncated model analyse the relevant factors impacting energy efficiency and propose relevant policy recommendations on how to improve energy efficiency.	The results show that per capita GDP, industrial structure, transport structure and energy price positively affect the energy efficiency of the provincial transport sector. The results show that energy efficiency shows a distinctly ladder-like distribution with the eastern province having the highest level, followed by the central and western provinces, and the energy efficiency gap among the provinces is narrowing.	Transport
MAKRIDOU ET AL (2016) [35]	This study evaluates the energy efficiency trends of five energy-intensive industries in 23 European Union(EU)countries from 2000 to2009.In particular, the performance of the construction, electricity, manufacturing, mining and quarrying, and transport sectors is examined. The analysis is based on Data Envelopment Analysis(DEA) combined with the Malmquist Productivity Index(MPI).	The empirical results showed that construction and transport are the most efficient sectors. On the other hand, the manufacturing and mining sectors present higher inefficiencies and stronger scale effects than other sectors. Thus, policymakers should give priority to improving the energy efficiency performance of these two sectors. The decomposition of MPI into its components showed that the improvements due to efficiency change have been modest, whereas the improvements due to changes in the technology factor have been significant in most of the sectors. According to the results of the cross-classified model, energy efficiency is higher for sectors that contribute more to the overall economic activity of a country and are characterised by high productivity and labour quality. Improving industrial energy efficiency can be an effective way to promote a country's economic growth, energy security, and sustainability,	Industry

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
MARTÍNEZ (2013) [37]	This is a comparative measure and is not absolute; with this in mind, this study is about the productive efficiency of federal entities in Mexico. The approach used is data envelopment analysis with the Malmquist Index. Using data from the Gross Domestic Product per state, labour, and capital inventory from 2005 to 2010.	The results of this research shows that with a relative productivity analysis, the national productivity is not growing, but does not present inefficiency problems. The analysis by entity concluded that federal entities in Mexico are mostly efficient and there are only two present problems with efficiency. The low efficiency is rejected according to the results of the research.	Mexican Industrial Sector
OMRANI ET AL (2019) [38]	In this paper, the energy efficiency of the transportation sector in 20 provinces in Iran is evaluated based on data envelopment analysis (DEA)—cooperative game approach. First, selected inputs and outputs are categorised into energy and non-energy inputs and desirable and undesirable outputs. Then, the classical DEA model is applied to evaluate and rank the provinces.	The results indicated that smaller provinces which have smaller transportation systems achieve better rankings. In contrast, big provinces with complex transportation systems performed poorly. Also, replacing high polluting fossil fuels with clean CNG will aid the improvement of energy efficiency.	Transport
RAMANATHAN (1999) [41]	In this paper data envelopment analysis (DEA) is used to study the energy sciences of transport modes in India.	The analysis has shown that the energy efficiency of rail transport has been increasing. According to all the years examined, the performance of rail transport was the best from 1993 to 1994 (which is the last year considered in the analysis), while the performance of road transport from 1993-94 was only 63% compared to the relative best. Thus, the DEA analysis highlights huge savings in energy consumption if rail transport is made in accordance with future transport requirements.	Transport

AUTHOR	SUMMARY	FINDINGS	SECTOR STUDIED
WU ET AL (2014) [46]	Data envelopment analysis (DEA) and Malmquist Indices have been used in this paper to investigate energy utilisation efficiency for 30 provinces, autonomous regions, and municipalities (apart from Hong Kong, Macau, Taiwan, and Tibet) in China. The industrial energy overall technical efficiency, industrial energy pure technical efficiency and industrial energy scale efficiency, etc. are examined for 30 different regions in China.	The average total factor energy efficiency (Malmquist Index) of China is not on the efficiency frontier. The main reason for this finding is that the technical efficiency (Ech) has decreased more than the improved technology progress rate (Tch) during the period. The total factor energy efficiency of the eastern region is the highest reaching efficiency frontier; however, the central and the western regions do not reach the efficiency frontier, which is similar to the DEA result. The energy efficiency of Beijing, Shanghai, Jiangsu, Zhejiang, Guangdong, and Hainan provinces is certainly effective, and the six regions with the lowest energy efficiency are Ningxia, Inner Mongolia, Shaanxi, Liaoning, Chongqing, and Jilin, with scores of 0.5 . The overall level of energy utilisation efficiency is low.	Chinese regions
ZHANG ET AL (2014) [48]	This paper proposes a non-radial Malmquist CO2 emission performance index (NMCPI) for measuring dynamic changes in total-factor CO2 emission performance over time. The NMCPI is calculated based on a non-radial directional distance function derived from several data envelopment analysis (DEA) models. This is because the NMCPI could be broken down into an efficiency change (EC) index and a technological change (TC) index.	The results indicate a 33% cumulative decrease in the CO2 emission performance during the sample period. The reduction in CO2 emission performance is caused by technological decline, which is also confirmed by the bootstrapping NMCPI. The results suggest that the government should develop low-carbon technology for the transportation industry to improve its CO2 emission performance.	Industry
ZHAOU ET AL (2010) [53]	This paper introduces a Malmquist CO2 emission performance index (MCPI) for measuring changes in total factor carbon emission performance over time. The MCPI is derived by solving several data envelopment analysis models. Using the index, the emission rate of the world's 18 top CO2 emitters from 1997 to 2004 was studied.	Among the countries studied, Germany ranks first while China and Indonesia have seen deteriorations in CO2 emission performance. This research has found thar the bootstrapping MCPI is a useful addition to the DEA analysis. The results from a cross-country regression analysis show that GDP per capita has a positive effect, while energy intensity has a negative effect on the total factor carbon emission.	Carbon Emissions

2.2 Factors that affect energy efficiency

By studying the energy efficiency levels, it is important to know which factors affect those levels. It could be something exogenous or endogenous. It is important to have this in mind because lots of models assume that something is affecting the efficiency levels of a country, industry, and so on. This section addresses which commonly studied factors affect energy efficiency according to some of the relevant literature and which of those are analysed in this thesis.

Whenever the SFA is used, there are two types of factors that affect efficiency. One factor is related to the independent variables used in the econometric model. An example of this is the work developed by Filippini & Hunt (2011), where the effects of the climate were studied as part of the estimation of the energy demand for OCDE countries by using DEA. This is because every independent variable considered in any model should affect a dependent variable. In some cases (Filippini & Hunt, 2011, 2012), (Llorca et al., 2017), (Orea et al., 2015) (Lundgren et al., 2016), energy demand is estimated and therefore, some of the independent variables used were the income and price. This is because of the correlation of those variables with the economic theory. In the case of this thesis, those variables are part of the model proposed and will be fully explained in the next chapter.

The second way in which something affects energy efficiency with SFA is in the component of inefficiency. This coefficient is part of the model and this means that it is causing problems in the explanation of the dependent variable. An example of this is the work of Lutz et al. (2017), which studied energy efficiency in the industrial sector of Germany, and the inefficient component of the proposed econometric model was affected by factors such as the investment in renewable technologies. The model proposed by those experts influenced the one used in this research.

Also, DEA is different since this methodology is based on input-output models. The variables chosen for the analysis of this thesis will be explained in the next section. However, CO_2 emissions are studied to see their effects on the energy efficiency. An example of this can be found in the work of P. Zhou, Ang, & Han (2010), where a Malmquist Index is used to

identify how the carbon emissions drive the energy efficiency in the top 18 CO_2 emitters. As well as in energy economics journals and other factors that affect the input such as the Gross Domestic Product (GDP) and its variants. Therefore, in the models proposed in this research, the CO_2 emissions will form part of the analysis. Also, the other variables that can affect efficiency from the output side depend on the sector being analysed. The role of these variables in the models will be explained in the next section and in the "methodology" chapter, where it was used to estimate the energy efficiency by SFA and DEA.

To conclude, this section explained how energy efficiency is affected. In SFA, it depends on the inefficiency component and the independent variables of the econometric model. While for DEA, the energy efficiency depends mostly on the consumption of energy, the GDP, and another input variable such as CO_2 emissions.

2.3 Transport sector case study

This section introduces some relevant literature about other research that is relevant for the transport sector. In two ways, by using SFA and DEA and analysing the Mexican case study. The related literature was analysed and there was some relevant literature. However, it is important to note that the model created for this sector was also based on complementary studies of other sectors.

There were some works that used SFA to estimate the energy demand and efficiency in the transport sector at country level in Latin American and European regions (Llorca et al., 2017; Llorca & Jamasb, 2017). The first work studied the energy demand, and Mexico was part of the dataset. However, this work uses SFA with a translog and Cobb-Douglas function to estimate the efficiency levels in the Latin American transport sector, due to the importance of the sector in the consumption of the total energy demanded (Llorca et al., 2017). While the other research explores the influence of key features in the energy efficiency of the freight sector of European countries and the rebound effect (Llorca & Jamasb, 2017). In addition, there are some studies relevant to particular countries and sectors related to the SFA efficiency measurement. However, the literature for this specific sector is limited.

Meanwhile, an example of studies that use DEA, where the energy efficiency based on the productivity was measured at country level, is the work created by Ramanathan (2000). Here the efficiency of the transport sector in India was studied by analysing the energy consumption, freight and passenger movements in the railways and roads (Ramanathan, 2000). The variables and functions used in this study were necessary to develop this research model for the Mexican case study.

Besides, there are other studies of the transport sectors in both China and Iran. Both studies used DEA to measure the efficiency levels of their transport sector. The first piece of research studied the efficiency of the Chinese provinces and the results showed the highest levels of efficiency in the eastern provinces (Liu & Lin, 2018). Also, this study focused on the impact of the carbon emissions on the energy efficiency of China's transport sector. The case study in Iran used the DEA and cooperative game approach to analyse the energy efficiency of the 20 provinces (Omrani, Shafaat, & Alizadeh, 2019).

There are studies in the transport sector that influence this research, not only because those studies tried to measure energy efficiency and demand, but because some are related to the Mexican transport sector case study, even if they were not related to any of the methodologies explained. Here the impact of gasoline demand was studied as a function of the income per capita; it covered the demand for the railways, air transport, and vehicles (Bauer, Mar, & Elizalde, 2003; Berndt & Botero, 1985). However, neither case analysed the energy efficiency; only the objectives and results related to the elasticities in the energy demand of the transport sector could be used as a reference and their research achieved only some of the objectives of this research.

2.4 Industrial sector case study

Some of the works relating to the industrial sector use SFA because this method was originally used to minimise costs for the producer (industries) by reallocating some variables in the production function (Aigner et al., 1977; Hokkanen, 2014). Over the years, this methodology started to be used in the energy fields. Previous examples of this have already been discussed earlier in this section. Also, it was the same for DEA because those methodologies are focused on productivity and efficiency. Therefore, there was plenty of

literature related to this sector because the origin of both methodologies was for industry and it is related to production efficiency.

Examples of the use of SFA to measure energy efficiency in industry mostly use translog and Cobb-Douglas functions. As previously mentioned, most of the research evaluates the energy demand as well as the efficiency, so variables such as income, price and energy consumption are commonly used. There is an example where SFA was used in the Swedish manufacturing sector. In this study, the energy demand was used for 14 sectors of Swedish industry, and the results showed that the energy efficiency should be improved for fuel and electricity use in all sectors (Lundgren et al., 2016). This study also evaluates the impact of CO_2 emissions, as does this research.

Other examples of the SFA in the industrial sector include differences in the approach to estimating the efficiency levels in the industrial sector. One piece of research related specifically to the Chinese chemical industry sector used a translog function to estimate energy efficiency and savings (Lin & Long, 2015). While research developed for the German industrial sector explored the drivers that affect the demand for energy (Lutz et al., 2017). Furthermore, another study for the Swedish industrial sector was created to check the rebound effect (Amjadi, Lundgren, & Persson, 2018). Therefore, the conclusions of those studies can be applied to the Mexican scenario, even if the data is significantly different.

Likewise, DEA has also been used in similar studies. For example, the Swedish industrial sector has been studied using both techniques and the same database (Lundgren et al., 2016; S. Zhang, 2016). In both cases, the aim was to measure energy efficiency with a parametric model (SFA) and a non-parametric model (DEA). Generally, the use of SFA is normal in industrial case studies due to its relationship with the economic producer theory (S. Zhang, 2016). However, plenty of literature regarding the industrial sector of several countries was identified and studied, in order to create a model that will be explained in the following section.

An example of the DEA analysis in European countries is the work of Makridou et al. (2016), where the CO_2 emissions and the Gross Added Value (GVA) were considered as inputs. The outputs selected for their model were capital, labour, and energy consumption. This research

took Makridou's model and applied it to the Mexican industrial sector. Similarly, there is also a study of the Jordanian industrial sector (Al-Refaie, Hammad, & Li, 2016).

Studies related to the Mexican industrial sector were limited. However, there are global studies regarding the energy demand of the aforementioned countries (Galindo, 2005). Also, there are plenty of studies in the manufacturing sector in Mexico due to its importance for the economy. However, this paragraph will show relevant literature associated with the use of DEA in this sector. In the first piece of research identified, the Malmquist Index was used to evaluate and rank the productivity in the industrial sector in all the Mexican states (Martínez-Damiàn et al., 2013). The second study shows the relationship between the energy consumption, industrial production and employment levels in Mexico (Marroquín Arreola, Neme Castillo, & Valderrama Santibáñez, 2015).

2.5 Policy and implications on a country level

Some of the implications of the study of energy efficiency in the world are related to improving the existing policies. Currently, the implication is linked to commercial, industrial competitiveness and oriented towards protecting the environment (Patterson, 1996). Therefore, countries and the United Nations are now more involved in the study of energy efficiency in order to identify possible gaps and increase the performance of their economies. In addition, to address and implement effective energy policies at any level, it is necessary to have some information to create energy efficiency indicators. Filippini et al. (2014) mentioned the importance of knowing the energy demand price and income elasticities in order to address the creation of new policies. In conclusion, energy efficiency research is vital to knowing how to create or modify energy policies.

Some research was identified in this chapter; most of which was related to the methodologies used to estimate energy efficiency. However, regardless of the applicable methodology, the purpose of this research was clear: address new energy policies. Some studies, such as this thesis, use both methodologies to establish energy efficiency levels. An example where both methodologies were used is provided by Zhou (2011). Moreover, the studies related to only one country can be used to distinguish the energy efficiency differences between states/regions or entire sectors (Ramanathan, 2000; Weyman-Jones et al., 2015). In

Ramanathan's (2000) research, the Indian transport sector was analysed using DEA. The policy implication focused on the comparison between road and rail sectors and what should the rate be in order to improve its efficiency (Ramanathan, 2000). On the other hand, Weyman-Jones et al. (2015) used SFA for the Portuguese residential sector. In that research, the policy implications of using SFA were how to introduce electricity-saving measures and the comparison with policy developments in Portugal (Weyman-Jones et al., 2015).

The Mexican case study mentioned research such as that undertaken by Bauer (2003) and Galindo (2005). Both pieces of research focused on the impacts of current energy policies in Mexico. One of the conclusions made was that energy control policy based on an increase in taxes was not a successful idea (Galindo, 2005). The 1965-2001 period was analysed, and energy demand in the short and long run was estimated. The other piece of research is related to energy demand, but it is focused on the transport sector, as is this thesis. The conclusion made in policy terms was that in general, energy policy in the country should be reviewed (Bauer et al., 2003). Both pieces of research answered some of the research questions proposed previously and with the methodologies described, it is expected to expand this type of literature for the country.

This thesis is focused on the estimation of energy efficiency and demand. It is important to analyse and interpret these types of studies because it could be relevant to the policymakers. Plenty of studies related to the implication of energy efficiency were identified, and most of them conclude that it is one of multiple steps in the process of creating new energy policies. To conclude, the methodologies explained that estimating the energy efficiency can be used to create new policies.

CHAPTER 3: METHODOLOGY

This section explains the database structure and the sources. Further information regarding the models and variables used will be discussed in the other sections of this chapter.

3.1 Data source and structure

In order to produce results in this work, three different types of databases were built. One of the databases was used for the SFA, and it includes information for both sectors. On the other hand, the other two databases were employed for the DEA methodology. Those databases contain different sets of information for each sector. To emphasise, the database for SFA uses variables that are common in the sectors studied, and the DEA databases have a different set of variables and periods for each sector.

The first database used in this study is the one related to SFA methodology. This database is composed of 340 observations for the period from 1997 to 2016. In total, 17 classes were analysed for the SFA methodology. From those classes studied, four came from the transport sector and 13 from the industrial sector. Moreover, four main variables were analysed because they were common in both sectors. Those variables are the gross domestic product (GDP), energy price index, energy demand and contamination. The next section of this chapter will discuss these variables and the other ones used in the econometric model in more detail.

The database used in the transport sector used for the DEA methodology has some of the characteristics of the first database, as well as differences. Firstly, this database only contains information on the transport sector. Therefore, the information analysed is shorter since it only contains 80 observations. The period used, from 1997 to 2016, is the same as the database used for the SFA. However, the two variables used, based on other works, were more closely related to the passenger and freight movement. In total, four categories were studied: automobile, aviation, railway, and maritime. More details about the variables and the model used will be explained later in this chapter.

In addition, the other database used for the DEA methodology is specialised in the industrial sector. For this database, the period from 2003 to 2016 was analysed with 182 observations

divided into 13 categories. The categories were: iron and steel, chemical, sugar, petrochemical, cement, mining, cellulose and paper, glass, beer and malt, fertilizers, automotive, water and non-alcoholic beverages, building, rubber, and tobacco. The variables used for this database were GDP, contamination, energy demand, labour, and capital. More information and further discussion will be provided in later sections of this chapter, where some numerical information and model specifications will be discussed.

The data was provided by the *Instituto Nacional de Estadística Geografía e Información* (INEGI), *Secretaría de Energía* (SENER) and *Instituto Nacional de Ecología y Cambio Climático* (INECC) (INEGI, 2018; INEGyCEI, 2018; SENER, 2017). Those data sources were used to obtain the information shared by both sectors and were relevant for this study. It was simply the expert's decision that this information was consolidated into one database to try and obtain results in the SFA methodology.

The other data sources specific to the transport sector came from Instituto Mexicano del Transporte (IMT) and Secretaría de Comunicaciones y Transportes (SCT) (IMT, 2000, 2004, 2005, 2009, 2015, 2017). Those data sources were used to get information for the freight and passenger movement in the years studied. Moreover, more variables were used but in the end, they were not applied in the final models. The data came from statistical manuals developed by both institutions mentioned. While the information obtained for the industrial sector database was from INEGI, the data is based on a specialised poll in this sector and in some cases, the organisation of the information changed, so it was necessary to skip the period from 1997 to 2002 (INEGI, 2007, 2018).

To conclude, this section demonstrated the structure of the three databases used in this study and the number of observations were discussed. Also, the source of the information was revealed. In this case, all of the information is from Mexican Institutes which are part of the government. The next section will discuss more details about the variables used in this work, such as the final models used to estimate the energy efficiency in the sectors selected.

3.2 Understanding the variables

The previous section of this chapter introduces and briefly explains the databases used in this work. However, in this section, a detailed explanation and examples of the data selected will

be presented. While the first part is related to the transport sector and its variables, the second part will focus on the industrial sector. The final part is specialised in the variable price for both sectors.

3.2.1 Transport sector

Table 3.1 shows a summary of all the variables used in the transport sector. Where the units and the abbreviation of each variable are reported, so is whether the variable was used for SFA or DEA. Meanwhile, Table 3.2 shows the descriptive statistics of the variables used. The next part of this section will focus on demonsrating some facts about the data used.

VARIABLE	ABBREVIATION	UNIT	USED IN SFA	USED IN DEA
ENERGY CONSUMED	Q	Petajoules	Yes	Yes
ENERGY PRICE INDEX	P	Index	Yes	Yes
GROSS DOMESTIC PRODUCT TRANSPORT SECTOR	GDP	Millions of Mexican Pesos	Yes	Yes
PEOPLE MOVEMENT	PM	Thousands of people per Kilometres	No	Yes
FREIGHT MOVEMENT	FM	Thousands of tons per Kilometres	No	Yes
CONTAMINATION	CO	CO_2	Yes	Yes

Table 3.1: Variables used in the transport sector

ABBREVIATION	AVERAGE	ST. DEVIATION	MAXIMUM	MINIMUM
Q	497	778	2252	21
P	96	55	222	13
GDP	148203	236426	697273	6595
PM	767	1322	3623	0.2
FM	136	186	536	0.1
CO	36270	58641	168506	1671

Table 3.2: Descriptive statistics for the transport sector

It is important to highlight some important aspects of every variable used in both methodologies, beside their units and source. Firstly, the variable Q (energy consumption) in the automobile sector is where almost all the energy is consumed. Second, the GDP variable has a year based on 2008 prices. Thirdly, the variable P (energy price index) was constructed by the researcher using Laspeyres methodology to create a price index. Fourthly, variables FM and PM were taken from statistical manuals. Also, the contamination variable was added to find out how contamination affects energy efficiency. In this section, some figures related to this sector where the automobile sector was omitted will be shown, because by itself, they represent almost the entire sector in any variable.

Figure 2 represents the energy consumption in the transport sector. The graph shows information from three of the four sectors because the automobile sector is bigger than the rest. By itself, the energy consumption represents more than 90% of the total consumption. Covering a demand of 1800 petajoules on average and this is only for the automobile sector. Therefore, the consumption of the other sectors is reported in the graph. Here the aviation sector has the second highest energy consumption level. While the railway and maritime sectors are similar in their energy consumption.

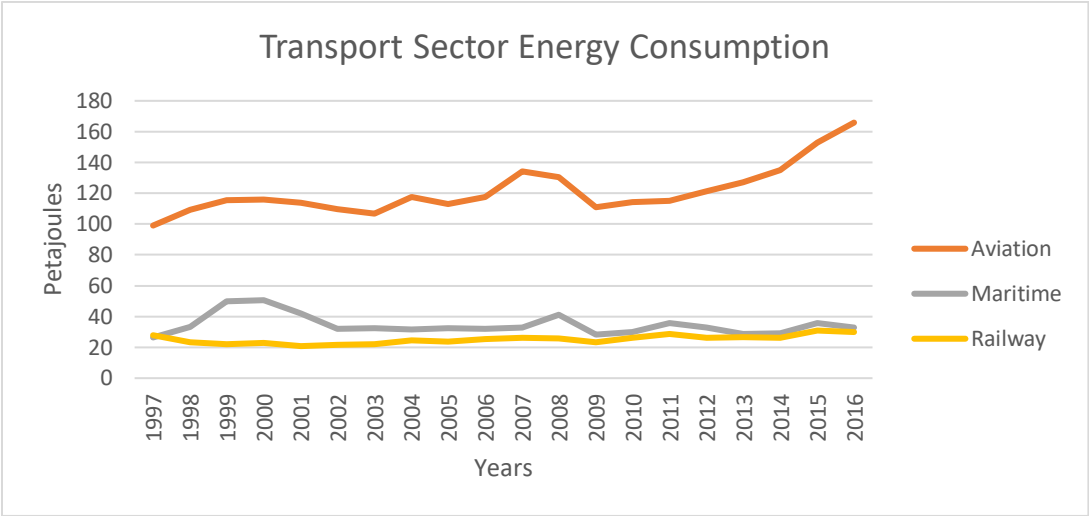

Figure 2: Energy consumption in the transport sector

In Figure 3, the division of the GDP in the transport sector is reported. Again, the data for the automobile sector was excluded, because it is larger than the other sectors. Also, the aviation sector continues to be the second most important sector. Another important fact to note regarding this variable is that in 2008 through to 2010, there was a decrease in the whole GDP. This is related to the 2008 crisis which affected the whole sector. Since 2011, the GDP of the sector has recovered. The GDP variable in the model is particularly important because once the results are done, the coefficient given will be the income elasticity of the transport sector. The result and interpretation of that coefficient can be used by the policymakers to understand what stimulates the demand for energy in this sector.

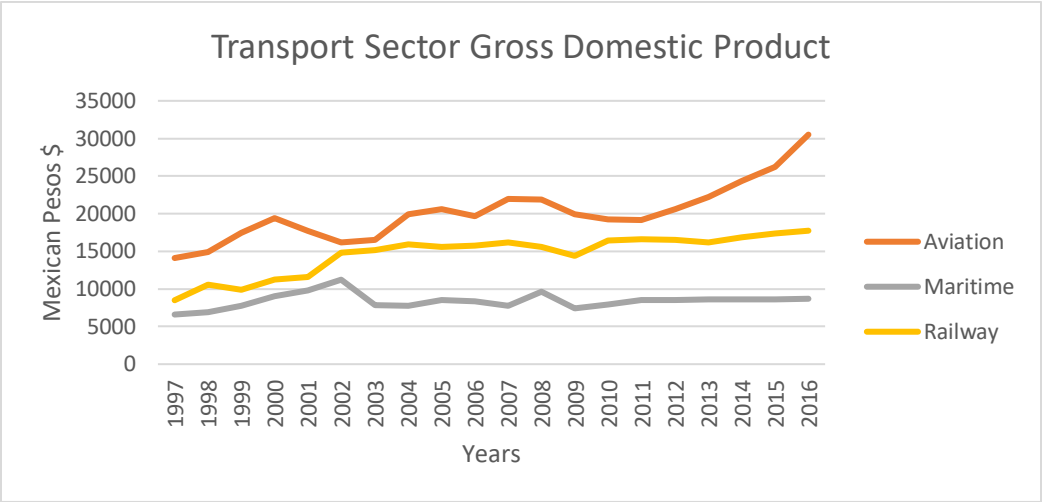

Figure 3: GDP in the transport sector

Figure 4 shows the information regarding the contamination in the transport sector. Again, the data of the automobile sector was omitted in the graph due to its size. The aviation sector is the second most polluted. Meanwhile, the maritime and railway sectors have had almost the same levels of pollution in recent years. This data was taken from INEGyCEI, which is a Mexican institute that collates the carbon emission information for the whole country and by sector (INEGyCEI, 2018). This variable was added because there could be a correlation between a high level of contamination and the use of old technology, thus affecting the efficiency levels.

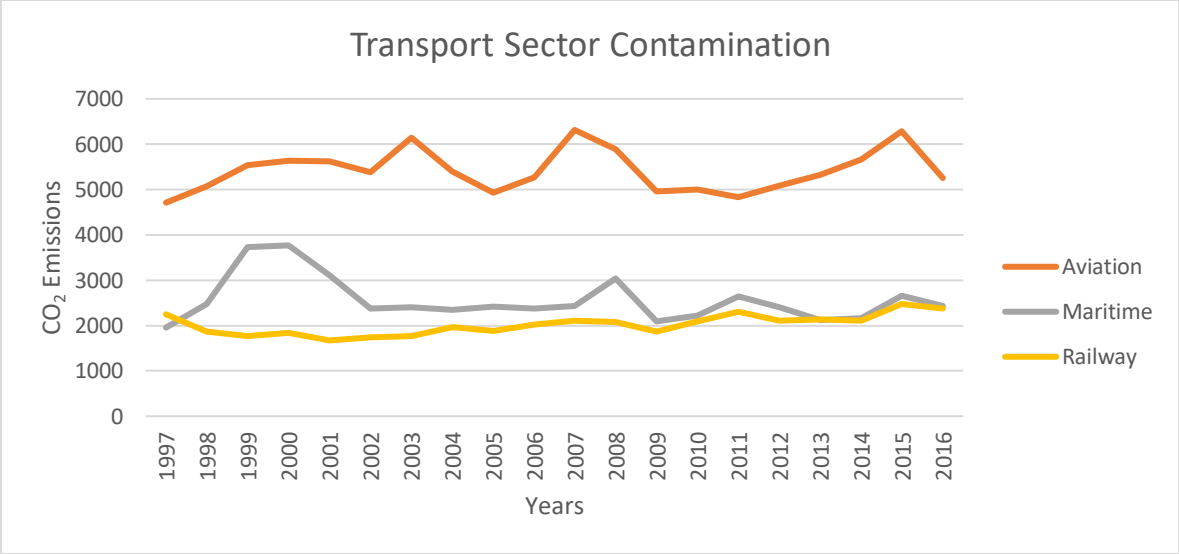

Figure 4: Contamination in the transport sector

Figures 5 and 6 show the passenger and freight movement in the transport sector. The variables shown do not include the automobile sector, because of its size compared to the other sectors. These variables were specifically used for the DEA methodology to estimate energy efficiency. Also, these variables provide interesting insights, such as the importance of the maritime sector for the freight movement and the increase of passengers in the railway sector. As the other variables showed, the automobile sector represents more than 90% of the whole sector. The difference compared to the other variables is that the aviation sector is not the second most important. Regarding the freight, according to INEGI, this originates from the maritime sector where the freight is moved, after the highways which is part of the automobile sector. According to the statistical manual of 2009, the railway sector increased its number of passengers due to the introduction of a train that connects Mexico City to Mexico State.

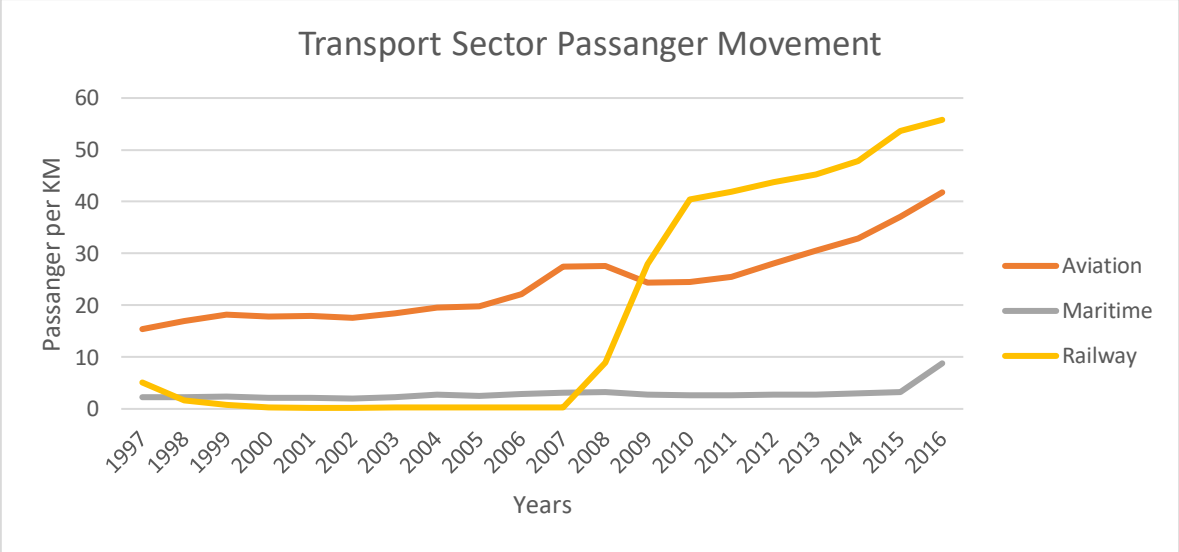

Figure 5: Passenger movement

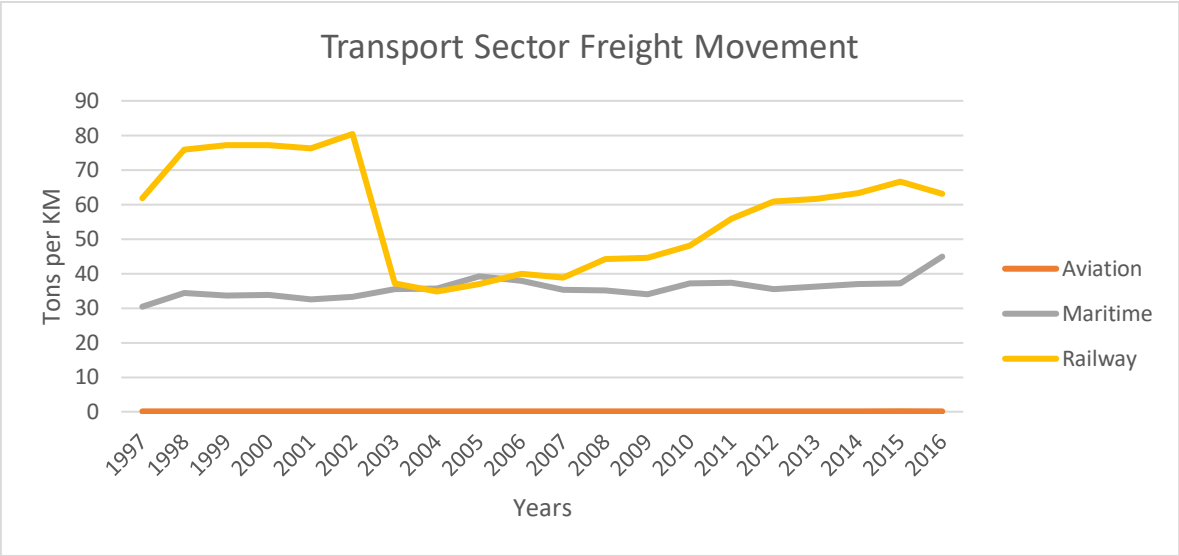

Figure 6: Freight movement

To summarise, this section of the chapter highlights important issues to be considered in the transport sector. For example, the automobile sector is the most important according to the number of users and the contribution to the Mexican GDP. Also, all the data shown is reported and counted solely for the national territory. All the international movements are registered in different accounts, so this does not include the imports received in the Mexican ports and the passengers that fly into Mexico from outside the country. In some cases, from 2008 to 2010, a decrease in the GDP could be seen which is related to the global recession and that affect all the variables used. Also, in 2008 a train that connects Mexico City to Mexico State, a highly-populated region, was introduced, so that made the number of passengers increase since 2008 (IMT, 2009). All the variables used are necessary to measure the energy efficiency and the purpose of this section was to explain the technical information regarding the transport sector database.

3.2.2 Industrial sector

The variables used in this sector were collected from SENER and INEGI, where the data source reported the value for the industrial sector in 13 different types of industries. As for the transport sector, the main data sources were INEGI and SENER. Even for the variables used for DEA, the data source was INEGI (INEGI, 2007, 2018; INEGyCEI, 2018; SENER,

2017). The data from INEGI was obtained by the national industrial poll, which is the source of some important variables such as the number of employees, capital, producer price index, GDP of the sector, materials, and the number of industries (INEGI, 2007).

In total, 13 industries will be analysed over the period of 1997 to 2016 in the SFA, and from 2003 to 2016 for DEA. Table 3.3 and 3.4 show all the variables used in this study and which methodology was employed and the descriptive statistics. The data reported in Table 4 is from 2003-2016, and it came from the database used for DEA. The information for the industries due to be analysed was provided by SENER and the categories are iron and steel, chemical, sugar, petrochemical, cement, cellulose and paper, glass, beer and malt, fertilizers, automotive, water and non-alcoholic beverages, rubber, and tobacco.

VARIABLE	ABBREVIATION	UNIT	USED IN SFA	USED IN DEA
ENERGY CONSUMED	Q	Petajoules	Yes	Yes
ENERGY PRICE INDEX	P	Index	Yes	Yes
GROSS DOMESTIC PRODUCT INDUSTRIAL SECTOR	GDP	Millions of Mexican Pesos	Yes	Yes
CAPITAL	K	Miles of Mexican Pesos	No	Yes
LABOUR	L	Number	No	Yes
CONTAMINATION	CO	CO_2	Yes	Yes

Table 3.3: Variables used in the industrial sector

ABBREVIATION	AVERAGE	STANDARD DEVIATION	MAXIMUM	MINIMUM
Q	57	60	243	0.4
P	112	44	222	36
GDP	176928720	244018465	1114905720	3049624
K	72938490	68989782	338199312	1213561
L	33189	38288	157526	1535
CO	4048	5691	19724	129

Table 3.4: Descriptive statistics for the industrial sector

Table 3.5 shows the average results of the variables used for the DEA. The variable price was omitted, because it is not part of the DEA methodology and will be explained in the next section of this chapter. On average, the sector that consumes more energy according to the data proportioned by SENER is the iron and steel industry. The chemical industry reports more for GDP and the number of employees. Finally, the industry that reported more capital on average was the petrochemical industry. As previously mentioned, all the data reported originated from the manufacturing industry poll created by INEGI. In some cases, the sample chosen for a specific sector varies according to the number of industries selected, but all of this was studied by experts (INEGI, 2007).

To conclude, the data used for the industrial sector shares some variables with the transport sector and also uses different variables for the DEA methodology. The main data source was INEGI, and the information reported came from a poll created by the same institutes which specialises in the industrial sector. The information between the samples selected varies because of the size of the industry and therefore, its own characteristics. For example, the technology, the number of workers and the role of the industry in the poll (INEGI, 2007). The data shown in this section is related to both SFA and DEA methodologies. However, the descriptive statistics reported, and the database used are the ones used for DEA.

Industry	Energy Consume (Q)	Gross Domestic Product (GDP)	Capital (K)	Labour (L)
Sugar	54	42906325	43048275	19135
Tabaco	0.5	34358027	5033637	2586
Beer and Malt	19	72792067	56659488	13811
Water and non-alcoholic beverages	9.5	127044403	49292722	56034
Paper	47	47320704	45994558	19582
Rubber	8.7	29293427	11134877	24211
Fertilizers	3	9587951	3143732	402,221,429
Chemical	91.1	**625433800**	188503231	**151520**
Cement	144	55125811	100029415	7396
Vehicles	11.7	561969345	114640524	54475
Glass	51.8	38017717	29652589	29799
Iron and Steel	**201.3**	124982415	107909081	20165
Petrochemical	94.16	531241368	**193158246**	28716

Table 3.5: Variables average per sector

3.2.1 Price Variable

This section explains how the variable P (energy price index) was created for both sectors. This variable is used in the SFA and is important because its interpretation is related to the price elasticity.

The index was developed by the researcher using Laspeyres price index formula expressed in equation 2. Where the P represents price and Q represents quantities of goods and services used. In this case and according to each sector analysed, the price and quantities selected were mostly from fuels, electricity, gas, and other energy sources. The exact information divided by the type of energy consumed in each sector was obtained from SENER. Also, the exact price from products such as petrol and gas were obtained from INEGI (INEGI, 2018; SENER, 2017).

$$P_{it} = \frac{\sum P_1 Q_0}{\sum P_0 Q_0}$$

Equation 2: Laspeyres Price Index

The development of the index is simple. First, the data was obtained and standardised into a yearly base. In this case, the base year was 2008 because the variable GDP has a base in this year as well. Therefore, the base of this index was the 2008 price of the energy source multiplied by the quantities of the same energy source and year. Then the numerator is composed by the quantities consumed in 2008 multiplied by the price of a specific year. At the end of the operation, the result was multiplied by 100 to interpret the results more easily. The final result of this index is a number from 0 to 100 and it shows the change in price, for example, in 2010 in terms of the prices and quantities consumed in the year 2008. The database begins in 1997 and ends in 2016.

Every price used in the index is expressed in Mexican Pesos, and the quantities are in petajoules. The data presented is the market price of certain fuels and other energy sources and the consumption of each in both sectors. The data originated from SENER for the quantities of energy consumed and for some energy prices, the rest came from INEGI

(INEGI, 2018; SENER, 2017). In the case of the transport sector, almost every energy source came from a type of fuel. Meanwhile, the industry sector has more variety in its energy sources. However, fuels have an important role in both sectors. The importance of this variable is related to the price elasticity coefficient that is expected to be obtained once the model is done. The type of information expected has the same relevance as the income elasticity because it could show what the energy demand in the sectors could be (Bauer et al., 2003; Berndt & Botero, 1985).

The type of fuel used bears a strong correlation to the category of transport section selected. For example, gasoline was only used in the automobile section due to almost 70% of the car users using this type of fuel, and in the aviation sector, 99% consume kerosene (IMT, 2017). While diesel was used in the railway and maritime sectors, with the consumption of this fuel being 99% and 97% (IMT, 2017). Whereas in the industrial sector, in general almost 30% of the energy consumed was from fuels, 40% from gas, 18% from electricity and 12% from another energy source (SENER, 2017).

In conclusion, this section describes how variable P was created. The reason for creating an energy price index was to mix both sectors in a single database for the SFA methodology. The index has information about prices and consumptions of fuels, gas, electricity, and other energy sources. The year base is 2008 and this is because the GDP variable has the same base (INEGI). The use of this variable is relevant in the SFA because the price elasticity could be interpreted.

3.3 Stochastic Frontier Analysis methodology

The purpose of this section is to show what model was used for the SFA, in more detail. In the previous section of this chapter, a description of the variables and databases was provided. Therefore, this section includes the variables employed for the stochastic model for further information.

The following econometric model reported in this section has some important specifications. First, it was based on the first aforementioned database. This means that the model has 340 observations for the period 1997-2016. Also, it involves two sectors: the transport and industrial sectors. Later in this chapter, a further description of the model will be given.

Equation 3 shows a simple model based partially on the work of Filippi and Hunt for estimate and energy demand (Filippini & Hunt, 2011, 2012, 2015; Filippini et al., 2014; Filippini & Zhang, 2016). This model was created for a specific country and it specialised in the sectors that demand more energy, see Amjadi et al., 2018; Filippini & Hunt, 2012; Filippini & Zhang, 2016; Lutz et al., 2017; Weyman-Jones et al., (2015), where Q represents the demand for energy or energy consumption for the sector "i" in the time specific time "t" as a dependent variable. The independent variables such as the income, expressed in the GDP, and the price are used to estimate the energy demand (Filippini & Hunt, 2011; Lin & Long, 2015; Llorca et al., 2017; Lutz et al., 2017). Also, a conjunct of dummy variables were added in this equation; the dummy variables were used as part of the model to specify a sector (Filippini & Hunt, 2012, 2015; Lutz et al., 2017; Orea et al., 2015).

$$Q_{it} = Q(P_{it}, GDP_{it}, X_{it})$$

Equation 3: Simple energy demand function

By using natural logarithm and assuming a Cobb-Douglas function, the model ends like this:

$$lnQ_{it} = lnQ(P_{it}, GDP_{it}, X_{it}) + v_{it} + u_{it}$$

Equation 4: Natural logarithmic energy demand function

Equation 4 expresses the natural logarithm form of a Cobb-Douglas function used in this study. As previously mentioned in this chapter, Q stands for the energy consumption, GDP for the gross domestic product and P for an energy price index. In addition, the variable X stands for a series of dummy variables represented using one letter to simplify the number of variables in the equation. The dummy variables have a value of 1 when a sector is analysed and 0 when it is not. The variables used for the 17 sector studies are: beer and malt (bd), water and non-alcoholic beverages (wad), paper (pd), fertilizer (fd), rubber (dr), cement (dc), the vehicle production industry (vd), glass (gd), iron and steel (di), chemicals (chd), petrochemicals (petrod), aviation (avd), maritime (mard), railway (raild) and automobile (autod).

Additionally, the error term is composed of two independent variables in equation 3 (of this chapter) and are expressed as v and u. The first error mentioned, v, captures the effects of

noise in the model and it is assumed that follows a normal distribution. The second error defined as u represents the inefficiency component captured in a non-negative disturbance (Aigner et al., 1977; Filippini & Hunt, 2011, 2012).

The main aim of this research is to try and find evidence that there is inefficiency in the sectors studied and then estimate its efficiency levels with SFA. The econometric specification of the Cobb-Douglas model for the industrial and transport sector is expressed in equation 5 and its definitions are provided in Table 3.6. Here all the variables are now expressed in natural logarithm with a lower caption and with the desegregation of the aforementioned dummy variables:

$$q_{it} = \beta_{it} + \beta_{gdp} gdp_{it} + \beta_p p_{it} + \beta_t t + \beta_{bd} bd_{it} + \beta_{wad} wad_{it} + \beta_{pd} pd_{it} + \beta_{dr} dr_{it} + \beta_{fd} fd_{it} + \beta_{dc} dc_{it} + \beta_{vd} vd_{it} + \beta_{gd} gd_{it} + \beta_{di} di_{it} + \beta_{petrod} petrod_{it} + \beta_{avd} avd_{it} + \beta_{mard} mard_{it} + \beta_{raild} raild_{it} + \beta_{chd} chd_{it} + \beta_{autod} autod_{it} + v_{it} + u_{it}$$

Where

$$\hat{u}_{it} = \beta + \beta_{co} co_{it}$$

Equation 5: SFA energy demand model

Variable	***Definition***
Q	Energy demand
it	Observations
P	Energy Price Index
GDP	Gross Domestic Product
t	Time trend
BD	Beer and Malt Sector Dummy
WAD	Water and Non-alcoholic Beverages Sector Dummy

PD	Paper Sector Dummy
DR	Rubber Sector Dummy
FD	Fertilizer Sector Dummy
DC	Cement Sector Dummy
VD	Vehicles production industry Sector Dummy
GD	Glass Sector Dummy
DI	Iron and Steel Sector Dummy
CHD	Chemical Sector Dummy
PETROD	Petrochemical Sector Dummy
AVD	Aviation Sector Dummy
MARD	Maritime Sector Dummy
RAILD	Railway Sector Dummy
AUTOD	Automobile Sector Dummy
Vit	Estimator error
$\boldsymbol{\beta}$	Parameter of estimation

$\hat{u}_{it}$	Inefficiency component
CO	Contamination

Table 3.6: Energy demand model variables

Note: some variables are capitalised, for example, Q and q. Both variables indicate energy demand, however, the capitalisation indicates an absolute value, Q, and a logarithmic value.

In addition, based on related works in the field, the contamination variable was added as a part of the model (Lutz et al., 2017). However, the aggregation of this variable was linked to the error term "u.". An improvement in the efficiency levels could be linked to the impact of some changes such as policy, technology, consumption, etc. (Filippini & Hunt, 2011; Filippini et al., 2014; Lundgren et al., 2016; Lutz et al., 2017). By adding the variable contamination, the model tries to measure the effects that could cause inefficiency in the sector studied.

In Table 3.7, the descriptive statistics are reported for the variables used in the model expressed in equation 4 and 5. The application of the model was possible with the statistical programme Stata 14 and the variables used were reported in equation 5.

The model was selected to follow a half-normal distribution in a Cobb-Douglas function. The distribution used is related to the inefficiency component that the model tries to predict. In this case the variable u.

VARIABLE	UNIT	MEAN	STD DEV	MIN	MAX
Q	Petajoules	161.2	422.6	0.4	2252.5
P	Price Index	90.6	52.1	12.9	222.1
GDP	Mexican Pesos	77475	133685	6595	697273
X	Number	0.05	0.23	0	1
CO	CO_2	11794	31805	129	168506

Table 3.7: SFA descriptive statistics

Once the model shown reports results, the energy efficiency of the sector is calculated. Equation 6 is used to show the efficiency levels by sector when the inefficiency varies over time:

$$EF_{it} = \exp\left(-\hat{u}_{it}\right)$$

Equation 6: Energy efficiency

Here the energy efficiency for the SFA is related to the estimation of the inefficient component of the model proposed (Filippini & Hunt, 2011). Therefore, the efficiency can be estimated in a parametric way, which is one of the objectives of this work.

To summarise, this section explained the model used in the SFA. The specification and descriptive statistics of the model were provided in this section. Also, an explanation of the process of how the energy efficiency is going to be estimated for the transport and industrial sectors was provided/ In the next section of this chapter, the DEA methodology is going to be discussed in more detail as a non-parametric way to estimate the energy efficiency of the sectors studied .

3.4 Data Envelopment Analysis methodology

In this section, the DEA methodology is going to be discussed in more detail. This methodology was used to estimate the levels of efficiency in the transport and industrial sectors in a non-parametric way. In this case study, the Malmquist Index was used to measure the efficiency over a period of time.

Studies in energy efficiency use the Malmquist Index to measure efficiency over a period of time. As previously explained in this work, this approach is a non-parametric one, which means that the sample studied is not necessarily subject to a statistical distribution. However, as in SFA, this methodology builds a frontier that is subject to some variables (Al-Refaie et al., 2016; Coelli et al., 2005; Martínez-Damiàn et al., 2013; Wu, Cao, & Liu, 2014; P. Zhou

et al., 2010). The next part of this chapter will explain which variables and model were used to measure the energy efficiency in the transport and industrial sectors of Mexico.

The explanation of the Malmquist Productivity Index (MPI) and DEA were provided in the literature review. Moreover, this section focuses on explaining the mathematical part of the model and what can be achieved by using this methodology.

The estimation of the Malmquist Index was measured in R Studio, which is the statistical programme that made it possible to report the results of this research. The steps followed to estimate the energy efficiency in the transport and industrial sector were based on the guide developed by Valencia University (Coll-Serrano, Benitez, & Bolos, 2018) . This guide was useful to estimate the following indicators: Malmquist Index, efficiency change, technical change, scale change and productivity change. Also, the variables selection was possible due to works such as Makridou, Andriosopoulos, Doumpos, & Zopounidis (2016), Ramanathan, (2000) and P. Zhou et al. (2010). The results of both sectors will be discussed in the next chapter of this research.

Equation 7 shows the mathematical components of the Malmquist Index. This formula is divided into two main components.

$$MPI_i(t,t+1) = \frac{\theta_i^{t+1}(X_i^{t+1}, Y_i^{t+1})}{\theta_i^{t}(X_i^{t}, Y_i^{t})} \times \sqrt{\left[\frac{\theta_i^{t}(X_i^{t+1}, Y_i^{t+1})}{\theta_i^{t+1}(X_i^{t+1}, Y_i^{t+1})} \times \frac{\theta_i^{t}(X_i^{t}, Y_i^{t})}{\theta_i^{t+1}(X_i^{t}, Y_i^{t})}\right]}$$

Equation 7: Malmquist Index

Formula based on the article written by Makridou et al., (2016)

Where the function and parameters used in the equation are distance functions for the sector “i” in the time “t” or “t+1” and are expressed in all Ɵ symbol, the other variables in this equation, X and Y, express the inputs and outputs used in the equation. Also, the equation has two important components. The first component is the one that is not affected by the square root. The second component is affected by the square root. A detailed explanation of both components is developed in the following paragraphs.

The first component shows the efficiency change and is expressed in the first part of the equation. The change is captured in the improvement or detriment of the DMU (outputs) selected. Moreover, this part could be broken down into the technical and scale efficiency change over time (Makridou et al., 2016; Martínez-Damiàn et al., 2013; P. Zhou et al., 2010).

The second component shows the technological change between the periods. These indicate progress in the efficiency and it is directly linked to the frontier that is analysed (P. Zhou et al., 2010).

Another important assumption is that this model presents a constant return of scale. This is associated with the production theory where it is inferred that to produce a finite number of outputs, a finite number of inputs are required.

The results of this methodology were obtained by using the R Studio statistical programme. In order to solve this function, it is necessary to use linear programming per sector. A guide and package for this methodology, developed by Coll-Serrano from Valencia University, were used to obtain results. The results obtained for the Malmquist Index are efficiency, technical, productivity, scale changes and the index. The technological and technical efficiency and MPI are explained in equation 7 as well.

The interpretation of the results obtained is simple and will be discussed at length in the following chapter. However, the basic interpretation is related to a number bigger or lower than 1. In any case, if the result is greater than 1, then there was an increase in efficiency and it is over the frontier. A result lower than 1 represents a decline in the efficiency and that is under the frontier. Finally, if the result is equal to 1, that means that there was a change over time and that is on the frontier (Al-Refaie et al., 2016; Coelli et al., 2005; P. Zhou et al., 2010).

Table 3.8 discloses the variables used to estimate the efficiency in the transport and industrial sectors. All the variables used were referred to in the final section of this chapter. Also, the descriptive statistics was given. The following works were used to create the models used (Filippini et al., 2014; Makridou et al., 2016; Ramanathan, 2000; Wu et al., 2014; P. Zhou et al., 2010). However, a justification for the use of these variables will be discussed.

OUTPUT	INPUT	SECTOR
CO_2 EMISSIONS	Energy Consumption	Transport
GDP TRANSPORT SECTOR	Freight Movement	
	Passenger Movement	
CO_2 EMISSIONS	Energy Consumption	Industrial
GDP INDUSTRIAL SECTOR	Capital	
	Labour	

Table 3.8: Variables used in DEA

The estimation of energy efficiency using DEA is not a new issue in the field. In the research carried out , a lot of studies use the carbon emissions **(**CO_2**)** and the GDP as outputs to measure the energy efficiency (Makridou et al., 2016; P. Zhou et al., 2010). Both sectors share the same outputs, because the GDP is the primary economic indicator, and the carbon emissions are classed as an undesirable output (Makridou et al., 2016). Moreover, this research tries to study factors that can affect the efficiency, and, in the outputs, those selected could be related to the lack of technology and innovation. Therefore, by using the CO_2 emission and the GDP as outputs, it is possible to find out what the energy efficiency is in the sectors selected. The justification for using these variables was the availability of the data sources and their relevance to other studies.

Moreover, both sectors studied share the energy consumption input. This is related to the purpose of the research regarding the levels of energy efficiency. In this case, it is employed as a part of a production function. Since the aim of this research is investigating the efficiency levels of the energy use in the transport and industrial sectors. It was logical and necessary to include this input in both models.

The function of the transport sector uses freight and passenger movement. These variables were considered as part of the function because movement of passengers and freight are how the transport sector quantifies money in its GDP. The energy efficiency can be estimated if the performance of the variables mentioned is taken into consideration (Ramanathan, 2000).

There are plenty of works that use capital, labour, and energy consumption as inputs to estimate the efficiency levels by DEA. These variables are considered because they are essential to producing units of GDP and carbon emissions in a simple model and they optimise energy efficiency performance (Makridou et al., 2016; P. Zhou et al., 2010).

In summary, this section of the chapter explains the DEA methodology in this research. In this section, the model used for both sectors with the aforementioned variables in the previous section was outlined. Including how the Malmquist Index works and its interpretation. Also, it explained that the results were calculated in R Studio. In the following chapter, the complete results will be presented and discussed.

CHAPTER 4: RESULTS AND DISCUSSION

In this section, the results and interpretation of the methodologies selected to estimate the energy efficiency levels for the sectors are presented. In addition, each section will compare the results with the estimated results according to the theory and other studies in the field. The complete results are also discussed as a whole.

4.1 Stochastic Frontier Analysis (SFA)

In the previous chapters, this work has explained why this research use SFA to estimate the energy efficiency levels. Also, the econometric model was introduced in the methodology section. Where the variables and the data were used, descriptive statistics were reported.

Following the specification of equation 5 mentioned in the methodology chapter, and after calculating the model in Stata based on the steps developed by Belotti et al (2013), the results are reported in Table 4.1; here the coefficient and statistics ratio are shown. In general, the results are in line with the economic theory and are statistically significant with at least 10%.

The variables in logarithmic form, GDP, and P, can be directly interpreted as elasticities. As proposed in the research questions for this work, the model estimates demand for energy. The results reported are for the transport and industrial sectors, where the estimated income elasticity is 3.41, and the price elasticity is -.21. Both sets of results obtained for a half-normal model, as well as further details and discussion will be provided in the final section of this chapter. The interpretation of the elasticities is straightforward; an increase in one of those variables represents an increase in the demand for energy (this is related to the GDP elasticity) or a decrease in the demand (this is related to the price elasticity) by the coefficient estimated. The important observation here is the range of the coefficient obtained for these elasticities. In the case of the price, the range is normal. However, the coefficient value for the income elasticity is a bit higher than the common range, but this could also be related to the importance of the production in each sector. Further explanation on this point will be provided in the final section of this chapter.

VARIABLE	EST.	Z-RATIO
FRONTIER PARAM.		
INTERCEPT	-30.5***	-23.1
LN(P)	-.2*	-1.8
LN(GDP)	3.4***	26.1
T	-.03**	-2.1
BD	-.2	-1.6
WAD	-2.7***	-14.9
PD	2.9***	22.7
DR	2.4***	14.7
FD	1.4***	9.1
DC	.12	0.7
VD	-6.5***	-15.9
GD	1.7***	11.2
DI	-.46**	-2.3
CHD	-5.9***	-16.3
PETROD	-2.3***	-9.5
AVD	2.7***	20.6
MARD	4.5***	26.7
RAILD	2.3***	16.5
AUTOD	-5.8***	-12.5
COMPOUND ERROR		
VIT		
CONSTANT	-1.6***	-18.4
UIT		
LN(CO)	-2.4**	-2.2
CONSTANT	13.1**	2.1
σ_v	.46	

Table 4.1: SFA model results[1]

*Note: 10% *, 5%**, 1%***; Statistical significance*

The variables that are not in logarithmic forms, such as the time trend (t) and all the dummy variables used, will be interpreted. Firstly, there are two dummy variables that were not statistically significant: beer and cement dummies. Therefore, the coefficient reported is not relevant. The rest of the dummy variables were statistically significant, with 99% confidence. This implies that the sector selected in the dummy is relevant and will affect the demand for energy in the model proposed. In total, six of the dummy variables have a negative coefficient and seven have a positive one. A negative coefficient is expected for the variables. However,

[1] The Z-Value is a statistical measurement calculated as $z = (x - \mu) / \sigma$;where x is an observation, μ is the sample mean and σ is the standard deviation. This value is reported in every statistical programme, in this case Stata, and it was used to determine the significant levels of the parameters estimated.

since the model used 15 dummy variables, the results are not necessarily in line with this rule. Also, the variables related to the sectors that have the biggest GDP and energy consumption have a negative coefficient, which mean that energy conservation is stronger than in other sectors (Lin & Long, 2015). In conclusion, this interpretation will be discussed later in this chapter.

4.1.1 Efficiency levels

Following our methodology and by using the results given by the Stata programme, the efficiency levels were estimated according to equation 6. The results reported in this section are the overall results of the transport and industrial sectors. Firstly, the descriptive statistics of the efficiency levels will be reported. Secondly, the yearly average and finally, the efficiency levels average by sector will be reported, ranked, and compared with the energy intensity indicator. Further discussion will be provided in this section.

Table 4.2 provides the descriptive statistics for the overall energy efficiency estimated in the industrial and transport sectors of Mexico. The results obtained from the econometric estimation shows a degree of variation between the minimum and maximum value reported. This could be linked to the efficiency of a specific sector. In that case, in the model there is an almost efficient sector and a sector that needs to improve a lot.

STATISTIC	ENERGY EFFICIENCY
MIN	0.2
MAX	1.0
AVERAGE	0.9
STD DEV	0.2

Table 4.2: Efficiency descriptive statistics

The efficiency levels are reported in Figure 7. In this case, the results are reported by year and are divided as the whole model, transport, and industrial sector averages. An initial observation is that the transport sector in Mexico is more efficient than the industrial sector because the level of efficiency is closer to 1 in almost every year analysed. Also, the industrial

sector seems to be more volatile due to the change in efficiency over the years. Both sectors could have been affected by the global economic crisis in 2008.

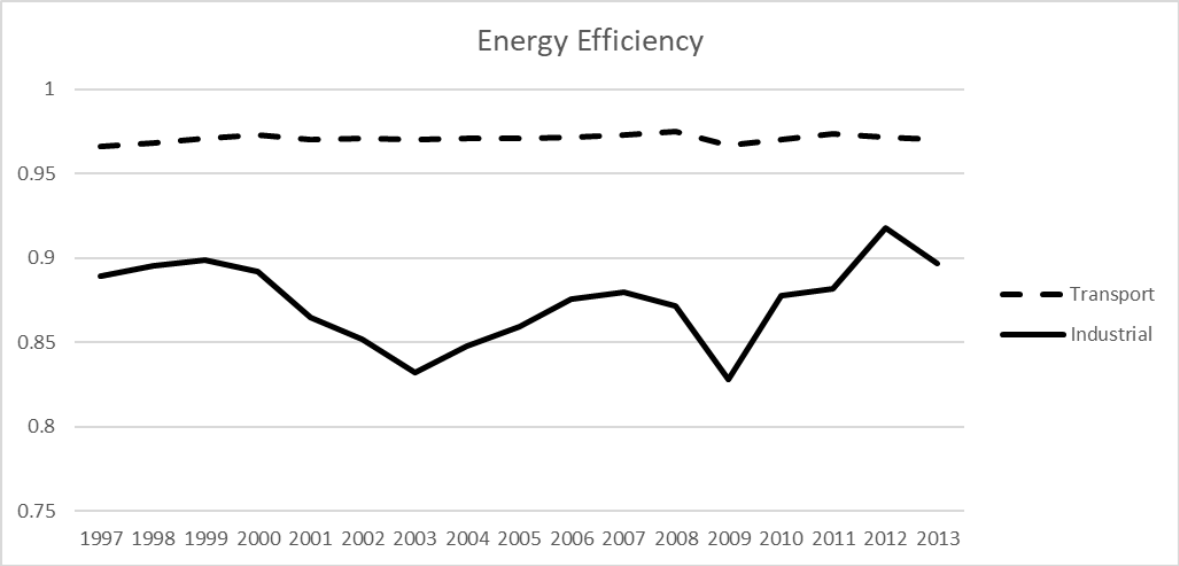

Figure 7: Energy efficiency results

Moreover, the efficiency levels by sector are reported in Table 4.3. The table shows the average levels of each sector studied and the energy intensity as well. In addition, the results of both, for every sector, were ranked in order to make a comparison. According to the data analysed and the results of the SFA model, the transport sector is more efficient on average than the industrial sector. Whereas the automobile sector is the most efficient and the vehicle manufacturing sector is the least efficient.

Energy efficiency is expected to be negative correlated with the energy intensity indicator because an increase in the energy intensity decreases with an increase in energy efficiency (Filippini & Orea Sánchez, 2014). In this case, the correlation was -.3, corroborating the assumption that there is a negative relation between those indicators.

SECTOR	ENERGY EFFICIENCY	RANK	ENERGY INTENSITY	RANK
SUGAR	0.95	11	2.3	8
TABACO	0.96	6	0.04	17
BEER AND MALT	0.96	7	0.7	12
WATER AND NON-ALCOHOLIC BEVERAGES	0.96	8	0.2	15
PAPER	0.96	10	3.4	4
RUBBER	0.75	14	0.9	11
FERTILIZERS	0.75	15	0.4	13
CEMENT	1	3	3.0	6
VEHICLES	0.50	17	0.1	16
GLASS	0.71	16	2.6	7
IRON AND STEEL	0.97	5	3.5	3
PETROCHEMICAL	0.94	12	1.2	10
AVIATION	0.98	4	6.1	1

MARITIME	0.96	9	4.1	2
RAILWAY	0.94	13	1.8	9
CHEMICAL	1	2	0.4	14
AUTOMOBILE	1	1	3.3	5

Table 4.3: Energy efficiency and intensity levels

4.2 Data Envelopment Analysis (DEA)

In this section, the result of the DEA methodology is presented. The results reported are the Malmquist Index, efficiency, and technical changes.

To better understand the results reported in this section, it is important to remember equation 7 and have its components in mind. Also, the solution and estimation of this were made possible by the R Studio programme and an instruction guide for carrying out this analysis (Coll-Serrano et al., 2018). This has already been explained in the methodology chapter.

4.2.1 Transport sector

Table 3.7 shows the variables used for this sector, based on the work of Rammanathan (2000) and Makridou et al (2016), after solving the model in R Studio. Results are reported in Figures 8-11, where the Malmquist Index is reported for four sectors. Also, the average over time is reported for the whole transport sector in every figure. It is important to emphasise that this analysis was affected for other variables explained in the methodology chapter.

According to the results, the efficiency, scale, and productivity changes were 1, which means that the part of equation 3.6 related to the efficiency change stays equal over time. Therefore, there was not a change in the efficiency, scale, and productivity levels in the transport sector.

However, this does not mean that a specific sector is inefficient; simply that since 1997 there has not been a significant change in the transport sector.

Figure 8 shows the information related to the automobile sector. The graph shows the tendency towards a steady level of efficiency. The average of the Malmquist Index in this sector is slightly over 1 (1.0009). Therefore, this means that this sector is on the frontier of efficiency according to the data used. Overall, this sector is the one that consumes more energy and produces GDP. Also, compared to the other sectors, this sector involves more movement of passengers and freight. Consequently, this implies that this sector is also the most polluted one in absolute terms. To conclude, the automobile sector is in the efficient frontier, but over the time analysed there was not a significant change in the efficiency levels.

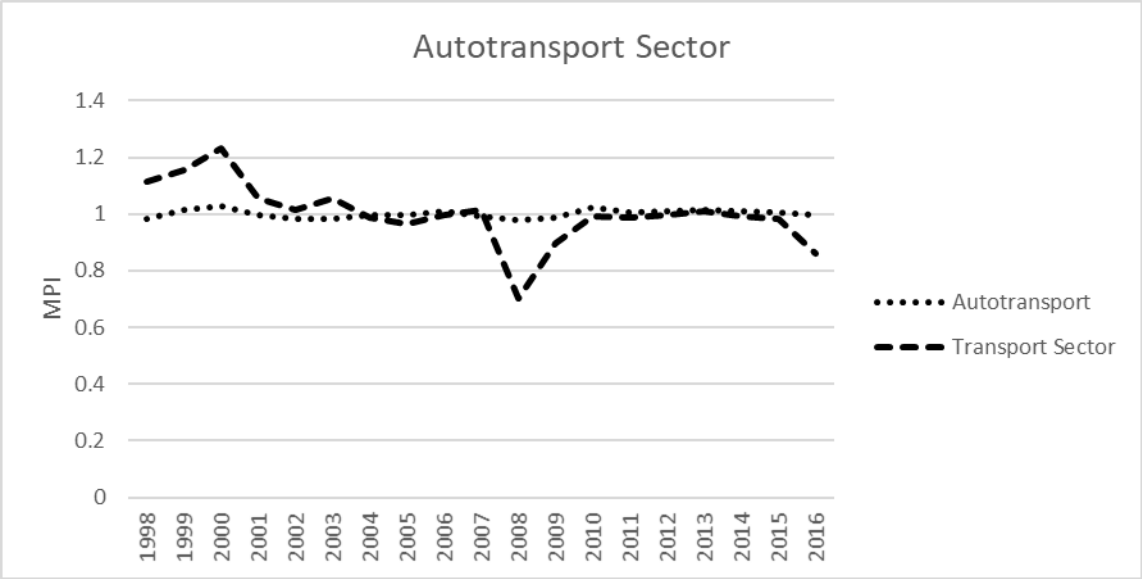

Figure 8: Energy efficiency DEA automobile sector

Figure 9 shows the Malmquist Index for the aviation sector. On average, this sector has a 0.9946 result in the Malmquist Index. This means that the aviation sector is below the efficiency frontier and the aviation sector shows a normal tendency between the years. Generally, making it above or close to its efficiency frontier. To conclude, the aviation sector is not in the efficient frontier and did not present a change in its efficiency levels.

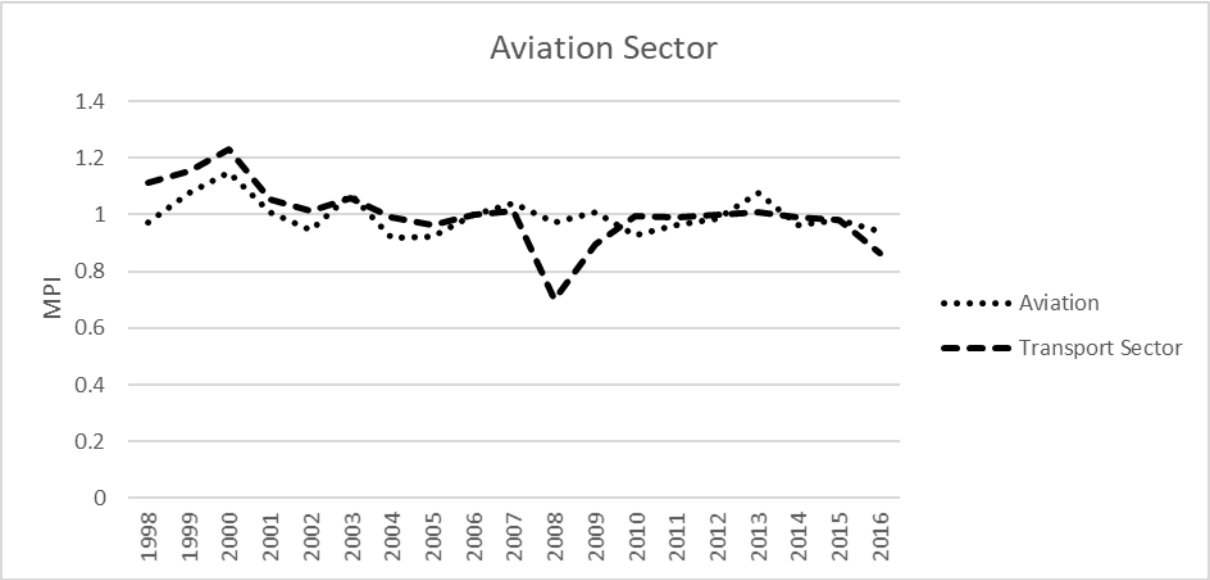

Figure 9: Energy efficiency DEA aviation sector

Figure 10 shows the results of the Malmquist Index for the maritime sector. Maritime sector efficiency was driven solely by technology and not by the improvement of efficiency. However, on average, this sector has an MPI of 0.985 which means that it is above the efficiency frontier. To conclude, the maritime sector is not in the efficient frontier and did not present a change in its efficiency levels.

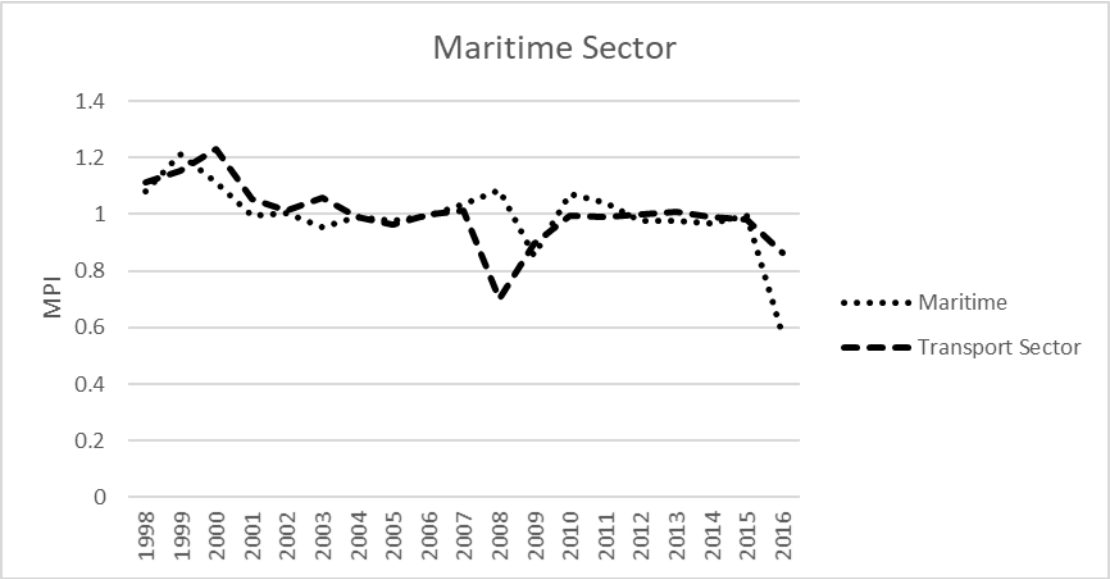

Figure 10: Energy efficiency DEA maritime sector

Figure 11 shows the results of the Malmquist Index for the railway sector. On average the MPI analysed over the years was 0.997 and did not achieve the efficiency frontier estimated. In 2008, a new railway line was established in Mexico (see Figure 5) which increased the number of passengers. Therefore, in 2008 a decrease in the efficiency levels was reported due the adjustment of the new passengers added to the analysis. To conclude, the railway sector is not in the efficient frontier and did not present a change in its efficiency levels.

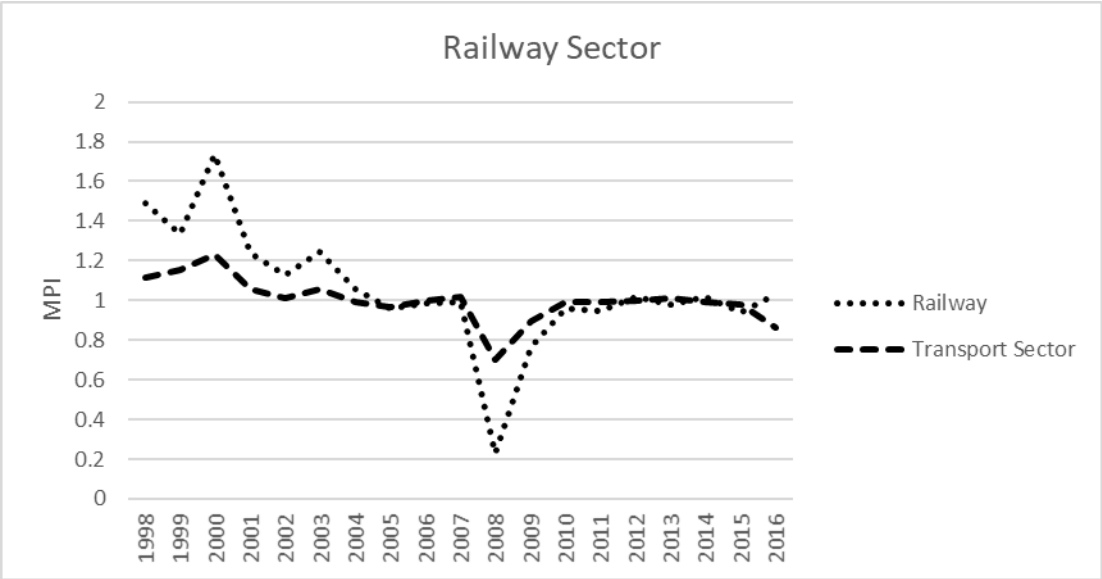

Figure 11: Energy efficiency DEA railway sector

To conclude, overall, the transport sector does not present an overall growth in efficiency. Plus, only the automobile sector is in the efficiency frontier estimated and the other sectors are close to achieving their efficiency levels and operating at their point of efficiency.

4.2.2 Industrial sector

Results are reported in Figure 12 and Table 4.4, where the average of the industrial sector is reported by year and sector division. The main difference between the industrial and transport sectors' results was that the industrial sector reported changes in its efficiency level.

Due to the panel nature of the data, the MPI was selected to estimate the efficiency levels, and the results are reported by year in Figure 12. Using 2003 as the base year, the results indicate the years where the whole industrial sector efficiency was above or below "progress". For those years where the score is bigger than 1, this indicates an improvement

in the sector or “progress”, whereas a score below 1 indicates the opposite; a decline in the efficiency and therefore no “progress”. Also, the score of the main components of MPI is reported. The efficiency and technical changes, which are negatively correlated in -0.86 and most of the improvements in the MPI are related to changes in the technology. There were four years, 2009, 2013-2015, where the MPI was below 1, which indicates a decrease in the efficiency compared to its level in 2003.

Figure 12: Energy efficiency DEA industrial sector

Table 4.4 shows the efficiency scores for each industrial sector studied by the averages over all the years analysed. In total, 10 of 13 sectors are operating beyond the optimal scale and according to the results, the sector related to beer and malt is the most efficient one. On the contrary, the highest inefficiencies reported are in the chemical, fertilizer, and tobacco sectors where the Malmquist Index reported is below 1. Therefore, those sectors are under its optimal scale of production.

Upon further examination of the scores shown in Table 6, this reveals that the other indicators that were obtained by using the R Studio programme were the efficiency and technical changes. Those changes are part of equation 7, representing each one as a component. For two sectors: the cement and tobacco industries, there was no change in the efficiency. Meanwhile, there were six sectors where, on average, there was no change in efficiency and five industries where there was an increase. It is based on the same logic as the MPI

interpretation, where in this case a score up to one represents an increase in efficiency and below one represents a decrease.

In addition, to obtain the results of the MPI, the technical change was estimated in R Studio. This is related to the component of equation 7 and the effects of technology in the sector studies where seven of the sectors improved their changes due to the technology and six did not.

SECTOR	Efficiency Change	Technical Change	MPI
Beer and Malt	1.04	1.08	1.12
Cement	1	1.02	1.02
Chemical	0.98	0.99	0.97
Fertilizers	1	0.96	0.96
Glass	1.04	0.99	1.03
Iron and Steel	0.95	1.08	1.03
Paper	1	1.04	1.04
Petrochemical	1	1.08	1.08
Rubber	1.02	0.99	1.01
Sugar	1.05	1.03	1.07
Tabaco	1	0.98	0.98
Vehicles	0.99	1.06	1.05
Water and non-alcoholic beverages	1.01	0.99	1

Table 4.4: Means by DMU industrial sector

4.3 Discussion

4.3.1 SFA discussion

In the results reported in the SFA, the independent variables related to price and income have responded in accordance with the economic theory and other studies. However, a disadvantage of the SFA model is that some of the estimated coefficients are not statistically significant at the 99%. Besides, the model works and can be used. For the transport sector, the expected results in the income and price elasticities are between 0.8 and -0.2 (Llorca et al., 2017; Llorca & Jamasb, 2017). According to the economic theory the income elasticity

should have a positive value due to the nature of the product studied, and the price elasticity a negative value. For income elasticity, the results denote that when the income increases, the demand for energy should also increase. Since the coefficient of the estimated elasticity is greater than one, this indicates that once the income increases, the demand for this type of product will increase more compared to other services and products. Whereas the value reported for the price elasticity has a negative value, which represents the negative slope of the demand curve. This means that an increase in the price should lower the demand for energy and a decrease in the price would have the opposite effect. However, the result of -.21 indicates that the price elasticity demand is relatively inelastic. Hence why, when the price of energy is raised or lowered, the demand for energy barely changes. In order to cause a big change, the income should be raised.

Furthermore, the results for the elasticities in the industrial sector should be between .1 to .5 but they differ according to the size of the sample and the level studied (Amjadi et al., 2018; Lin & Long, 2015; Lundgren et al., 2016; Lutz et al., 2017). Whereas studies specialised in the energy demand in Mexico reported elasticities from -0.1 to -0.4 for the price and 0.45 to 0.64 for the income (Galindo, 2005). Further research in this field should add more variables and provide more observations to find an accurate estimate for the energy demand in Mexico.

The use of time dummies is not new in this type of research, where the energy demand is estimated by SFA methodology. For example, Filippini and Hunt estimate the energy demand by using time dummies for the OECD countries (Filippini & Hunt, 2011), as well as for specific countries and for sectors such as the industrial and residential sectors, different types of dummies were used. An example of this is in the work of Lin and Long, where dummy variables were used to classify regions of China (Lin & Long, 2015). Other examples include the use of renewable technology or weather conditions (Filippini & Hunt, 2012; Lutz et al., 2017). However, in this study, it was necessary to use a dummy variable in nearly every sector. A combination and other types of variables were used to achieve significance in the inefficiency term and coherence with the expected results. In the end, the model reported in equation 3.4 was the only one that successfully achieved all the objectives necessary to estimate the energy demand and efficiency. Therefore, the model ended up being estimated in the way proposed.

Plenty of studies use a different function such as the translog, plus a different distribution for their SFA models. In this research, a Cobb-Douglas function was used because at the end, the results expected were in line with the economic theory and the other research results. Also, the half-normal distribution was used during this research. The results obtained by using a translog function and other statistical methods were not significant, had different results to those expected or did not report the existence of the inefficiency component in the model. To test this function and other distributions, an extension of this work could increase the number of observations and variables used.

Furthermore, the inefficiency was estimated for energy demand. For the model used, an independent variable was added to the inefficiency component. The variable chosen was the contamination measured in CO_2. Based on the literature for the industrial sector in Germany, some variables were linked to the use of renewable energy sources and energy expenditure (Lutz et al., 2017). Where, in the energy demand estimated the result was statistically significant and therefore, an inefficient component was identified in our model, and then the efficiency levels were calculated.

After running the model shown, the efficiency levels were presented for the transport and industrial sector, which is the main aim of this research. Thus, showing that the transport sector, in general, is more efficient than the industrial sector. After carrying out thorough research, there are no studies focusing on the Mexican transport and industrial sector efficiency levels in particular. However, there are studies for other countries in those sectors where Mexico is part of the dataset (Filippini & Hunt, 2011, 2015; Llorca et al., 2017). This section reported the efficiency levels estimated in the transport and industrial sectors and compared these with the energy intensity indicator. The results were shown by the average efficiency through years and the average by sectors.

4.3.2 DEA discussion

The estimation of energy efficiency by DEA used two types of functions. One was linked to the transport sector and the other to the industrial sector. The variables chosen for the transport sector were based on research on the Indian transport sector (Ramanathan, 2000). While industrial sector function and variables were taken from research that evaluates the

efficiency of the energy-intensive industries in European countries (Makridou et al., 2016). The difference between the DEA and SFA is that it was easier to simply use the variables that were used in other research because there was no need to do any statistical tests to get results. It was necessary to run the function in R Studio and use the package developed by Coll-Serrano (2018). Therefore, this section will discuss some variables which were explored in order to make a comparison between this research and other works.

Previously, each sector explained why the variables chosen were selected to estimate the energy efficiency, whereas the input variables are the same for both sectors. According to the results of this study, the transport sector was not influenced by the changes in their efficiency. While the industrial sector's Malmquist index was affected by changes in the technological and efficiency components. Normally, in the studies where these variables are calculated, both components change over the time studied (Makridou et al., 2016; P. Zhou et al., 2010). Therefore, the transport sector database could be improved in order to find a possible change due to the efficiency.

For the transport sector, the results obtained indicate that the transport sector in Mexico is partially efficient due to the Malmquist Index. According to the variables chosen for the input and output, the automobile sector was the only sector beyond the efficiency. While, the other three sectors studied were close to the efficiency frontier. A study on the Chinese transport sector, categorised by regions, concludes that the sector efficiency is highly influenced by the industrial activity and wealth of a region (Liu & Lin, 2018). Similarly, a study carried out in a province in Iran concludes that smaller provinces have better energy efficiency (Omrani et al., 2019). Finally, a study that compares India's road and rail sectors by using indicators such as passenger and freight movement concludes that the road sector decreases its efficiency levels in the Nineties, while the railway sector increases its efficiency levels (Ramanathan, 2000). Therefore, a different DEA approach or data sample could be studied to evaluate the energy efficiency in this sector.

The results obtained in the industrial sector, by using the Malmquist Index to estimate the energy efficiency, were diverse. Firstly, some sectors were operating beyond its efficiency frontier. Secondly, the index, in this case, was affected by the components of efficiency and technology. Thirdly, some research related to the industrial sector for specific countries

concluded that technological changes are primarily responsible for the improvements in efficiency (Makridou et al., 2016). While, studies regarding the carbon emissions in the Chinese industrial sector concluded that in Chinese regions, CO_2 decrease is linked to a technological decline (N. Zhang, Zhou, & Kung, 2015). In addition, a study focused on the energy efficiency and productivity in the Jordanian industrial sector identified that CO_2 emissions had a negative effect on efficiency and on productivity growth (Al-Refaie et al., 2016). In conclusion, the results reported for the Mexican industrial sector show that technological changes affected the efficiency in this sector. Further tests and research are needed to achieve the aim of creating a policy that is useful in increasing the energy efficiency levels in these Mexican industries.

In conclusion, this section reported the results of the methodologies selected to estimate the energy efficiency in the transport and industrial sectors. Also, the results were compared and contrasted in detail, together with relevant research in the field. According to the research carried out, the issue and field of study is unique. However, some improvements could be made in order for this analysis to be linked to an increase in the number of observations in the database and to add other methodologies to the analysis. It is necessary to carry out further research in this field in order to have another point of reference. These issues are going to be developed upon in the final chapter of this work, where future research is proposed.

CHAPTER 5: CONCLUSIONS AND FUTURE WORK

5.1 General conclusions

This research showed the efficiency levels of the Mexican transport and industrial sectors. To establish these levels, two types of approaches were implemented. The first is a parametric approach called Stochastic Frontier Analysis (SFA) and the second is a non-parametric approach named Data Envelopment Analysis (DEA). Both analyses are currently popular in estimating the energy efficiency in the energy economics field. Table 5.1 summarised the most important results drawn from this research where the reference tables are mentioned so as to highlight the results.

METHOD	INDUSTRIAL	TRANSPORT
SFA	**Most efficient:** Chemical industry	**Most efficient:** Automobile sector
	Price elasticity: -0.2	**Same**
	Income elasticity: 3.4	Same
	Reference: See Tables 4.1 and 4.3	**Reference:** See Tables 4.1 and 4.3
DEA	**Most efficient:** 10 of the 13 sectors	**Most efficient:** Automobile sector
	In**efficient Sectors:** Tobacco, chemical and fertilizers	In**efficient Sectors:** Aviation, railway and maritime
	Reference: See Figure 12 and Table 4.4.	**Reference:** See Figures 8-11.

Table 5.1: Summary table

From the SFA results, the conclusions made are that most of the sectors seems to be efficient. A comparison between the transport and industrial sector showed that the industrial sector is less efficient. However, this sector has more categories and the available data came from governmental polls. In addition, the results related to the energy demand were normal from the price elasticity and a bit higher for the income. The results obtained were expected according to the economic theory and the coefficient were statistically significant with at least 10%. Moreover, the energy efficiency level was estimated and compered with the energy intensity. The results show a negative correlation between these concepts, as expected, and rank which of the 17 sectors is more efficient.

According to the DEA results, the conclusions are that most of the sectors are in their efficient frontier according to the data used. The automobile sector was the only sector which reached the efficient frontier, while the other sectors were close to it. In addition, the results for the industrial sector indicate that 10 of 13 sectors analysed were efficient. From these results, it is possible that the policy makers focus their attention on the inefficient sectors. As in the SFA methodology, the DEA also used the CO_2 emission as an output; future works and policies should study how this variable affects the energy efficiency in more depth.

Finally, in both methodologies used, our results successfully showed the energy efficiency levels. However, there are lot of improvements that can be made before initiating any policy implications. Evidence has been presented indicating that in general, the transport sector is more efficient than the industrial sector. Also, it seems that both sectors are almost efficient in most of the cases, according to their levels of production.

Nevertheless, as this research was carried out as part of a master's degree, a lot of work could be done to improve the results and analysis. However, after examining the current literature and research, this research could be the first to investigate the energy efficiency in the most relevant sectors in Mexico. In the following sections of the conclusion, the scope and limitations will be explored, in order to highlight the future work recommended for this research.

5.2 Scopes and limitations

This thesis studies the energy efficiency of the industrial and transport sectors in Mexico. The research is focused on studying the performance of these sectors by using parametric and non-parametric methodologies. The study could be the first of its kind to study Mexican energy efficiency in the sectors selected. However, due to the time constraint of this research and the lack of some information, this research could be improved upon. Therefore, this section specifies the limitations and the next section specifies what can be done to improve this research.

As mentioned throughout this research, this work use techniques to estimate the energy efficiency in the aforementioned sectors. The first technique is a parametric measure, SFA, which uses econometrical and time series models. The second is a no-parametrical measure referred to as DEA. Both techniques are popular in the field and estimate a frontier, which represents where the efficient points are in a specific sector. However, defining which method is the most appropriate to estimate the energy efficiency is not part of the scope of this research. Therefore, this work focussed on the use of both techniques to obtain a result that could be useful for policy makers and to initiate related research in the case study selected.

Furthermore, the possibility to carry out further research for each methodology is huge. For example, if this thesis were focused solely on SFA, other types of functions and statistical distribution could be applied; this is also covered in the following section. However, to do so, more data and newer versions of statistical programmes are required. Therefore, many features of the literature consulted regarding energy efficiency are useful, but not everything could be addressed due to the time constraint.

Thus, this work had three main objectives to estimate the energy efficiency and these are going to be explained. The first was to explain and use the main methodologies to estimate the energy efficiency. The second was to use those techniques for the sectors that consumed the most energy in Mexico. The third aim was to scope what can be relevant for the creation or improvement of energy policies. Moreover, there are still a lot of improvements which can be made to achieve our objectives. However, this research presented an initial estimation and can be developed as part of doctoral research.

5.3 Future works

After analysing the current research, this research presented an initial approach to estimating the energy efficiency levels in the transport and industrial sectors in Mexico. However, due to the time constraints of this research and the data available, this study cannot be developed fully. There are still a lot of approaches which can be explored to improve this research. The best suggestion could be to apply one of the methodologies, develop it for the case study, and increase the number of observations. Each suggestion for every methodology will be discussed in this final section where all the details are assessed.

The first methodology described and used in this research was the Stochastic Frontier Analysis (SFA). There are a lot of improvements that could be carried out with regards to this; mainly improvements in relation to the use of different functions and statistical distributions. To do so, it is necessary to carry out more observations and use more variables. Therefore, a lot of time would be needed to use any of the suggestions mentioned. However, the attempt and the model proposed could be the first of its kind to stimulate similar studies for a Mexican case study.

With regards to the DEA, some improvements could be made to the methodology used. Firstly, if a Malmquist Index is used, then the analysis should be complemented with an econometric model. By doing so, the estimation of the energy demand could be carried out, as well as the energy efficiency in a non-parametric way, as mentioned in relevant literature. Secondly, different types of approaches could be implemented by using different outputs, statistical programmes, and datasets. In addition, other sectors and types of DEA can be used for this type of research. Therefore, this approach to energy efficiency can be useful, as well as for estimating the energy demand.

In conclusion, this research was carried out as part of a master's degree and therefore, the time and resources to pursue all the objectives proposed were limited. However, this research could initiate or be developed into a doctoral research proposal, where SFA and DEA methodologies could be explored in their different variants and with more data. In addition, a different sector or type of analysis could be carried out. For example, analysis of the Mexican states or even more specific research. Moreover, the link between the energy

efficiency and the policies needs to be explored in more depth as well, in order to find a practical application for this research.

REFERENCES:

1. Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of econometrics, 6*(1), 21-37.
2. Al-Refaie, A., Hammad, M., & Li, M.-H. (2016). DEA window analysis and Malmquist index to assess energy efficiency and productivity in Jordanian industrial sector. *Energy Efficiency, 9*(6), 1299-1313.
3. Amjadi, G., Lundgren, T., & Persson, L. (2018). The rebound effect in Swedish heavy industry. *Energy Economics, 71*, 140-148.
4. Bauer, M., Mar, E., & Elizalde, A. (2003). Transport and energy demand in Mexico: the personal income shock. *Energy Policy, 31*(14), 1475-1480.
5. Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic frontier analysis using Stata. *The Stata Journal, 13*(4), 719-758.
6. Berndt, E. R., & Botero, G. (1985). Energy demand in the transportation sector of Mexico. *Journal of Development Economics, 17*(3), 219-238.
7. 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.
8. Coll-Serrano, V., Benitez, R., & Bolos, V. (2018). Data Evelopment Analysis with deaR. *1*(Universidad de Valencia), 50.
9. Cui, Q., & Li, Y. (2014). The evaluation of transportation energy efficiency: An application of three-stage virtual frontier DEA. *Transportation Research Part D: Transport and Environment, 29*, 1-11.
10. Filippini, M., & Hunt, L. C. (2011). Energy demand and energy efficiency in the OECD countries: a stochastic demand frontier approach. *The Energy Journal*, 59-80.
11. Filippini, M., & Hunt, L. C. (2012). US residential energy demand and energy efficiency: A stochastic demand frontier approach. *Energy Economics, 34*(5), 1484-1491.
12. Filippini, M., & Hunt, L. C. (2015). Measurement of energy efficiency based on economic foundations. *Energy Economics, 52*, S5-S16.
13. Filippini, M., & Hunt, L. C. (2016). Measuring persistent and transient energy efficiency in the US. *Energy Efficiency, 9*(3), 663-675.
14. Filippini, M., Hunt, L. C., & Zorić, J. (2014). Impact of energy policy instruments on the estimated level of underlying energy efficiency in the EU residential sector. *Energy Policy, 69*, 73-81.
15. Filippini, M., & Orea Sánchez, L. (2014). Applications of the stochastic frontier approach in the analysis of energy issues. *Economics and Business Letters, 3, n. 1*.
16. Filippini, M., & Zhang, L. (2016). Estimation of the energy efficiency in Chinese provinces. *Energy Efficiency, 9*(6), 1315-1328.
17. Galindo, L. M. (2005). Short-and long-run demand for energy in Mexico: a cointegration approach. *Energy Policy, 33*(9), 1179-1185.
18. Hokkanen, T. (2014). Estimating technical efficiency in Finnish industry: A stochastic frontier approach.
19. IMT. (2000). *Manual de Estadísticas en el Sector Transporte*.

20. IMT. (2004). *Manual de Estadísticas en el Sector Transporte*.
21. IMT. (2005). *Manual de Estadísticas en el Sector Transporte*.
22. IMT. (2009). *Manual de Estadísticas en el Sector Transporte*.
23. IMT. (2015). *Manual de Estadísticas en el Sector Transporte*.
24. IMT. (2017). *Manual de Estadísticas en el Sector Transporte*.
25. INEGI. (2007). Síntesis metodológica de la Encuesta Anual de la Industria Manufacturera
26. INEGI. (2018). Banco de Informacion Economica. Retrieved Octobe 2018, from INEGI https://www.inegi.org.mx/sistemas/bie
27. INEGyCEI. (2018). Inventario Nacional de Emisiones de Gases y Compuestos de Efecto Invernadero. Retrieved from https://www.gob.mx/inecc/acciones-y-programas/inventario-nacional-de-emisiones-de-gases-y-compuestos-de-efecto-invernadero
28. Kokkinou, A. (2012). *An industry and country analysis of Technical Efficiency in the European Union, 1980-2005.* University of Glasgow,
29. Lin, B., & Long, H. (2015). A stochastic frontier analysis of energy efficiency of China's chemical industry. *Journal of Cleaner Production, 87*, 235-244.
30. Liu, W., & Lin, B. (2018). Analysis of energy efficiency and its influencing factors in China's transport sector. *Journal of Cleaner Production, 170*, 674-682.
31. Llorca, M., Baños, J., Somoza, J., & Arbués, P. (2017). A stochastic frontier analysis approach for estimating energy demand and efficiency in the transport sector of Latin America and the Caribbean. *Energy Journal, 38*(5).
32. Llorca, M., & Jamasb, T. (2017). Energy efficiency and rebound effect in European road freight transport. *Transportation Research Part A: Policy and Practice, 101*, 98-110.
33. Lundgren, T., Marklund, P.-O., & Zhang, S. (2016). Industrial energy demand and energy efficiency–Evidence from Sweden. *Resource and Energy Economics, 43*, 130-152.
34. Lutz, B. J., Massier, P., Sommerfeld, K., & Löschel, A. (2017). Drivers of energy efficiency in German manufacturing: A firm-level stochastic frontier analysis. *ZEW-Centre for European Economic Research Discussion Paper*(17-68).
35. Makridou, G., Andriosopoulos, K., Doumpos, M., & Zopounidis, C. (2016). Measuring the efficiency of energy-intensive industries across European countries. *Energy Policy, 88*, 573-583.
36. Marroquín Arreola, J., Neme Castillo, O., & Valderrama Santibáñez, A. (2015). Producción Manufacturera, Consumo De Energía Y Empleo En México: Un Análisis Por Clases Manufactureras (Manufacturing Production, Consumption Energy and Employment in Mexico: An Analysis by Class Manufacturing). *Cuadernos de Economía, 34*(65), 377-400.
37. Martínez-Damiàn, M., Brambila-Paz, J., & García-Mata, R. (2013). Malmquist index and state productivity in México. *Agricultura, Sociedad y Desarrollo, 10*(3), 359-369.
38. Omrani, H., Shafaat, K., & Alizadeh, A. (2019). Integrated data envelopment analysis and cooperative game for evaluating energy efficiency of transportation sector: a case of Iran. *Annals of Operations Research, 274*(1-2), 471-499.

39. Orea, L., Llorca, M., & Filippini, M. (2015). A new approach to measuring the rebound effect associated to energy efficiency improvements: An application to the US residential energy demand. *Energy Economics, 49*, 599-609.
40. Patterson, M. G. (1996). What is energy efficiency?: Concepts, indicators and methodological issues. *Energy Policy, 24*(5), 377-390.
41. Ramanathan, R. (2000). A holistic approach to compare energy efficiencies of different transport modes. *Energy Policy, 28*(11), 743-747.
42. Schuschny, A. R. (2007). *El método DEA y su aplicación al estudio del sector energético y las emisiones de* CO_2 *en América Latina y el Caribe*: CEPAL.
43. SENER. (2017). Estadisticas Energeticas Nacionales. Retrieved from http://sie.energia.gob.mx/bdiController.do?action=temas
44. Series, D. E. C. (1995). Measuring Energy Efficiency in the United States' Economy: A Beginning. *US DOE, Energy Information Administration*.
45. Weyman-Jones, T., Boucinha, J. M., & Inácio, C. F. (2015). Measuring electric energy efficiency in Portuguese households: a tool for energy policy. *Management of Environmental Quality: An International Journal, 26*(3), 407-422.
46. Wu, A.-H., Cao, Y.-Y., & Liu, B. (2014). Energy efficiency evaluation for regions in China: an application of DEA and Malmquist indices. *Energy Efficiency, 7*(3), 429-439.
47. Zhang, M. (2012). *The comparison of stochastic frontier analysis with panel data models.* © Miao Zhang,
48. Zhang, N., Zhou, P., & Kung, C.-C. (2015). Total-factor carbon emission performance of the Chinese transportation industry: A bootstrapped non-radial Malmquist index analysis. *Renewable and Sustainable Energy Reviews, 41*, 584-593.
49. Zhang, S. (2016). *Energy Efficiency and Firm Performance: Evidence from Swedish Industry*: Department of Forest Economics, Swedish University of Agricultural Sciences.
50. Zhang, X.-P., Cheng, X.-M., Yuan, J.-H., & Gao, X.-J. (2011). Total-factor energy efficiency in developing countries. *Energy Policy, 39*(2), 644-650.
51. Zheng, W. (2015). *Efficiency measurement. A methodological comparison of parametric and non-parametric approaches.* University of Bradford,
52. Zhou, G., Chung, W., & Zhang, Y. (2014). Measuring energy efficiency performance of China's transport sector: A data envelopment analysis approach. *Expert Systems with Applications, 41*(2), 709-722.
53. Zhou, P., Ang, B., & Han, J. (2010). Total factor carbon emission performance: a Malmquist index analysis. *Energy Economics, 32*(1), 194-201.
54. Zhou, P., Ang, B. W., & Zhou, D. (2012). Measuring economy-wide energy efficiency performance: a parametric frontier approach. *Applied Energy, 90*(1), 196-200.