Measuring Organizational Culture Using Natural Language Processing and Its Applications in Finance

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Abstract

Organizational culture is a comprehensive concept, encompassing both implicit and explicit contracts to govern internal behavior within organizations. Diagnosing cultural types and understanding evolving cultural preferences is crucial for organizations to guide their operations more efficiently. External investors are also interested in cultural information to make better judgments. This thesis includes three studies that leverage innovative methodologies and empirical analyses to provide new insights into the measurement of organizational culture and its practical applications in corporate management and risk management.

The first study introduces a novel methodology for quantifying organizational culture using text-based analysis of 10-K filings. By employing a bag-of-words approach derived from the Organizational Culture Assessment Instrument (OCAI) scale, this study offers a new way for both internal and external stakeholders to identify critical cultural information from publicly disclosed documents. Unlike previous studies that rely extensively on surveys or financial indicators, this method utilizes big data tools to analyze archival data, enabling large-scale, longitudinal analyses. The construct validity of the organizational culture measures is empirically established, contributing to the literature by developing an accessible and reliable measure of organizational culture, which allows for conducting large-scale longitudinal analyses of its antecedents and consequences. Furthermore, this study applies the methodology to analyze cultural shifts during the COVID-19 pandemic, providing insights into how organizations adapt their cultures in response to significant external shocks.

The second study investigates the impact of bank competition culture on earnings management activity. By implementing the methodology proposed in first study, this study quantifies bank competition culture. I find the empirical evidence indicating that banks with higher levels of competition culture tend to have a higher probability to meet and/or beat analysts' forecasts and have reduced tendencies in manipulating earnings through discretionary loan loss provision activity. Additionally, this study presents evidence of a negative relationship between the propensity to meet and/or beat analysts' forecasts and discretionary loan loss provisioning, specifically within banks characterized by a strong competition culture. The results indicate that the presence of a competition culture

within banks leads to a decrease in discretionary loan loss provisioning, which in turn increases the likelihood of meeting/beating analysts' forecasts. The findings of this chapter have important policy implications as they signal that the competition culture can affect accounting choices, information environments, and economic outcomes in banks.

The third study explores the intricate relationship between internal-focused organizational culture, specifically collaborate and control culture, and their impacts on cybersecurity outcomes. Utilizing a firm-level cyber risk measurement derived from 10-K filings and data breach dataset from the Privacy Rights Clearinghouse, the study investigates how these cultures influence the incidence and management of cyber risks and data breaches. Empirical results indicate that control culture significantly enhances cyber risk management across various organizational sizes due to their structured compliance and risk mitigation approaches. In contrast, the effectiveness of collaborate culture varies, showing benefits in relatively smaller (employees less than 10,000) organizations but potential vulnerabilities in more extensive settings. The study provides new insights into the strategic alignment between corporate culture and cybersecurity management, offering valuable implications for both theory and practice.

Overall, this thesis contributes to the literature by providing a novel methodology for measuring organizational culture, empirically demonstrating its impact on critical business outcomes, and offering practical insights for enhancing organizational effectiveness and resilience in the domains of corporate management and risk management.

Declaration

I, Wenrui Zhang, hereby declare that this is entirely my own work unless referenced to the contrary in the text. No part of this thesis has previously been submitted elsewhere for any other degree or qualification in this or any other institution.

Statement of Copyright

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1 Introduction

1.1 Background and Motivation

Organizational culture is a crucial element that shapes internal behaviors and influences both organizational performance and external perceptions.. It represents a complex system of implicit norms, explicit contracts, values, and shared expectations that shape how organizations operate and adapt to changing environments. While the theoretical importance of organizational culture has been firmly established, its measurement and practical applications remain challenging. Existing literature underscores that cultural attributes significantly influence organizational performance, innovation, employee satisfaction, and risk management. Despite this, traditional methods for assessing organizational culture have notable limitations.

The Competing Values Framework (CVF), developed by Quinn and Rohrbaugh (1983), categorizes organizational culture into four dimensions: Clan (Collaborate), Adhocracy (Create), Market (Compete), and Hierarchy (Control). This widely accepted framework captures key cultural archetypes along two dimensions: flexibility versus stability and internal versus external focus. Building on CVF, Cameron and Quinn’s (2011) Organizational Culture Assessment Instrument (OCAI) provide a diagnostic tool for identifying cultural orientations through employee surveys. However, surveys are resource-intensive, limited in scope, and inaccessible to external stakeholders, such as investors or policymakers.

Traditional approaches to measuring organizational culture, including surveys and financial metrics, are inherently constrained (Kirca et al., 2005; Graham et al., 2022). Surveys rely on employee participation, which can introduce bias and typically provide only static, point-in-time assessments. Financial indicators, on the other hand, fail to capture the nuanced and evolving nature of cultural dynamics. Furthermore, these methods often overlook the accessibility needs of external stakeholders who seek to understand cultural influences on organizational behavior.

Advancements in natural language processing (NLP) offer a transformative opportunity to overcome these limitations. By analyzing archival data such as 10-K filings, it becomes possible to measure organizational culture objectively, at scale, and over time. Leveraging the CVF and OCAI constructs, this thesis introduces a text-based methodology that utilizes a bag-of-words approach to quantify cultural attributes. This method not only enhances accessibility but also enables longitudinal analysis of cultural evolution, offering fresh insights for both internal and external stakeholders. This research is organized into three studies that explore the measurement and implications of organizational culture, each addressing a distinct research question:

The first study focuses on developing a novel methodology to measure organizational culture using text-based analysis of 10-K filings over the period 1994–2021. While surveys and financial metrics have traditionally been used to capture cultural attributes, these approaches are constrained by accessibility, bias, and limited scope. This study seeks to fill these gaps by employing a bag-of-words approach derived from CVF and OCAI to create a scalable and objective cultural measurement framework. The key question guiding this research is: *How can organizational culture be quantified using text-based analysis, and what validity measures ensure the robustness of this new approach?*

Building on the methodology developed in the first study, the second study investigates how cultural dynamics influence financial decision-making within the banking sector from 1994 to 2018. Banks play a critical role in the global economy, and their stability and transparency are essential for maintaining market confidence. This study examines how competition culture impacts key financial outcomes, such as the likelihood of meeting or exceeding analysts' earnings forecasts and the use of discretionary loan loss provisions. By doing so, it aims to uncover the broader implications of cultural attributes for financial reporting and regulatory practices. The research is guided by the following question: *How does competition culture within banks influence key financial decisions, such as meeting earnings forecasts and managing loan loss provisions?*

The third study extends the application of the text-based methodology to the domain of cybersecurity, focusing on the period 2007–2018. As organizations face increasingly complex cyber threats, understanding the role of organizational culture in managing such risks becomes imperative. This study explores how internal-focused cultural attributes, particularly collaborate and control cultures, affect cybersecurity outcomes, including the incidence and management of data breaches. It also examines whether these cultural dimensions enhance organizational resilience in mitigating cyber risks. The guiding question for this research is: *How do internal-focused organizational cultures (collaborate and control) impact cybersecurity risk management and the occurrence of data breaches?*

Together, these three studies aim to contribute to the understanding of organizational culture by addressing theoretical, methodological, and practical challenges. They provide a comprehensive framework for measuring cultural dynamics, analyzing their impact across industries, and informing both academic inquiry and managerial practice. Future research can build upon this methodology to explore additional dimensions of organizational culture, examine its impact across different industries and regions, and integrate cultural measures with other organizational metrics.

1.2 Contributions of This Thesis

This thesis contributes to the understanding of organizational culture by addressing both methodological and philosophical dimensions, offering novel insights into its measurement, implications, and broader significance. The contributions extend beyond the development of tools and techniques to engage with fundamental questions about the nature and role of culture in organizations.

First, this thesis provides a methodological innovation by introducing a text-based framework for quantifying organizational culture. This framework leverages natural language processing (NLP) and archival data, enabling a longitudinal and scalable analysis of culture across industries. By grounding the methodology in the Competing Values Framework (CVF) and Organizational Culture Assessment Instrument (OCAI), the research bridges the gap between qualitative cultural insights and quantitative analytical tools. This contribution is particularly significant for advancing the accessibility and reliability of cultural measurement in both academic and practical contexts.

Beyond methodology, the thesis makes a philosophical contribution by reframing organizational culture as a dynamic and evolving construct rather than a static attribute. By exploring culture in the context of financial decision-making, cybersecurity risks, and organizational resilience, the research underscores its pervasive influence on corporate behavior and strategy. This perspective challenges conventional approaches that often treat culture as an ancillary factor, emphasizing instead its centrality to organizational adaptability and long-term sustainability.

The thesis also contributes to the theoretical understanding of culture's interaction with external shocks, such as economic crises and cyber threats. By analyzing how organizations with varying cultural orientations respond to these challenges, the research sheds light on the mechanisms through which culture shapes resilience and performance.

These insights have broader implications for theories of organizational change and stability, as they highlight the interplay between internal values and external pressures.

Practically, the findings inform policymakers, investors, and organizational leaders about the strategic importance of culture in navigating uncertainty and achieving sustainable growth. Whether through promoting transparency in financial reporting or enhancing cybersecurity practices, the research demonstrates how aligning cultural strategies with organizational objectives can yield significant benefits. By combining methodological rigor with philosophical inquiry, this thesis not only advances the study of organizational culture but also enriches broader debates on how organizations adapt, innovate, and thrive in complex environments.

1.3 Structure of This Thesis

This thesis is structured as follows. Chapter 2 reviews the existing literature on organizational culture. The first study, presented in Chapter 3, presents the methodology for quantifying organizational culture using text-based analysis. It details the development of the OCAI-based bag-of-words approach and validates the construct through various tests. The second empirical study presented in Chapter 4 applies the culture measurement methodology to the banking sector, investigating the relationship between competition culture and earnings management activities, specifically the probability of meeting and/or beating analysts' forecasts and discretionary loan loss provisioning. The third empirical study, presented in Chapter 5, explores how organizational culture impacts cybersecurity outcomes, utilizing data on cyber risks and data breaches to examine the effectiveness of collaborate and control cultures in mitigating these risks. The final chapter, Chapter 6, summarizes the key findings of the thesis, discusses their implications for theory and practice, and suggests directions for future research. It emphasizes the contributions of the thesis to the literature on organizational culture and its practical applications in management and risk mitigation.

2 Literature Review on Organizational Culture

2.1 Organizational Culture

The current literature has its roots in the early 1980, since then, a number of scholars[1] have established integrative frameworks of organizational culture. Deal and Kennedy (1983) point out that the difference between a successful enterprise and a less successful one is that the former has clear and common norms and values in organizational operation. Kotter and Heskett (2008) further explore the importance of adaptability and the fit between an organization and its environment; Fey and Denison (2003) demonstrate that culture influences human behaviour and thinking, so it is significant to comprehend the culture in an organization; whereas Grieves (2000) underlines that organizational development can accelerate humanistic values.

Since culture is an intricate phenomenon, ranging from latent beliefs and assumptions to visible structures and practices, some researchers question whether culture can be measured on a comparable basis or not. Scholars aim to measure the relative contribution of variables constituting organizational culture to performance levels (Sheridan,1992), to provide managers with information to evaluate key organizational processes and design strategies, and ultimately to improve overall effectiveness. According to Andrew (1998), organizational culture is a catalyst to enhance corporate performance. Edgar et al.(2017) demonstrate that culture can influence employee motivation, morale, productivity, efficiency, workmanship, innovation, creativity and the attitude of employees in the workplace. On the other hand, organizational culture has an indirect impact on employee behaviour through the use of reasonable management tools. Managers could use procedures and common values to

[1] A non-exhaustive list of studies includes Allaire and Firsirotu (1984), Ott (1989), Schein (1990), Hatch (1993), Denison and Mishra (1995) and Fey and Denison (2003).

control and guide employee behaviour. Similarly, Don et al. (2001) add that organizational culture has the potential to improve organizational performance, personal satisfaction and problem-solving. Thus, it is important for managers and outside investors to understand more about a target company’s culture to judge whether its current culture reacts actively to its current business cycle and whether there is a culture gap between the target company and its industrial benchmark.

2.2 Competing Value Framework

The importance of organizational culture and its potential impact on organizational performance must be defined in terms of theory and methodology, but there is little consensus in general theory. The Competing Value Framework (CVF) is a theory built by Quinn and Rohrbaugh (1983) and emerged from studies of the factors that account for highly effective organizational performance (Cameron et al., 2022). It responds to the need for an extensively applicable framework to cultivate successful leaders, improve organizational productiveness and facilitate value creation. The CVF has been tested and validated in different organizations from various aspects over 30 years (Cameron and Quinn, 1983; Quinn and Rohrbaugh, 1983; Berrio, 2003; Cameron and Quinn, 2011). The basic framework consists of two fundamental dimensions (see Figure 2.1). Graphically, the Competing Values Framework (CVF) is divided into four dominant quadrants: Clan (collaborate), Adhocracy (create), Market (compete), and Hierarchy (control). While both sets of terms have been mentioned in the CVF framework, throughout this thesis, I will use these terms interchangeably, but will primarily refer to them as collaborate, create, compete, and control.

[Insert Figure 2.1 here]

The study regards two dimensions as two polarities or two choices that affect an organization's effectiveness. Specifically, researchers have observed higher effectiveness in some companies that are changing, adaptable, and tolerant of more freedom. For example, Apple Inc., which operates in highly competitive and rapidly evolving industries, relies on agility and flexibility as key factors for its success. Apple’s emphasis on innovation and its ability to rapidly iterate and adapt to consumer preferences have been central to its market dominance. Additionally, Apple’s organizational flexibility enables it to integrate cutting-edge technology with creative product designs, demonstrating its commitment to adaptability and innovation (Lashinsky, 2012). By contrast, some organizations achieve higher effectiveness through stability and control. For instance, government agencies prioritize steadiness to ensure consistency in public service delivery (Wilson, 1989). Another example is the Coca-Cola Company, which has built its global success on a foundation of persistent product quality and consistent brand identity. Coca-Cola’s ability to maintain its core values while making minor adaptations for local markets underscores the importance of stability in achieving long-term success (Isdell and Beasley, 2011).

The vertical axis (see Figure 2.1) shows flexibility and discretion at the top, and the opposite is shown at the bottom. Similarly, internal focus and integration versus external focus and differentiation is the second core dimension that determines the company's effectiveness. More specifically, some companies tend to be more effective if they have harmonious internal characteristics. Others are noticed to be more effective when they interact more or compete more with outside rivals. Thus, the horizontal axis shows internal focus and integration on the left side, as well as external focus and differentiation on the right side. The Competing Value Framework lies in a two-by-two figure with four quadrants: collaborate (upper left), create (upper right), compete (lower right) and control (lower left). Below, I discuss the four cultural types in detail.

Collaborate: Value-enhancing activities in a collaborate culture deal with building human resources, increasing trust, encouraging teamwork and participation and solidifying a collaborate culture. Collaborative organizations tend to pay less attention to organization structure and control but focus more on corporate flexibility. People in collaboration-oriented companies do not achieve their operating goals or outputs through strict rules and principles. Contrary to the control culture, companies with collaborate culture usually have a flat structure in which employees and teams behave more autonomously (Cameron et al., 2022). The culture gives employees a sense of family where they are driven by loyalty and common consensus to work together (Deshpandé and Farley, 2004). Although the corporate rules and principles are not necessarily recorded, they still exist and are often socially communicated and instilled.

Collaborative leaders act in a way that promote and support their employees, playing an important role similar to a parent in a family. The leaders mentor or facilitate the employees' development by providing them with a better working environment, not only the physical environment, but also the mental environment. They provide extra training for better human resources; they emphasize teamwork and participation for higher mutual trust and loyalty; they show more concern for employees and give them more flexibility to show their openness. These approaches produce effectiveness in collaborate culture.

Collaborative organizations seek to develop human competencies and strengthen organizational culture through consensus building. The underlying logic behind this culture is that the built interpersonal relationship helps generate a positive emotional attitude towards the organization. Companies with this culture are more likely to succeed because they employ, develop and retain talent resources as a base. Thus, under this culture, employee tend to have higher retention rate and satisfaction (Lund,2003; Lok and Crawford, 1999; Tsai, 2011). At the same time, companies assign a large proportion from budget for stress-released health care costs and education because their culture is employee-oriented (Fernández et al.,2003).

Create: Value-enhancing activities in create culture deal with greater flexibility in organizational planning and innovations in the organization's services and products (Hogan and Coote, 2014). Create culture always welcomes change and is always on the lookout for inspiration and new ideas. If the market has been changed with a brand-new characteristic, the experts with high efficiency and adaptiveness will quickly form a team to meet these new challenges and widely use prototyping and experimentation instead of long-term big bang projects (Sarros,2008). Therefore, creative organizations excel at being pioneers and definers of industry or sector trends (Lau and Ngo, 2004).

Creative leaders are visionary and innovative entrepreneurs who take risks to achieve significant gains. They balance the conflicts over resources, evaluate new challenges and allow the maximum freedom for their employees to stimulate creation, innovations and entrepreneurship. They aim at providing new services and products, creating new market niches, and effectively handling discontinuity, change and risk. Thus, this kind of organizational cultural style produces the greatest value in a highly turbulent and rapidly changing environment, which requires cutting-edge ideas and innovations.

Creative Organizations provide employees with a risk-taking, unique and free environment. Even failures are acceptable because failures are inevitable in seeking new concepts. Create culture cares more about whether their employees can learn from failures and shape themselves better. Therefore, more R&D expenditure will be distributed to related departments, and the following revenues derived from new products or services will be increased to a large extent. And there will be more outputs about new ideas, new products and new patents (Hurley et al., 1998; Chandler et al., 2000; Cameron et al., 2022; Hogan and Coote,2014). The more patents or more patent citations will signal a created culture.

Compete: Value-enhancing activities in compete culture deal with a more active and powerful pursuit of competition. Outstanding organizations in compete culture stress and establish their competitive position. Compete culture is different from create culture, which dominates the market share by introducing new products. When the products are similar, the competitive leaders are likely to aggressively seek to provide goods with quality at the lowest price to acquire market share and gain customer satisfaction. They want to decrease costs by economies of scale and by cutting down transaction costs (Cameron et al., 2022).

Competitive leaders tend to be hard-driving, directive and commanding. They believe that aggressive competition and customer focus produce effectiveness. Thus they force their employees to work hard, try their best to decrease transactions costs and gain more market share (Deshpandé and Farley, 2004). It is important to note that market-oriented organizations are not only focused on marketing but also pay attention to both internal and external transactions in market terms. Exchange of value happens when transactions are executed in the market, where value flows among people and stakeholders with minimal cost and delay.

Competitive organizations put customers and clients as the first priority, monitor feedback from the marketplace, and consistently highlight creating values for shareholders. Fast response and high-speed reaction are traits of value-creating activities. Competitive strategies concentrate on delivering short-term profitability for shareholders, enabling the company to have a strong position among investors by creating a remarkable reputation for its superior short-term financial performance. Thus companies with compete culture care more about profitability, which can be represented by return on assets. They may have aggressive activities like expanding working capital, outsourcing selected aspects of services or production, acquiring other firms to win the market share (HHI) and achieving good overall performance ranking in the industry (Narver and Slater, 1990 and 1994; Hurley et al., 1998; Andreou et al., 2020a)

Control: Value-enhancing activities in a control culture deal with implementing better processes to pursue improvement in efficacy. Organizational effectiveness is associated with capable processes, measurement, and control. The control-oriented culture had been considered as the only effective one for many years in the past. Control culture shows respect for position and power. Organizations with a control culture usually follow specific corporate policies, principles and rules. Changes and exceptions are not welcome because control-oriented leaders prefer to run organizations smoothly. Thus, obtaining a substantial degree of statistical predictability is one of the hallmarks of control culture (Cameron et al., 2022).

Control-oriented leaders are usually coordinators, monitors or organizers. They pay close attention to details, analyze information accurately, focus on the best way to achieve goals and make prudent decisions. They tend to be conservative and prudent in logical analysis to help eliminate errors and increase the regularity and consistency of results. They follow the agenda, strictly enforce it, and gain power through their own information control and technical expertise. (Tannenbaum et al.,1977). Control-oriented organizations aim to create value by improving certainty, predictability, and regularity, as well as by eliminating any constraints on a predetermined routine. This culture includes an internal-centric, disciplined strategy that involves improving efficacy and taking cost out of production. The broad use of routines, emphasis on rule-reinforcement, standardized procedures, and uniformity are hallmarks of this culture. Thus, under strict control, higher inventory turnover and more auditors can be expected. In production procedures, quality control processes like cost and productivity improvement, decrease in error or defect rates, and reduction in redundancy or waste will also signal a control culture.

Among the four quadrants (see Figure 2.1), what is notable is that they represent competing or opposite assumptions. Each end of the horizontal or vertical axis emphasizes different value creation processes and key performance standards, as opposed to the other end of each axis. Therefore, the quadrants based on the two basic dimensions are also contradictory or competitive on the diagonal line. The contradictory elements in each quadrant explain the existence and necessity of paradox, which is one of the most important features of the Competing Value Framework. A great deal of research has confirmed that leaders and organizations gravitate to one or more of these quadrants over time (Cameron et al., 2011). For leaders, this means that they develop a specific set of thinking patterns, management skills and competitiveness strategies, which are characterized by one or more of these cultures; for organizations, this means that they form a specific combination of the dominant organizational culture, core competencies and strategic intentions, which are biased towards one or more of these cultures. The Competing Value Framework help leaders and organizations diagnose and interpret these styles and utilize them in value-creation activities.

2.3 Organizational Culture Assessment Instrument (OCAI)

The Competing Values Framework (CVF) and the Organizational Culture Assessment Instrument (OCAI) are closely related, with OCAI being a practical tool developed to assess and measure the cultural dimensions proposed by the CVF. The Competing Values Framework is a theoretical model that categorizes organizational culture into four key types: collaborate, create, compete, and control(see Figure 2.1). The Organizational Culture Assessment Instrument (OCAI) is a survey-based tool that operationalizes the CVF by asking respondents to evaluate their organization along the four quadrants identified in the CVF. OCAI helps to identify how an organization aligns with one of the four cultural types. It is designed to measure cultural values in a concrete way through a set of survey items.

The six aspects (see Figure 2.2) of OCAI likely refer to the different elements of organizational culture that the OCAI assesses. Each aspect will offer four alternatives (A: Collaborate; B: Create; C: Compete; D: Control). These aspects are intended to capture the full complexity of an organization's culture by looking at various dimensions: 1) dominant characteristics – describes the key traits of the organization; 2) organizational leadership – the style of leadership present within the organization; 3) management of employees – focuses on how the organization treats its employees; 4) organizational glue – the factors that bond the organization together; 5) strategic emphasis – reflects the organization's strategic; 6) criteria of success – defines what success looks like in the organization.

[Insert Figure 2.2 here]

The six aspects of OCAI are derived from the Competing Values Framework (CVF) and aimed to measure organizational culture in a structured, quantifiable way. Each of these six aspects maps to different quadrants in the CVF, and the OCAI helps organizations identify where they fall on the spectrum of each aspect, based on survey responses. In fact, the method for implementing the questionnaire is easy. See Figure 2.3: Organizational Culture Assessment Instrument - Current Profile form. Firstly, the questionnaires will be distributed, and the respondents will be asked to assign 100 points within each dimension, according to the extent to which each alternative is similar to their own organization. People need to give the highest points to the alternative which is most similar to their organizations; for example, they can assign 80 points to A and 5 points to B, C, and D, respectively. The next step is simple arithmetic computations for the four types of culture (see Figure 2.4). For example, add all A- responses together in the 'Now' column and divide by 6 to get the average score for A-alternative in the 'Now' column. Then repeat the calculations for B, C and D alternatives in the 'Now' column. After finishing all the 'Now' column calculations, respondents repeat the calculations in the 'Preferred' column. Respondents assign 100 points within each dimension, according to the extent to which each alternative to their organization tends to be in the five years and do the calculations again. For example, add together all A-responses in the 'Preferred' column and divide by 6 to get the average score for A-alternative in the 'Preferred' column. Then repeat the calculations for B, C and D alternatives in the 'Preferred' column. Based on the scores, executives can get plots, which serve as an organizational culture profile and signal the culture change strategy.[2]

[Insert Figure 2.3 here]

[Insert Figure 2.4 here]

To get the culture profile plots, executives should follow three steps. Firstly, plot the average scores from the 'Now' column for each alternative on the organizational culture profile form (see Figure 2.5). The A, B, C and D, representing clan (collaborate), adhocracy (create), market (compete) and hierarchy (control), are plotted on the diagonal line extending upward in the top left quadrant, upward in the top right quadrant, downward in the bottom left quadrant and downward in the bottom right quadrant respectively (see Figure 2.1). Secondly, connect the points in each quadrant to form a four-sided figure. Thirdly, repeat the above-mentioned procedures on the scores from the 'Preferred' column and plot with different lines on the same profile. For example, for Firm X, its current average four scores are 24, 30, 35, and 11, and I plot the scores and draw solid lines in Figure 2.6. While its preferred average four scores are 30, 34, 25, and 11, and I plot the scores and draw dashed lines in Figure 2.6. By comparing the four-sided figures in different lines, which contain both current and future conditions, I will have a direct visual impression and a better understanding of the gap between the existing cultural orientation and the prospective cultural type. The OCAI instrument concentrates on an organization's core attributes that most reflect its culture. The responses on six dimensions from employees help identify the dominant cultural type of the organization and construct the organizational culture profile. Compared to the straightforward numbers in the questionnaire, the culture profile plots, which visualize the

[2] The OCAI use the survey methodology to measure the current state and the change of culture. My bag-of-words is based on the OCAI questionnaire. Similarly, the textual analysis methodology will identify the current cultural type and use longitudinal analysis to study the changes in culture across time.

organizational culture, are supposed to be more useful in diagnosing and interpreting the cultural evolution mechanism.

[Insert Figure 2.5 here]

[Insert Figure 2.6 here]

Moreover, if the managers prefer more detailed information transmitted from the OCAI instrument, they can plot scores in each dimension of the OCAI instrument (see Figure 2.7). The detailed plots will allow executives to highlight the extent to which the culture plots are congruent and the extent to which the current culture is in accordance with the preferred one. Following similar procedures for a general culture profile, executives plot the numbers in the 'Now' column from the first dimension (dominant characteristics) and connect the points in each quadrant to form a four-sided figure, then repeat the process for the 'Preferred' column and connect the points with lines in a different colour to distinguish the differences. Executives can produce detailed profiles for each of the dimensions of the OCAI instrument.

[Insert Figure 2.7 here]

2.4 Strengths and Weaknesses of OCAI

On the basis of the general organizational culture profile and six detailed culture attributes, managers can now interpret the cultural orientations from at least the following comparable aspects (Cameron and Quinn, 1999): (1) the gap between current and preferred dominant cultural type in a company; (2) the gap between current and preferred culture attributes in a company; (3) the strength of the cultural type that dominates the organization; (4) the congruence of the culture profile generated from different attributes by different individuals; (5) the differences between the company's culture profile and the industrial benchmark's; (6) the future trends of the industry. Through the OCAI instrument, managers can understand the strengths and potential of culture change in their organization and the similarity and uniqueness between it and the benchmark (Cameron et al., 2022).

The OCAI instrument offers several practical advantages. Its application raises awareness among employees and managers by encouraging them to reflect on their daily experiences and cultural dynamics, fostering a deeper understanding of the value-creation effects of organizational culture. Furthermore, the OCAI's integration of quantitative scores with qualitative perceptions provides a balanced view of organizational culture, making it accessible to individuals who prefer data-driven insights. By engaging in the OCAI workshop process, employees can collectively diagnose their current and preferred cultural states, fostering dialogue and consensus across organizational levels. Additionally, the instrument allows senior leaders to gain diverse perspectives from various levels of the organization, offering valuable insights to refine strategic planning.

Despite these strengths, the OCAI instrument has notable limitations. The reliance on survey-based responses introduces subjectivity, as some participants may struggle to contextualize their answers within the broader organizational framework. Furthermore, participants may inadvertently skew the results by overemphasizing specific preferences or misunderstandings. These limitations are particularly pronounced for external stakeholders, such as investors, who lack access to internal survey responses and therefore cannot leverage the instrument for longitudinal analysis. These challenges necessitate alternative methodologies to complement and enhance the utility of the OCAI framework.

To address these limitations, this study proposes a novel OCAI bag-of-words methodology. This approach leverages textual analysis techniques to operationalize the OCAI framework through corporate disclosure documents, such as 10-K filings. By focusing on publicly available data curated by management, this methodology offers an alternative perspective that overcomes the subjectivity and access limitations associated with traditional survey-based applications of OCAI.

2.5 Research Gaps and Study Contributions

The review of the existing literature highlights critical gaps in the methodologies for measuring organizational culture. Traditional approaches, including the OCAI instrument, rely heavily on subjective survey responses, which are prone to biases and constrained by the challenges of scalability. Additionally, these methodologies lack the capacity to provide longitudinal insights, limiting their ability to capture cultural evolution over time. These gaps underscore the need for a more objective, scalable, and dynamic approach to cultural measurement.

This study introduces a novel textual analysis methodology that applies the principles of the OCAI framework to corporate disclosure documents, such as 10-K filings. Unlike traditional OCAI surveys, which are designed to elicit employee perspectives for internal managerial use, the textual approach leverages managerial disclosures that synthesize information from across organizational levels. This distinction positions the textual methodology as a tool for external stakeholders, including investors, who seek to evaluate organizational culture efficiently and objectively.

The textual analysis approach addresses the limitations of the traditional OCAI methodology in several ways. First, by analyzing 10-K filings, the textual method captures a manager-curated perspective that integrates insights from employees and other stakeholders, offering a comprehensive view of organizational culture. Second, the scalability of textual analysis enables the processing of large datasets, allowing for industry-wide comparisons and longitudinal assessments of cultural trends. Third, the reliance on publicly available disclosure documents ensures that external stakeholders can access and evaluate cultural data with high reliability and efficiency.

Through this innovative approach, the study contributes to the literature by advancing the application of OCAI principles to new empirical contexts and demonstrating the robustness and versatility of textual analysis in understanding the relationship between corporate culture and organizational outcomes. By bridging the gap between traditional survey-based methods and contemporary analytical tools, this study lays the foundation for a more comprehensive and accessible framework for cultural assessment.

Figures

Figure 2.1: The Competing Values Framework (CVF)

This figure presents the basic framework of Competing Value Framework, consisting of two fundamental dimensions. Graphically (the vertical axis shows flexibility and discretion at the top and the opposite is shown at the bottom. Similarly, internal focus and integration versus external focus and differentiation is the second core dimension that determines the company's effectiveness.). There are four dominant quadrants (collaborate, create, compete, and control) divided by the core vertical and horizontal dimensions. The figure source Cameron, K. S., Quinn, R. E., DeGraff, J., & Thakor, A. V. (2022). Competing values leadership. Edward Elgar Publishing, pp.32

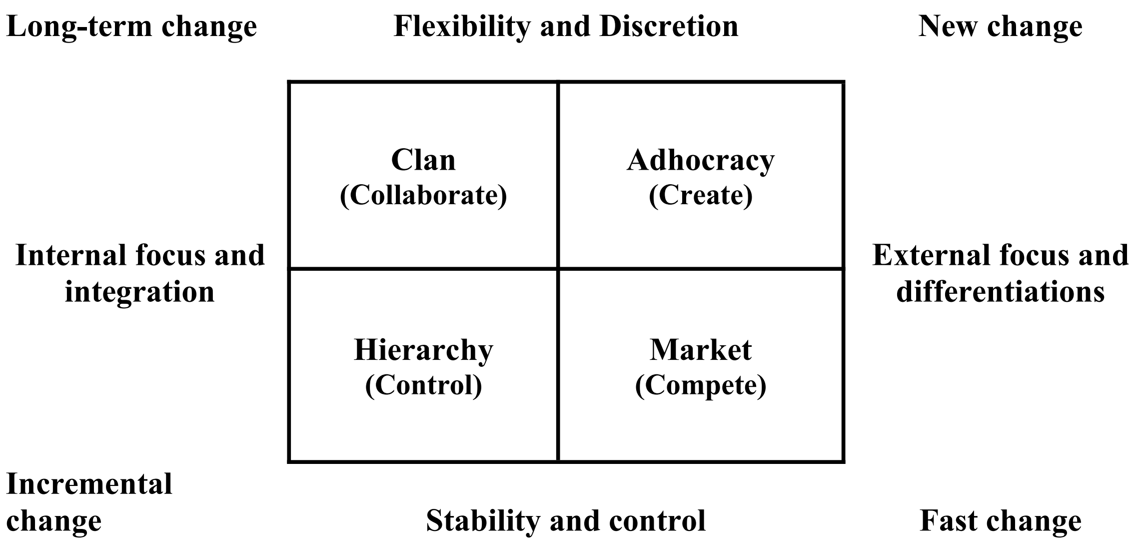


Figure 2.2: Questionnaire of Organizational Culture Assessment Instrument (OCAI)

The following items are the questionnaire of Organizational Culture Assessment Instrument (OCAI). The OCAI questionnaire analyses the organizational culture from six dimensions: the dominant characteristics, organizational leadership, management of employees, organization glue, strategic emphases and criteria of success. Each dimension will offer 4 alternatives (A: collaborate; B: create; C: compete; D: control).

1.Dominant Characteristics

A. The organization is a very personal place. It is like an extended family. People seem to share a lot of themselves.
B. The organization is a very dynamic and entrepreneurial place. People are willing to stick their necks out and take risks.
C. The organization is very results oriented. A major concern is with getting the job done. People are very competitive and achievement oriented.
D. The organization is a very controlled and structured place. Formal procedures generally govern what people do.

2. Organizational Leadership

A. The leadership in the organization is generally considered to exemplify mentoring, facilitating, or nurturing.
B. The leadership in the organization is generally considered to exemplify entrepreneurship, innovation, or risk taking.
C. The leadership in the organization is generally considered to exemplify a no-nonsense, aggressive, results-oriented focus.
D. The leadership in the organization is generally considered to exemplify coordinating, organizing, or smooth-running efficiency.

3. Management of Employees

A. The management style in the organization is characterized by teamwork, consensus, and participation.
B. The management style in the organization is characterized by individual risk taking, innovation, freedom, and uniqueness.
C. The management style in the organization is characterized by hard-driving competitiveness, high demands, and achievement.
D. The management style in the organization is characterized by security of employment, conformity, predictability, and stability in relationships.

4. Organization Glue

A. The glue that holds the organization together is loyalty and mutual trust. Commitment to this organization runs high.
B. The glue that holds the organization together is commitment to innovation and development. There is an emphasis on being on the cutting edge.
C. The glue that holds the organization together is the emphasis on achievement and goal accomplishment.
D. The glue that holds the organization together is formal rules and policies. Maintaining a smooth- running organization is important.

5. Strategic Emphases
   A. The organization emphasizes human development. High trust, openness, and participation persist.
   B. The organization emphasizes acquiring new resources and creating new challenges. Trying new things and prospecting for opportunities are valued.
   C. The organization emphasizes competitive actions and achievement. Hitting stretch targets and winning in the marketplace are dominant.
   D. The organization emphasizes permanence and stability. Efficiency, control, and smooth operations are important.

6. Criteria of Success
   A. The organization defines success on the basis of the development of human resources, teamwork, employee commitment, and concern for people.
   B. The organization defines success on the basis of having the most unique or newest products. It is a product leader and innovator.
   C. The organization defines success on the basis of winning in the marketplace and outpacing the competition. Competitive market leadership is key.
   D. The organization defines success on the basis of efficiency. Dependable delivery, smooth scheduling, and low-cost production are critical.

Figure 2.3: The Organizational Culture Assessment Instrument - Current Profile

This is the Organizational Culture Assessment Instrument - Current Profile. The left-hand column is labelled 'Now', the respondents will be asked to assign 100 points within each dimension, according to the extent to which each alternative is similar to their own organization. People need to give the highest points to the alternative which is most similar to their organizations. After finishing the current organizational culture rating, respondents assign 100 points within each dimension, according to the extent to which each alternative to their organization tends to be in the five years and do the calculations again. The figures source from Quinn, R. E. (2011). Diagnosing and changing organizational culture: Based on the competing values framework. Jossey-Bass, pp.31-33.

1. Dominant Characteristics	*Now*	*Preferred*
A The organization is a very personal place. It is like an extended family. People seem to share a lot of themselves.		
B The organization is a dynamic and entrepreneurial place. People are willing to stick their necks out and take risks.		
C The organization is very results oriented. A major concern is with getting the job done. People are very competitive and achievement oriented.		
D The organization is a very controlled and structured place. Formal procedures generally govern what people do.		
Total	100	100
2. Organizational Leadership	*Now*	*Preferred*
A The leadership in the organization is generally considered to exemplify mentoring, facilitating, or nurturing.		
B The leadership in the organization is generally considered to exemplify entrepreneurship, innovation, or risk taking.		
C The leadership in the organization is generally considered to exemplify a no-nonsense, aggressive, results-oriented focus.		
D The leadership in the organization is generally considered to exemplify coordinating, organizing, or smooth-running efficiency.		
Total	100	100

Figure 2.3 cont'd.

3. Management of Employees	*Now*	*Preferred*
A The management style in the organization is characterized by teamwork, consensus, and participation.		
B The management style in the organization is characterized by individual risk taking, innovation, freedom, and uniqueness.		
C The management style in the organization is characterized by hard-driving competitiveness, high demands, and achievement.		
D The management style in the organization is characterized by security of employment, conformity, predictability, and stability in relationships.		
Total	100	100

4. Organization Glue	*Now*	*Preferred*
A The glue that holds the organization together is loyalty and mutual trust. Commitment to this organization runs high.		
B The glue that holds the organization together is commitment to innovation and development. There is an emphasis on being on the cutting edge.		
C The glue that holds the organization together is the emphasis on achievement and goal accomplishment.		
D The glue that holds the organization together is formal rules and policies. Maintaining a smoothly running organization is important.		
Total	100	100

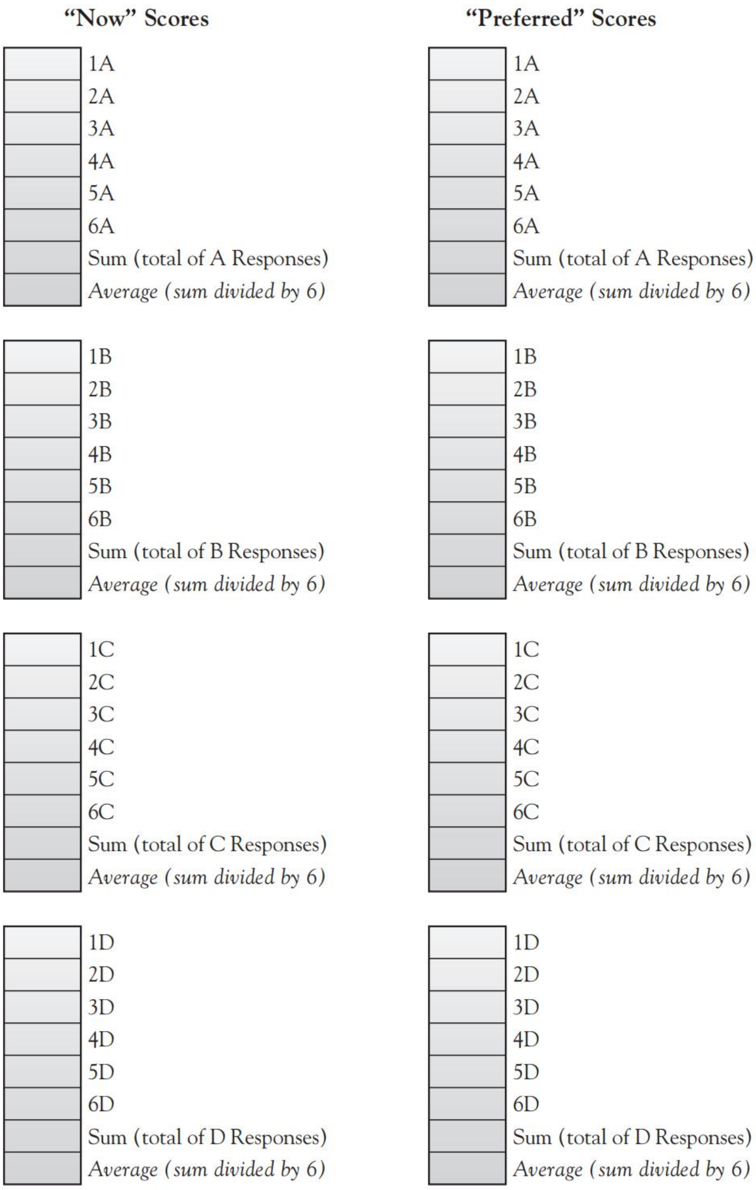
Figure 2.3 cont'd.

5. Strategic Emphases	*Now*	*Preferred*
A The organization emphasizes human development. High trust, openness, and participation persist.		
B The organization emphasizes acquiring new resources and creating new challenges. Trying new things and prospecting for opportunities are valued.		
C The organization emphasizes competitive actions and achievement. Hitting stretch targets and winning in the marketplace are dominant.		
D The organization emphasizes permanence and stability. Efficiency, control, and smooth operations are important.		
Total	100	100

6. Criteria of Success	*Now*	*Preferred*
A The organization defines success on the basis of the development of human resources, teamwork, employee commitment, and concern for people.		
B The organization defines success on the basis of having unique or the newest products. It is a product leader and innovator.		
C The organization defines success on the basis of winning in the marketplace and outpacing the competition. Competitive market leadership is key.		
D The organization defines success on the basis of efficiency. Dependable delivery, smooth scheduling, and low-cost production are critical.		
Total	100	100

Figure 2.4: Worksheet for Scoring the OCAI

This is the worksheet for scoring the OCAI. For example, respondents can record all A- responses and add them together in the 'Now' column and divide by 6 to get the average score for A-alternative in the 'Now' column. Then repeat the calculations for B, C and D alternatives in the 'Now' column. After finishing all the 'Now' column calculations, respondents repeat the calculations in the 'Preferred' column. The figures source from Quinn, R. E. (2011). Diagnosing and changing organizational culture: Based on the competing values framework. Jossey-Bass, pp.34.



"Now" Scores	"Preferred" Scores
1A	1A
2A	2A
3A	3A
4A	4A
5A	5A
6A	6A
Sum (total of A Responses)	Sum (total of A Responses)
Average (sum divided by 6)	*Average (sum divided by 6)*
1B	1B
2B	2B
3B	3B
4B	4B
5B	5B
6B	6B
Sum (total of B Responses)	Sum (total of B Responses)
Average (sum divided by 6)	*Average (sum divided by 6)*
1C	1C
2C	2C
3C	3C
4C	4C
5C	5C
6C	6C
Sum (total of C Responses)	Sum (total of C Responses)
Average (sum divided by 6)	*Average (sum divided by 6)*
1D	1D
2D	2D
3D	3D
4D	4D
5D	5D
6D	6D
Sum (total of D Responses)	Sum (total of D Responses)
Average (sum divided by 6)	*Average (sum divided by 6)*

Figure 2.5: Organizational Culture Profile

This is the Organizational Culture Profile. Researchers can draw both current and preferred culture profile in this to visualize culture information captured by OCAI questionnaire. The figures source from Quinn, R. E. (2011). Diagnosing and changing organizational culture: Based on the competing values framework. Jossey-Bass pp.76

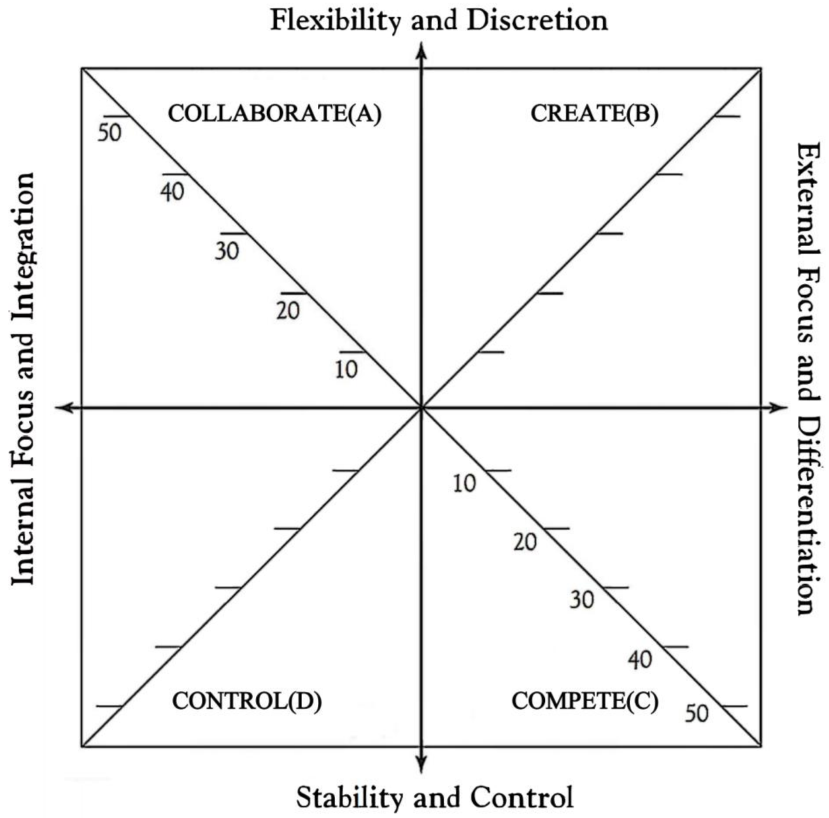


Figure 2.6: Example of Organizational Culture Profile

This is the Organizational Culture Profile for firm X. Researchers can draw both current and preferred culture profile in this to visualize culture information captured by OCAI questionnaire. Its current average four scores are 24, 30, 35, 11 and I plot the scores and draw solid lines in Figure 2.4. While its preferred average four scores are 30, 34, 25, 11 and I plot the scores and draw dashed lines in Figure 2.4. By comparing the four-sided figures in different lines which contains both current and future conditions, managers will have a direct visual impression and have better understanding of the gap between the existing culture orientation and the prospective cultural type.

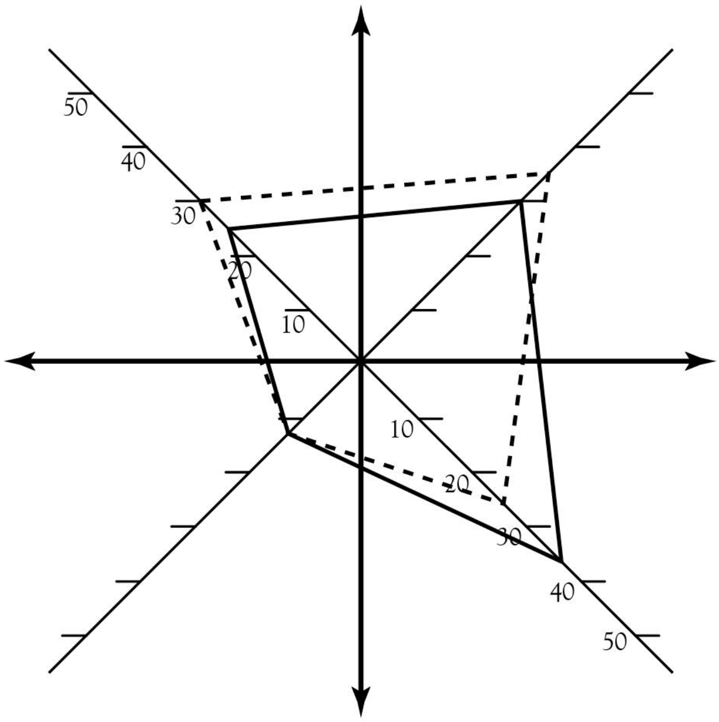
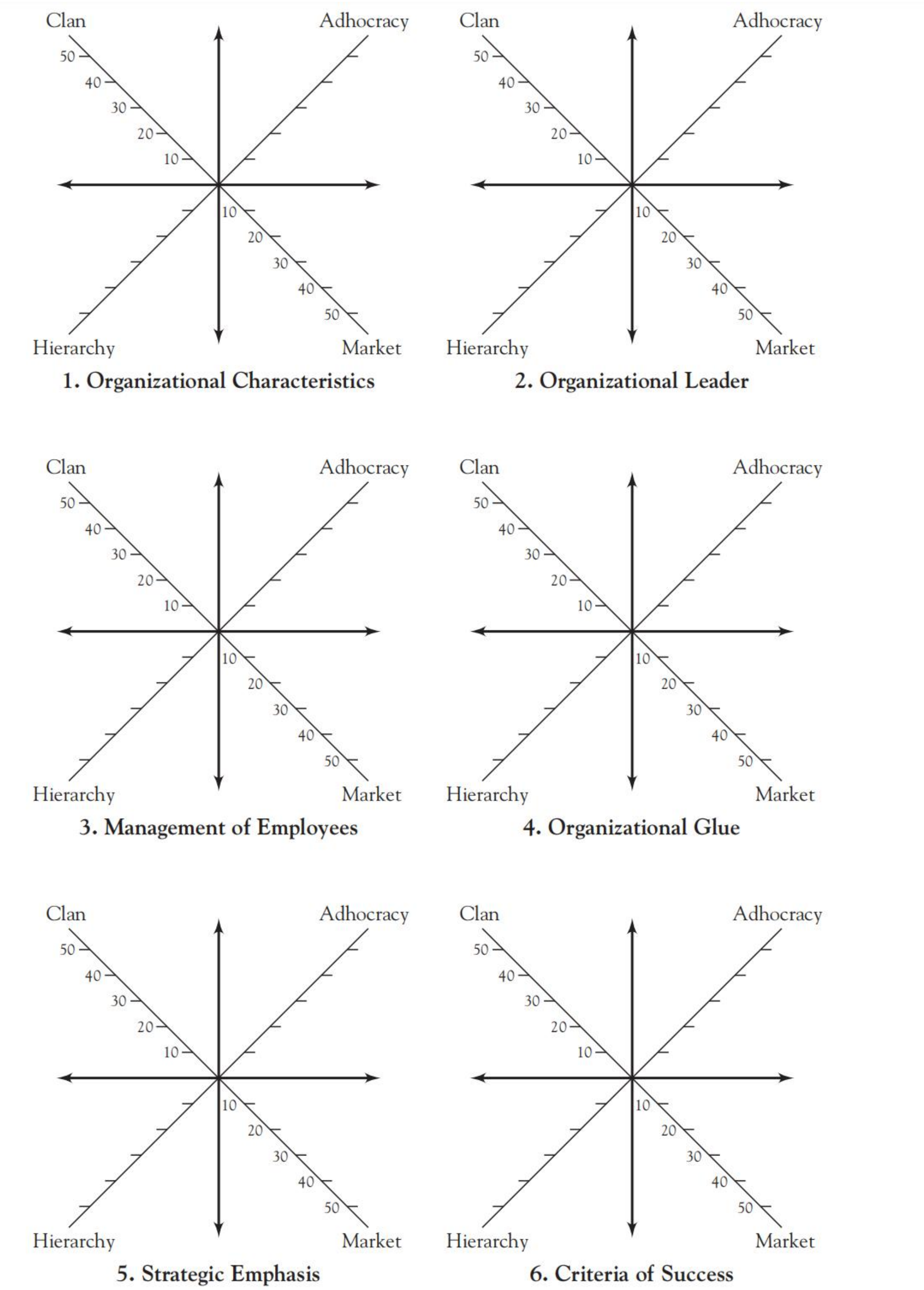


Figure 2.7: Profiles for Individual Dimentions on the OCAI

This is the profiles for individual dimentions on the OCAI. Researchers can draw both current and preferred culture profile in this to visualize culture information captured by OCAI questionnaire. The figures source from Quinn, R. E. (2011). Diagnosing and changing organizational culture: Based on the competing values framework. Jossey-Bass, pp.78.



3 Measuring Organizational Culture Using Textual Analysis of 10-K Filings

3.1 Introduction

Organizational culture is a crucial and complex issue, and both internal executives and external investors are eager to understand the organization's cultural evolution to help make better judgments (Schein, 1990). Extensive literature focuses on surveys or financial indicators that signal organizational culture orientations.[3] Predominately, researchers study a small sample of companies, investigate their financial performance and conclude some financial indicators are positively correlated with certain organizational culture (see. e.g., Graham et al., 2005; Graham et al., 2016 and 2022). [4] However, straightforward financial measurements can seldom indicate the process by which organizational values change. Furthermore, surveys more often than not are internal documents and must maintain a narrow focus to be effective, typically relying on a single point-in-time sampling and are frequently based on small interview samples (Kirca et al., 2005; Graham et al., 2022).

Conversely, in this chapter, I provide a methodology that is inclusive and caters to the needs of various users, including internal managerial teams, external individual investors, and investment managers. My methodology enables users to access organizational cultural

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[3] A non-exhaustive list of literature that focuses on surveys or financial indicators that signal organizational culture orientations includes Sheridan (1992), Marcoulides and Heck (1993); Denison and Mishra (1995); Zahra *et al.* (2004), Kirca et al. (2005); Hartmann (2006), Ke and Wei (2008), Sun (2008), Cameron and Quinn (2011) and Graham *et al.* (2022).

[4] Several studies have explored the relationship between organizational culture and financial performance using surveys or interviews. Graham et al. (2005) investigate how management practices, including aspects of organizational culture, influence financial reporting decisions. Building on this, Graham et al. (2016) provide empirical evidence on the link between corporate culture and firm outcomes, using surveys and interviews to uncover the impact on financial performance. More recently, Graham et al. (2022) demonstrate how corporate culture shapes organizational decisions, particularly financial and ethical outcomes, highlighting the integral role of culture in driving firm behaviour and success.

information on a longitudinal basis from publicly disclosed documents, facilitating analyses at a large cross-industry scale. I detail this novel measurement approach that identifies organizational culture using big data tools and assesses the generalizability of its relationship with performance based on a large sample of US publicly traded companies from 1994 to 2021. This study contributes to the literature by developing a text-based measure of organizational culture, which allows for conducting large-scale analyses. Therefore, my methodology values the diverse needs of users, allowing them to elicit public documents, gauge the process of evolving organizational culture, and make better decisions.

Value creation to a large extent serves as a measurement of the contribution of employees or managers. Many researchers have investigated the value creation issue and demonstrate the relationship between value creation and organizational culture (Graham et al., 2022). Traditionally, researchers use some financial indicators to measure whether the extant organization structure can boost value creation for shareholders (Siehl et al., 1989). However, Cameron et al. (2022) state that experienced leaders measure it much more comprehensively by taking organizational culture into consideration. Since Quinn and Rohrbaugh (1983) built the foundation of the Competing Value Framework (CVF), it has been widely cited and verified in the field of organizational taxonomy.[5] Based on Quinn and Rohrbaugh, Cameron and Quinn (2011) then divided competing cultures into four dominant quadrants (collaborate, create, compete and control).

A burgeoning literature extensively explains and validates the CVF through three predominant dimensions: cultural strength, cultural congruence, and cultural types (Cameron, 1985; Newman et al., 1996; Sørensen, 2002). Building on these dimensions, Cameron and Quinn (2011) developed the Organizational Culture Assessment Instrument (OCAI) to diagnose organizational culture across universally recognized dimensions. The OCAI

[5] A non-exhaustive list of studies includes Hooijberg *et al.* (1993), Cameron and Quinn (2011), Goodman *et al.* (2011), Hartnell *et al.* (2011) and Andreou *et al.* (2022).

questionnaire has since been widely used and researched (Cameron, 2008; Bellot and Jennifer, 2011; Bremer, 2012; Heritage et al., 2014). Company managers frequently implement the OCAI questionnaire to identify their organization's cultural profile based on employee responses. However, the OCAI questionnaire is an internal document. If external stakeholders wish to understand the culture, which is typically unobservable, their access to this information is severely limited.

Conversely, I provide the methodology to help both internal and external users extract cultural information content from a public database, allowing them to understand the cultural information captured by OCAI dimensions on a longitude basis. My study demonstrates how OCAI cultural information can be elicited from 10-K filings using textual analysis, thereby for the first time enabling outside investors to evaluate organizational culture according to the OCAI scale. This study considers all the 10-K filings of publicly listed firms from the Security and Exchange Commission's (SEC) EDGAR website between 1994 and 2021. My methodology will be applied to these 10-K filings to find the latent organizational cultural attributes.

More specifically, to operationalize my measure, in this chapter, I develop an OCAI bag of words based on the OCAI questionnaire. The word-roots are words appearing in the OCAI questionnaire and their synonyms which characterize the cultural concepts. The keywords are variants stemming from word-roots and capture cultural contexts semantically. For the four cultural types, I manually select a total of 89 word-roots and 261 keywords according to their usage reflected by their contextual words. To the best of my knowledge, this chapter for the first time uses a bag-of-words approach to appraise organizational culture captured by OCAI dimensions using textual analysis of public data.

Although consistent guidance on the implementation of textual analysis tools is lacking, this study reviews a broad range of research utilizing these methods and incorporates a rigorous verification analysis of the textual analysis methodology, focusing on five key aspects: content validity, reliability validity, external validity, dimensionality validity, and predictive validity (Duriau et al., 2007; Short et al., 2010; Pandey and Pandey, 2019). These validity tests ensure the measure is reliable and explicable: content validity ensures that word selection is grounded in sound theoretical and semantic contexts; reliability validity guarantees consistency in word counts across constructs; external validity will ensure the confidence for researchers to generalize findings under multiple circumstances by implementing this methodology; dimensionality validity will ensure each dimension is related to but distinct from other dimensions; and predictive validity evaluates the alignment of the measurement with theoretical expectations. My methodology passes these validity tests, supporting its robustness for analyzing 10-K filings from 1994 to 2021.

In the methodology implementation part of this study, I apply this methodology to analyze cultural shifts during the COVID-19 pandemic. This period provides a unique context to demonstrate the adaptability of organizational culture in response to external shocks. My findings reveal significant changes towards more flexible cultures (collaborate and create), emphasizing the importance of cultural adaptability in times of uncertainty. This application not only validates the methodology but also offers valuable insights for managers and policymakers on fostering resilient and adaptable organizational cultures.

While several studies have employed textual analysis of 10-K filings to explore aspects of organizational culture, my research is the first to combine the Competing Values Framework (CVF) and the Organizational Culture Assessment Instrument (OCAI) to construct a semantically grounded bag-of-words with full validation. For instance, Fiordelisi et al. (2014) used textual analysis based on the CVF but did not semantically ground their bag-of-words in specific CVF dimensions, resulting in a broader and noisier measure. Similarly, Chen et al. (2022) focused exclusively on collaboration culture and its effect on audit pricing, without extending their analysis to other cultural dimensions. Beecken (2024) employed advanced NLP techniques to examine cultural attributes in the context of mergers and acquisitions but lacked theoretical grounding in CVF and robust validation procedures. Fang et al. (2023) utilized the CVF to analyze cultural dynamics during financial crises but focused narrowly on financial stability and did not provide comprehensive validation. In contrast, my study uniquely integrates CVF and OCAI to operationalize all four cultural types (collaborate, create, compete, and control) across six dimensions. [6] Furthermore, my methodology spans a broad timeframe (1994–2021) and demonstrates the adaptability of culture through significant events like the COVID-19 pandemic. These innovations establish my research as a foundational contribution to the literature, offering a versatile and theoretically rigorous framework for measuring organizational culture.

This chapter introduces a novel methodology for measuring organizational culture. Ontologically, the research adopts a constructivist stance, conceptualizing organizational culture as a dynamic and socially constructed phenomenon that emerges through interactions and shared norms within organizations. This perspective enables the inference of cultural attributes from textual artifacts, such as 10-K filings, which act as proxies for underlying cultural dimensions. Epistemologically, the study aligns with a positivist approach, employing structured, replicable, and scalable methods to objectively quantify cultural attributes. By operationalizing the Organizational Culture Assessment Instrument (OCAI) dimensions through natural language processing (NLP), this methodology provides a robust framework for longitudinal and cross-industry analysis. The application of this approach to 10-K filings from US publicly traded companies between 1994 and 2021 ensures accessibility

[6] The six dimensions defined by the OCAI questionnaire are: dominant characteristics dimension, organizational leadership dimension, management of employee dimension, organization glue dimension, strategic emphases dimension and criteria of success dimension. Please see Figure 2.2 for further details of OCAI questionnaire.

and comparability across contexts, bridging the gap between internal organizational assessments and external stakeholders' needs.

This research makes significant contributions to both theory and practice. Theoretically, it extends the Competing Values Framework (CVF) by introducing a method to measure cultural dynamics over time, overcoming the static nature of traditional survey-based tools. Methodologically, it establishes a rigorous and scalable approach to quantifying culture using textual data, incorporating extensive validity tests to ensure robustness. Practically, it empowers managers, policymakers, and investors to analyze cultural evolution and make better-informed decisions, particularly in contexts requiring cultural adaptability and resilience.

This chapter is structured as follows. Section 3.2 provides the literature review; Section 3.3 details the measurement of organizational culture; Section 3.4 presents the construct validity of the culture measurement methodology; Section 3.5 provides methodology implementation results; and Section 3.6 concludes.

3.2 Literature Review

3.2.1 Organizational Culture Measurement

Organizational culture is a crucial and complex issue that plays a significant role in shaping a firm's identity by establishing its beliefs and operational philosophy (Schein, 1990). In measuring corporate culture, many researchers have relied on the competing values framework (CVF), which is a theory developed by Quinn and Rohrbaugh (1983) and emerging from studies of the factors that account for highly effective organizational performance (Cameron et al., 2022). In advancing my measure I acknowledge that the chosen CVF framework is not the definitive or most superior method for evaluating culture in firms given the number of available alternative cultural frameworks and approaches (see. e.g., Hofstede et al., 1990; Hofstede, 2011; O'Reilly, 2014). However, I argue that their methodology is grounded in a valid theory of organizational culture, as the CVF is extensively supported by existing theoretical and empirical literature, and the underlying dimensions have demonstrated a robust basis (Quinn and Rohrbaugh, 1983; Hartnell et al., 2011; Schneider et al., 2013; Cameron et al., 2022; Fiordelisi and Ricci, 2014a; Fiordelisi et al., 2019). For a detailed literature review on organizational culture, please refer to Chapter 2 of this thesis.

I reviewed the extensive literature in this area to quantify the organizational culture. Traditionally, scholars rely on a small sample of interviews or point-in-time surveys to explore the impact of organizational culture on various outcomes, such as employee performance, organizational effectiveness, and innovation (Sheridan (1992); Denison and Mishra (1995); Ke and Wei (2008); Kotter (2008); Cameron et al. (2011) and Graham et al. (2022)). These studies have contributed significantly to my understanding of how cultural attributes influence organizational outcomes and have provided managers with actionable insights to foster desirable cultural traits within their organizations.

However, surveys or interviews, accompanied by high time and economic costs, have notable limitations. One major issue is the reliance on a single point-in-time data collection approach, which means these tools fail to account for the evolving nature of organizational culture (Cooke & Rousseau, 1988). Additionally, surveys or interviews, accompanied by high time and economic costs, are often internal documents and must maintain a narrow focus to be effective (Kirca et al., 2005; Graham et al., 2022). Moreover, as these methods often require direct access to employees and internal documents, they are not feasible for external analysts or investors who need to assess the culture of organizations they do not directly manage.

In addition to employing survey-based methodologies, with the advancement of technology and the continuous increase in regulatory and disclosure requirements, there has been a growing trend in utilizing textual analysis techniques to assess different dimensions of corporate culture quantitatively. This approach has gained popularity in recent years, as evidenced by the works of Loughran and McDonald (2009, 2011, 2016), Hoberg and Phillips (2010, 2016), Li et al. (2013), Hoberg et al. (2014), Fiordelisi and Ricci (2014), Fiordelisi et al. (2019), Grennan (2019), Andreou et al. (2020a), Andreou et al. (2020b) and Andreou et al. (2022). The rationale for employing textual analysis is taking advantage of the big data tools with more diverse and informative ways under higher levels of public disclosure requirements to interpret cultural information hidden in public archival data and convey information. Furthermore, the increased number of tools developed in computer science (for example, machine learning and natural language processing (NPL)) helps to actively embrace the premise that words chosen by management in producing firms' disclosures are representative of firms' culture. Thus, there has been a growing application of diverse textual analysis methodology in the finance and accounting literature pertaining to corporate culture to boost insights into the relationship between organizational culture and various economic phenomena.

3.2.2 Construct Validity

The advent of textual analysis has provided researchers with powerful tools to analyze large volumes of data. The development, refinement, and implementation of the coding scheme are central to the quality of textual analysis (Carley, 1993; Gephart, 1993). However, despite its increasing popularity, many studies employing textual analysis have faced criticism regarding the validity of their methods and findings. These concerns have been raised by esteemed scholars in the field, such as Weber (1990), Neuendorf (2002), and Short et al. (2010). Based on the sample (a detailed description and statistics of papers using text/content analysis published in high-quality journals during the period 1980-2005) provided by Duriau et al. (2007), Short et al. (2010) point out that only a few textual analysis implementations describe procedures of how words were selected for the word dictionary and how to make sure the words are selected accurately representing the studies constructs, and reveal sufficient evidence for the use and verification of this method in their papers. Scholars have raised concerns about the lack of supporting evidence and transparency in the procedures used to select words for dictionaries, emphasizing that such transparency is critical to ensuring the selected words accurately represent the study's constructs and validate the textual analysis methodology.

Content validity, the first step in ensuring the validity of textual analysis, involves verifying that the measurement tool accurately reflects the theoretical construct it is intended to measure. According to Pandey and Pandey (2019), researchers perform content validity to ensure the word selection lies in a sound theoretical context and is meaningful semantically. Thus, most content validity involves experts or judges to ensure the adequacy of the word bag (Pandey and Pandey, 2019). Reliability, the second aspect, refers to the consistency of a measurement tool. In textual analysis, this involves ensuring that different coders would produce similar results when analyzing the same texts (Gephart, 1993). External validity, the third aspect, refers to whether we are able to generalize the measurement to, for example, different population segments and settings (Cook & Campbell, 1979). In addition, dimensionality refers to testing whether the measurement is distinctly related to the construct being assessed (Edwards, 2000). Moreover, predictive validity is defined as the extent to which the measure predicts the constructs of interests, thereby aligning with theoretically derived expectations Pandey and Pandey, (2019). As scholars have raised concerns about the lack of validity in textual analysis, to address these concerns, in this chapter, I follow Pandey and Pandey (2019) to conduct construct validity tests, including content validity, reliability validity, external validity, dimensionality validity, and predictive validity, ensuring the highest level of rigour in my methodology.

3.3 Measurement of Organizational Culture

A detailed explanation has been provided in this section to demonstrate how the philosophical foundations directly inform the methodological choices. This includes a discussion of how the constructivist perspective supports the use of organizational artifacts (10-K filings) as cultural proxies and how the positivist approach ensures replicability and generalizability through natural language processing techniques.

Organizational cultures are implicit and hard to capture visually, but the culture indicated by managers is often reflected in the decisions of various management. For example, outstanding organizations in a compete culture stress and establish their competitive position by dealing with a more active and powerful pursuit of competition (Cameron et al., 2022). Companies with compete culture concentrate on delivering short-term profitability for shareholders, enabling the company to have a strong position among investors by creating a remarkable reputation for its superior short-term financial performance. And they may have aggressive activities like expanding working capital, outsourcing selected aspects of services or production, acquiring other firms to win the market share (HHI) and achieving good overall performance ranking in the industry (Narver and Slater, 1990 and 1994; Hurley et al., 1998). To distinguish one culture from other cultures, this study develops a measurement using information from the 10-K filings for the period 1994–2021.

Traditional measures rely extensively on surveys or personal interviews. However, surveys more often than not are internal documents and must maintain a narrow focus to be effective, typically relying on a single point-in-time sampling and are frequently based on small interview samples (Graham et al., 2022). Therefore, traditional measures have limitations in terms of sample size, sample effectiveness and sample transparency. Instead, this study provides a new methodology that both internal and external stakeholders can implement to identify the critical cultural information in publicly disclosed documents.

This study compiles bag-of-words based on the Competing Value Framework (CVF). The Competing Value Framework (CVF) is a theory which has been tested and validated in different organizations from various aspects over 30 years (Cameron and Quinn, 1983; Quinn and Rohrbaugh, 1983; Berrio, 2003; Cameron and Quinn, 2011). Based on CVF, Cameron and Quinn (2011) did extensive research and developed the Organizational Culture Assessment Instrument (OCAI) for diagnosing the four CVF cultures from universally recognized dimensions. The OCAI questionnaire has been widely used and researched since its development (Cameron, 2008; Bellot and Jennifer, 2011; Bremer, 2012; Heritage et al., 2014). Based on CVF and OCAI, I develop a bag of words to capture competitive and other culture traits. And then conduct textual analysis on 10-K filings, which already has shown strong empirical support from recent literature since narrative disclosure in 10-K filings has been identified as a channel for managers to convey valuable and important information about distinctive, yet latent, firm traits (Loughran and McDonald, 2009, 2011). 10-K filings are different from annual reports, which include glossary and marketing materials. 10-K filings provide management's disclosure of the company's businesses and operations, including its main products and services, the market environment and conditions, the risk factors and prospects the company faces and so on, thus providing a natural setting for eliciting important information about culture.

Before implementing my methodology, I parse 10-K filings and conduct a strict data filtering process to screen out meaningful 10-K filings. I download 10-X filings of publicly listed firms whose filing dates are in the range of 1994 and 2021 from the EDGAR website. All tables for Chapter 3 are provided at the end of this chapter. The original 10-X variants (see Table 3.1) data includes 10-K, 10-KA, 10-Q, 10-QA, 10-KT and 10-QT. After filtering out duplicates and retaining only the 10-K filings 10-K, 10-KSB, 10-K405 and 10-KSB40, my sample size decreased from 1,140,486 to 265,560. Most studies using textual analysis focus mainly on the textual content of the document, while a substantial portion of an original EDGAR text filing's content consists of HTML code, embedded PDFs, jpg and other artefacts not typically of interest. I parse the original data sources associated with 10-K filings and then extract extraneous materials. After filtering, the files exclude markup tags, ASCII-encoded graphics, and tables, which are usually not the focus of textual analysis. Furthermore, acronyms, proper nouns, all numbers, and single letters should be removed from my analysis so it will be easier to identify and count the collection of characters as words in the analysis. I follow Loughran and McDonald (2011) to delete files with less than 2,000 words[7] in analysis, reducing the sample size to 259,189. Lastly, I only keep filings whose fiscal years are between 1994 and 2021 and those that can be classified into Fama French 48 Industry Classification, thus obtaining my sample to 251,707 firm-year observations (see Table 3.2).

[Insert Table 3.1 Here]

[Insert Table 3.2 Here]

To implement my measurement, firstly, I conclude word-root and keywords from the Organizational Culture Assessment Instrument (OCAI). Then I consider contextual words, I extract three contextual words before and after keywords, analyze their related frequencies and delete unrelated keywords according to the top 10 contextual words in frequency. The textual analysis process on firms' 10-K filings enables the qualification of my bag of words

[7]A typical 10-K filing includes a full report covering risk factors, management discussion, and financial statements. Shorter filings may not provide a complete picture, making these samples less representative and unable to fully capture the company's culture and operations. Moreover, shorter filings are likely to introduce noise into the dataset due to their insufficient detail for analysis. By excluding these, the remaining samples are ensured to be more representative and meaningful for capturing organizational culture and operations.

for a large sample of publicly listed US firms. In the next step, I exploit the frequency of each keyword appearance in one file (all capitalized forms are excluded except for capital letters at the beginning of sentences), add the frequencies of keywords belonging to the same culture type together, and then divide the one culture frequencies by total frequencies of all cultural keywords in each file to get the normalized scores for the corresponding cultural type. This study uses the scores to do further validations.

In detail, firstly, I take words from the OCAI questionnaire and check their corresponding synonyms from the Princeton University WorldNet lexical database and Harvard IV-4 psychosocial dictionary. For example, I select the word-root 'ambition' as the competitive cultural part. Competitive leaders are likely to ambitiously seek to provide goods of quality at the lowest price to acquire the biggest market share and gain customer satisfaction. Thus, the word-root "ambition" and its variants "ambitious" and "ambitiously" can be included in my word bag.

The next step is to consider whether all the variants have specific cultural meanings as I only want to retain variants with a certain semantic meaning, so I make the selection based on their contexts captured in the 10-K filings, check the contextual words to understand whether the usage of these variants is meaningful in the financial area. Considering the effect of negation words in the sentences, I create a negation word list including nine negation words: no, not, less, few, never, neither, none, nobody, limited. When I count the frequency and contextual words of variants in one 10-K file, if the negation words appear in the predetermined distance around the variant, the frequency will not be added; thus, the contextual words will not be considered either. Specifically, I take minus three and plus three contextual words around each variant, listing them, deleting stop indicators (see Table 3.3), calculating the frequencies and taking the top ten (10) frequency contextual words. I seek help from a linguist and work together to manually check if, in the semantic space, the variants occurring are aligned with the OCAI and CVF or not. Furthermore, I only take those variants as keywords that consistently appear to capture only the semantic cultural meaning in 10-K filings. For example, the top ten (10) contextual words for the keyword "ambition" are "business", "ecosystem", "oceans", "major", "support", "markets", "multinational", "build", "good", "cover", the top ten (10) contextual words for keyword "ambitious" are "growth", "embarked", "company", "program", "plan", "development", "business", "achieve", "standard", "expansion". Thus, I keep the keyword "ambitious" and delete "ambition" for the latter one, which is more pronounced to describe other situations instead of competitive cultural features in 10-K filings.

[Insert Table 3.3 Here]

Finally, I collect 89 word-roots and retain 261 keywords (see Table 3.4) to construct a bag of words. I consider the top ten (10) contextual words of the keywords I selected based on 10-K filings in the 1994-2016 time period from a plus/minus three words scale. In accordance with the OCAI and CVF, my bag of words builds up four types of culture (see Table 3.4): Collaborate: 16 word-roots and 38 keywords; Create: 30 word-roots and 91 keywords; Compete: 20 word-roots and 68 keywords; Control: 23 word-roots and 64 keywords. To the best of my knowledge, this work for the first time uses a bag-of-words approach to appraise compete culture captured by OCAI dimensions using textual analysis of public data.

[Insert Table 3.4 Here]

Using the new methodology, I collect the total frequency of words appearing in the firm's 10-K filing that belong to the corresponding culture's OCAI bag of words divided by a total number of lexical tokens describing all kinds of cultures to calculate the culture scores of the firm. Specifically, collaborate culture score (*COLLABORATE*), create culture score

($CREATE$), compete culture score ($COMPETE$), compete culture score ($CONTROL$) are computed as:

$$COLLABORATE = \frac{Number\ of\ lexical\ tokens\ describing\ the\ Collaborate\ Culture}{Total\ number\ of\ lexical\ tokens\ words\ describing\ all\ cultures}\ ;$$

$$CREATE = \frac{Number\ of\ lexical\ tokens\ describing\ the\ Create\ Culture}{Total\ number\ of\ lexical\ tokens\ words\ describing\ all\ cultures}\ ;$$

$$COMPETE = \frac{Number\ of\ lexical\ tokens\ describing\ the\ Compete\ Culture}{Total\ number\ of\ lexical\ tokens\ words\ describing\ all\ cultures}\ ;$$

$$CONTROL = \frac{Number\ of\ lexical\ tokens\ describing\ the\ Control\ Culture}{Total\ number\ of\ lexical\ tokens\ words\ describing\ all\ cultures}\ .$$

Compared with the traditional method, my new method has several advantages. Firstly, my new measurement of culture orientation will help users understand the cultural information captured by OCAI dimensions on a longitude basis other than a single point-in-time analysis. Secondly, thanks to the nature of 10-K documents, managers must disclose regularly and are held liable and accountable before the law if they provide false or misleading information in their communications or disclosures; the content I extract from 10-K filings is effective and reliable. Thirdly, my methodology provides access for both internal and external stakeholders to identify the critical cultural information in publicly disclosed documents.

3.4 Construct Validity of the Culture Measurement Methodology

Textual analysis is widely implemented in finance research (see, for instance, Loughran and McDonald, 2009; Hoberg and Phillips, 2010, 2016; Li et al., 2013; Hoberg et al., 2014). However, scholars have expressed concerns for the lack of supporting validity in the implementation of textual analysis (Weber, 1990; Neuendorf, 2002; Short et al., 2010). Considering the concerns in construct validity, in this section, this study follows Pandey and Pandey (2019) to conduct validity tests including content validity, reliability validity, external validity, dimensionality validity, and predictive validity. All tables for Chapter 3 are included at the end of this chapter and all variables are defined in Table 3.15.

[Insert Table 3.15 Here]

3.4.1 Content Validity and Reliability Validity

Researchers perform content validity to ensure the word selection lies in a sound theoretical context and is meaningful semantically. Thus, most content validity involves experts or judges to ensure the adequacy of the word bag (Pandey and Pandey, 2019). By examining the process of my rigorous word selection procedures, I find that my word bag construction process itself already includes content validity. In detail, I implement a deductive approach to use prior theories, the Competing Value Framework and the Organizational Culture Assessment Instrument (OCAI) questionnaire; then, I do an initial assessment of construct dimensionality based on existing literature. In the process of my word-bag formation, I develop an exhaustive word list and collect three words before and after keywords. By summarizing the top 10 contextual words in frequency and comprehensively considering the opinions combined by linguistics and finance scholars, I form the final version of my OCAI word bag. When I look back to the definition of content validity, I are sure that my OCAI keyword selection indeed lies in a sound theoretical context and is meaningful semantically. Thus, my word bag has reasonable support in content validity by nature. Furthermore, reliability validity is often executed to validate the consistency achieved in construct measurement. I adopt the word-count coding process in the whole keyword selection process carefully and seek advice from linguists. Thus, my word bag has reasonable support in reliability validity by nature as well.

3.4.2 External Validity

External validity, as defined by Cook and Campbell (1979), is the ability to generalize a measurement to different population segments and settings. In my study, I aim to test the generalizability of the OCAI-based culture measure. This measure has proven effective in capturing the subcultures that exist within various industry groupings. Given the diverse operating environments and regulatory frameworks across industries, I anticipate that firms in different sectors will exhibit distinct organizational structures and ecosystems. Therefore, my research focuses on whether my culture measure can effectively differentiate firms based on industry type. Additionally, I compare the culture score rankings of different industries for the competing culture pairs –collaborate vs. compete and create vs. control – to assess the internal consistency in measurement.

Table 3.5 reports the summary statistics for each culture score of firms separated according to the Fama and French 48 industry classification (exclude industry: Almost Nothing) for the period 1994 – 2021. The final column in all the panels provides the mean rank of the competing culture within the CVF framework. This enables us to compare the industry ranks for the cross-diagonal competing cultures. For example, in Panel A, where I examine the industry ranks for the collaborate culture, the final column displays the mean ranks of the industry when sorted according to the compete culture.

The results from Table 3.5 indicate that my firm-level measure of culture from 1994 to 2021 consistently ranks industries as I expect within the CVF framework (Hartnell et al., 2011; Cameron et al., 2022). To discuss the results from Panel A for the collaborate culture, I observe that the top-ranked collaborate culture industries are personal services, transportation and printing and publishing, while the industries with the lowest-ranked collaborate culture include competitive industries such as pharmaceutical products, electronic equipment and measuring and control equipment. When comparing the industry ranks for the contrasting culture, which in this case is the compete culture, I find that the highest ranked industries for compete are ranked low in collaborate culture and vice-versa. The rank correlation between the two competing cultures is -0.4507 and significant. A similar picture emerges when I study the other three cultures, create, compete and control, in Panels B, C, and D, whereby I observe consistency in ranking industries and a clear inverse pattern in ranks for the competing culture. Overall, the industry-level examination of the culture scores provides a strong indication of the internal consistency in the measurement of the various cultures.

[Insert Table 3.5 Here]

3.4.3 Dimensionality Validity

Dimensionality refers to testing whether the measurement is distinctly related to the construct being assessed. According to previous research (Durian et al., 2007; Short et al., 2010; Pandey and Pandey, 2019), the correlation matrix validity is especially suitable for validating multiple word lists, which were compiled to capture multidimensional constructs of interest. If dimensions are uncorrelated, they may evaluate absolutely opposite constructs, and the dimensions may have problems of convergent validity. Previous studies consider a correlation lower than 60 percent to be valid (Pandey and Pandey, 2019) and when the correlation is too high (over 0.8), researchers should consider the necessity of multi-dimensions. This study tabulates both Pearson correlation results and Spearman correlation results for dimensional validity.

In my case of organizational culture, I measure four types of culture with their own bags of words derived from the OCAI using 10-K filings from 1994 to 2021. The cultures in the opposing domains are collaborate vs. compete and create vs. control, which are theoretically the most distinct. While these four culture types do overlap in certain aspects-collaborate and control are both internal-focused; create and compete are both external-focused; collaborate and create emphasize flexibility and discretion; and compete and control emphasize stability-they fundamentally represent different ends of the horizontal or vertical axis of the Competing Values Framework. Therefore, I expect the correlations between the four cultures to be significant, however, they are not to be perfectly correlated (or else the cultures would not be distinct).

In Table 3.6, I tabulate the Pearson correlations as the Pearson correlation measures the strength and direction of a linear relationship between two continuous variables. It assumes that the variables are normally distributed and is widely used for its simplicity and effectiveness in identifying linear dependencies (Greene, 2008). I conduct correlation coefficient difference tests and confirm that all correlations are significantly different from zero. Interestingly, I find that the cultures in the opposing domains are all large and negatively correlated, which is as expected under the CVF framework since firms loading high on a particular culture will at the same time be loading low on the opposing culture. The largest negative Pearson correlation is observed between collaborate and compete scores (-0.47). Overall, I verify that the correlations between the culture scores are as expected and none of the culture measures are collinear to each other.

[Insert Table 3.6 here]

Further, I conduct an additional correlation analysis to test that the cultural dimensions are distinct from each other. For this investigation, I define the top 10% of firms with the highest scores for a particular culture as champions within that culture. Thus, for each year from 1994 to 2021, I have champions in the collaborate, create, compete, and control cultures. For dimensional validity, I expect that there should only be a small pairwise overlap (less than 10%, as in other studies) between the four samples of champions. Table 3.7

presents the results for the pairwise correlations for the four champions. I observe that the culture measures' cross-correlations align well with the theoretical framework, with culture champions overlapping by less than 3%, which is far better than expected. The results are consistent with my expectations and validate that the culture measures are distinct from each other.

[Insert Table 3.7 here]

Finally, to gauge that my four culture measures capture distinct dimensions, I conduct firm-level decile sorting. That is, I sort firms into 1 (lowest) to 10 (highest) decile groups based on one culture and calculate decile-specific mean values of other cultures for the period 1994−2021. I expect that firms in the lower deciles for one culture, say the control culture, will have a higher score for the competing cross-diagonal culture, which is the create culture. The decile sorting results are reported in Table 3.8.

In Panel A, I find that as the collaborate culture decile average values in column (1) increase from low to high, the average compete values in column (2) decrease uniformly. A similar inverse pattern is observed in Panel C, where I sort compete culture scores from low to high and estimate the average decile-level collaborate culture scores. Panels B and D evaluate the relationship between create and control cultures and I find consistent results. In all panels, I test the difference between the decile 10 and 1 and find the high and low culture deciles significantly different from each other (at 1% tolerance level), depicting that my decile sorting is meaningful. Overall, the results show that the competing nature of the four culture measures is also identified at the firm-decile-level, providing further support for dimensionality validity.

[Insert Table 3.8 here]

3.4.4 Predictive Validity

Predictive validity is defined as the extent to which the measure predicts the constructs of interests, thereby aligning with theoretically derived expectations. Therefore, if the measure that is developed is indeed capturing organizational culture, I expect the measure to be slow-moving and show some persistency over time, similar to the attributes of firms (Narver and Slater, 1990). To examine this, I sort firms into deciles and estimate the mean probability of firms remaining in the same decile next period for the period 1994−2021. If the culture measures have no persistent information and are completely random, then a firm's probability of remaining in the same decile next period should be approximately 10%. That is, if there is a random assignment of firms to deciles, a high/low probability occurring in one month should say nothing about the probability in the following month. Equally, I do not expect culture to be a fixed firm characteristic, which does not change or evolve over time.

Table 3.9 presents the mean annual transition probabilities by deciles for all cultures. I find that for the case of all cultures, the diagonal elements of the transition matrix are much higher than the random 10%, with the extreme deciles showing high persistence. Specifically, in Panel A, I report the average annual transition probabilities by deciles for my collaborate culture measure. I observe that firms in the lowest (1st) decile of collaborate in any one year have a 57% chance of remaining in the lowest decile of collaborate in the following year, while firms in the highest (10th) decile remain in that decile in the following year with a probability of 48%. Panel B provides the average annual transition probabilities by deciles for create culture. Here, I find that when firms are in the 1st decile of create, they have a 67% chance of staying in that lowest decile in the following year. Conversely, I observe that when firms are in the 10th decile of create culture, they have a 67% chance of staying in that lowest decile in the following year. In Panel C, I provide the transition analysis for the compete culture. I find that those firms ranked in the lowest decile of compete remain in that decile with a 62% likelihood in the following year, while firms in the highest decile remain in that decile in the following year with a 59% chance. Finally, Panel D provide average annual transition probabilities control culture. As with my previous results, I find that firms in the lowest decile remain in that decile 61% percent of the time, and firms in the highest decile remain in that decile 75% of the time in the following year. These results illustrate that the culture measurement is non-random and is a persistent quantity (i.e., prior period culture measure predicts current period culture). These results are consistent with the past literature suggesting persistence in organizational cultures (Guiso et al., 2006; Hartnell et al., 2011; Cameron et al., 2022; Guiso et al., 2015a, 2015b; Andreou et al., 2021).

[Insert Table 3.9 Here]

To further assess the predictive validity of my textual measure of organizational culture, I examine how corporate culture interacts with an exogenous shock, specifically the COVID-19 pandemic, to influence firm performance and investor confidence. This analysis provides additional evidence that the proposed measure captures meaningful cultural differences that translate into organizational outcomes. The objective of this test is to validate that firms with strong corporate cultures, as identified through my methodology, demonstrate resilience and adaptability during external shocks, supporting the theoretical link between culture and performance under dynamic conditions.

For exploring the roles corporate cultures play in confronting COVID-19, the unpredictable exogenous shock, I select quarterly data, a shorter time interval instead of annual for several reasons. Firstly, I define the beginning of the crisis as March 11, 2020, when the World Health Organization officially declared COVID-19 a pandemic. If I use yearly data, for most companies, the annual reports inevitably include both pre and post pandemic data, which may distort my regression results. Secondly, the methodology is used to characterize companies with different organizational cultures and investigate the effectiveness in respond to COVID-19 respectively. Additionally, organizational culture, although evolving over the long term, often manifests in instinctive responses to sudden shocks, making quarterly data more suitable for capturing critical volatility.

My sample consists of yearly culture data from the fiscal year 2016 and quarterly performance data extracted from March 01, 2019, to February 28, 2021(four quarters before and four quarters after the onset of the pandemic).I employ a difference-in-differences (DiD) approach to estimate the interaction effect of strong corporate culture with the pandemic shock. Specifically, the dummy variable $COVID_t$, captures quarters after March 2020; and the variable $STRONG\_CULTURE_{i,t}$ identifies firms with 3-year average scores scoring a decile rank of 10 in one culture and a low decile rank of 1 in the opposing culture within the Competing Values Framework (collaborate vs. compete; create vs. control) during the pre-COVID period (2016–2018). The pandemic effect is captured through an interaction term between the dummy variable $COVID_t$ and $STRONG\_CULTURE_{i,t}$.

To measure the firm performance and investor confidence after COVID-19, we define $OPERATING\_PROFIT_{i,t}$ (= [revenue - cost of goods sold - reported sales, general, and administrative expenses]/ total assets) computed as in Ball et al.(2016); $TOBINQ_{i,t}$ [=market value of assets (total assets + market value of common equity - common equity - deferred taxes)/(0.9*book value of total assets + 0.1*market value of assets)] computed as in Kaplan and Zingales (1997); $ASSET\_TURNOVER_{i,t}$, total sales scaled by total assets and $CASH\_TURNOVER_{i,t}$, total sales scaled by cash and short-term investments. Following Duchin et al. (2010), I exclude financial firms and utilities (SIC codes: 4900–4949 and 6000–6999), firms with a market capitalization of less than 50 million, and those experiencing a quarterly asset or sales growth greater than 100% during the sample period, to minimize distortions in the results caused by extreme outliers..

The regression analysis includes the following control variables, chosen for their theoretical relevance and established roles in explaining firm performance in the literature: $CASH_{i,t}$, defined as cash and short-term investments scaled by total current liabilities, accounts for a firm's liquidity position, which is crucial for maintaining operational flexibility during crises. Liquidity is expected to positively influence firm performance metrics, consistent with the findings of Duchin et al. (2010); $LEVERAGE_{i,t}$ *(ST),* measured as short-term debt scaled by total assets, captures the financial constraints imposed by debt obligations. Higher leverage is associated with increased financial risk and reduced flexibility, leading to a negative expected relationship with firm performance, as supported by Kaplan and Zingales (1997); and $SIZE_{i,t}$, the natural logarithm of total assets at the end of the fiscal year, which can confer advantages such as economies of scale and resource access. Larger firms are generally more resilient during economic shocks, suggesting a positive relationship with performance measures, as indicated by Ball et al. (2016). To conduct the analysis, I estimate the following regression model:

$$PERFORMANCE_{i,t} = \alpha_1 + \alpha_2 COVID_t + \alpha_3 COVID_t * STRONG\_CULTURE_{i,t} + \alpha_4 CASH_{i,t} + \alpha_5 LEVERAGE_{i,t}\,(ST) + \alpha_6 SIZE_{i,t} + \mu_i + \varepsilon_{i,t} \qquad (3.1)$$

where, the variable $PERFORMANCE_{it}$ is measured by one of $OPERATING\_PROFIT_{i,t}$, $TOBINQ_{i,t}$, $ASSET\_TURNOVER_{i,t}$ and $CASH\_TURNOVER_{i,t}$. All regressions include firm fixed effects (μ_i), which control for unobservable, time-invariant characteristics at the firm level that may influence performance. The inclusion of μ_{it} ensures that the analysis isolates the within-firm variation over time, focusing on the impact of the $COVID_t$ dummy variable and the interaction term with $STRONG\_CULTURE_{i,t}$. To address the potential influence of outliers, all continuous variables are winsorized at the 1% and 99% levels. This ensures that extreme values do not disproportionately affect the regression results while preserving the variability of the data. The standard errors are clustered at the firm-level. All other variables are as previously defined.

The results in Table 3.10 align with theoretical expectations and highlight the economic and statistical significance of the findings. The coefficients for $COVID_t$ are negative and highly significant across all columns, indicating that the pandemic had a substantial adverse effect on firm performance: -0.113 for $OPERATING\_PROFIT_{i,t}$, -0.030 for $TOBINQ_{i,t}$, -0.114 for $ASSET\_TURNOVER_{i,t}$, and -0.192 for $CASH\_TURNOVER_{i,t}$. In contrast, the interaction term $COVID_t{*}STRONG\_CULTURE_{i,t}$ shows positive and significant coefficients (0.084, 0.060, 0.078, and 0.120, respectively), demonstrating that firms characterized by strong corporate cultures were better able to mitigate these negative effects. For instance, the combined coefficients suggest that firms with strong cultures experienced a substantially smaller decline in profitability and, in some cases, even positive outcomes, as reflected in $TOBINQ_{i,t}$. These findings are consistent with Li et al. (2021), who demonstrate that firms with strong corporate cultures outperform their peers, particularly during periods of crisis.

[Insert Table 3.10 Here]

The results for the control variables in Table 3.10 provide nuanced insights, some of which align with theoretical expectations, while others reflect the unique circumstances of the COVID-19 pandemic. $CASH_{i,t}$ is negative and statistically significant in most specifications, which contrasts with the expected positive relationship often observed in the literature. This may be attributed to firms holding excess liquidity as a precautionary measure during the pandemic, prioritizing survival over performance, which diluted its positive effects. For $LEVERAGE_{i,t}$ *(ST),* the coefficient is consistently negative and significant, aligning with theoretical expectations that higher leverage increases financial risk and constrains firms during crises. The results for $SIZE_{i,t}$, show varied effects: a positive and significant relationship with $OPERATING\_PROFIT_{i,t}$, suggesting that larger firms benefited from resource availability and economies of scale. However, $SIZE_{i,t}$, is negatively associated with $ASSET\_TURNOVER_{i,t}$, reflecting the pandemic's disproportionate impact on sales for larger firms, as many faced operational shutdowns or demand declines, which were not offset by reductions in their asset bases. Similarly, the negative coefficient for $SIZE_{i,t}$, in $TOBINQ_{i,t}$, likely reflects investor concerns about larger firms' flexibility during the pandemic, particularly in heavily affected industries, while its lack of significance in $CASH\_TURNOVER_{i,t}$, suggests limited influence of size on cash management strategies. These deviations from theoretical expectations can also be attributed to the use of quarterly data, which captures short-term volatility, and the unprecedented nature of the pandemic, which introduced industry- and firm-specific variations. Despite these differences, the overall consistency of key findings reinforces the credibility of the model and highlights the robustness of the primary results.

3.5 Methodology Applications

3.5.1 Application to Covid Period Analysis

The COVID-19 has had a significant impact on manner in which people work and live. In particular, individuals' means and ways of working have been significantly disrupted and the telecommuting has become an unexpected but logical alternative to non-essential office activities, which brings a significant challenge for managers. As corporate culture is a reflection of managements' tendencies and leadership philosophy, it is reasonable to expect that the covid-19 period has made it harder to build, maintain and strengthened corporate culture as everyone is working from home (howard-greenville, 2020; Kniffin et al., 2020). Under this macro environment, academics are becoming increasing curious regarding the questions whether and how organizational cultures actually changes when there is a wide scale societal jolt and disruption in firms' operating environment or does corporate culture remain the same even under these circumstances? Also, if corporate culture does indeed change, questions related to which cultural types and what direction of cultural development is preferred by firms and/or do different firms have differing tendencies to change corporate culture as a result of the influence of COVID-19 remain unaddressed (Spicer, A., 2020)?

Next, I assess corporate culture change as a result of the COVID-19 disruption. To achieve this, I first note that before the exogenous COVID-19 shock in 2019, corporate culture was observed to be sticky as it changed relatively slowly (please see Table 3.9). Therefore, for the years around the initial COVID-19 period 2016 to 2021, I divide these years in my sample into two parts. Specifically, I denote the period 2016 to 2018 as the pre-COVID period and 2020 to 2021 as the post-COVID period and, based on these pre and post-COVID periods, develop several text-based measures of corporate culture for each firm. Particularly, I define *PRE_COLLABORATE*, *PRE_CREATE*, *PRE_COMPETE* and *PRE_CONTROL* as the three (3) year average corporate culture scores for the respective cultural orientations for the pre-COVID period of 2016 to 2018, while I use the variables *POST_COLLABORATE*, *POST_CREATE*, *POST_COMPETE* and *POST_CONTROL* represent the two (2) year average corporate culture scores for the post-COVID period of 2020 to 2021. In addition, I compute the variables $\Delta\,COLLABORATE\,\%$, $\Delta\,CREATE\,\%$, $\Delta COMPETE\,\%$, and $\Delta CONTROL\,\%$, as the difference between my post- and pre- COVID corporate culture cultures divided by pre-COVID cultures. I provide an example of how these variables are computed for $\Delta COLLABORATE\%$ below:

$$\Delta COLLABORATE\% = \frac{POST\_COLLABORATE - PRE\_COLLABORATE}{PRE\_COLLABORATE}$$

Table 3.11 presents the mean values for Δ *COLLABORATE %*, Δ *CREATE %*, Δ*COMPETE %*, and Δ*CONTROL %*, sorted based on firms from 1st (lowest/Contenders) to 10th (highest/Champions) decile rank of *PRE_COLLABORATE*, *PRE_CREATE*, *PRE_COMPETE* and *PRE_CONTROL* in Panels A, B, C and D, respectively. Some of the more interesting results are provided in Panel A, where I find that, on average, those firms which score in the lowest decile of collaborate in the pre-COVID period increase their level of collaborate culture by a massive 57% over the COVID-19 period. In addition, I find in Panel A that firms in the highest decile of pre-COVID collaborate culture increased their level of create culture over the COVID-19 disruption by 26%. Likewise, selected results from Panel B show that, on average, those firms in the highest decile of create culture in the pre-COVID period increased their level of collaborate culture by 18%; meanwhile, those firms in the lowest decile of create culture increased their orientation towards that culture by 48% during the COVID period. A similar pattern observed in Panel C, where I find that, on average, those firms that are in the highest decile of pre-COVID compete culture increase their level of collaborate culture by 29% over the COVID-19 period. Furthermore, I find that firms in the highest decile of pre-COVID compete culture increased their level of create corporate culture by 24% during COVID-19. In Panel D, I report that, on average, those firms falling into the highest decile of pre-COVID control culture increase their level of collaborate culture by 15% and the level of create culture by 32% after the COVID disruption. Overall, these striking results suggest that far from remaining stagnant in their cultural orientation, over the COVID-19 crisis period firms have tended to lean towards the collaborate and create corporate cultures, i.e., towards the flexibility dimension.

[Insert Table 3.11 Here]

I conduct further analysis related to the change in corporate culture over the COVID-19 period by considering the movement in culture for those firms with *STRONG_CULTURE* (i.e., decile rank 10 in one culture and decile rank 1 in the competing culture in the CVF)[8] in the pre-COVID period. As before, I compute the variables Δ *COLLABORATE %*, Δ*CREATE %*, Δ*COMPETE %*, and Δ*CONTROL %*, as the difference between the post- and pre- COVID corporate cultures divided by pre-COVID cultures and use these variables to understand whether and how firms which has strong in each of the four cultural types tend to shift their cultural orientation during the COVID-19 disruption.

Table 3.12 below presents the results of this analysis, where I find that, on average, those firms which are strong in collaborate culture during the pre-COVID period, tended to shift their cultural orientation towards the create culture as they increased the level of that culture by 21% during the COVID-19 period. In addition, I note that those who were strong in create culture in the pre-COVID period increased their level of collaborate culture by 17% during COVID-19. Interestingly, I find that those firms which are strong in pre-COVID compete culture and those that are strong in pre-COVID control culture increased their respective levels of collaborate over the COVID-19 period by 62% and 13%. Similarly, I note that those same firms also tended to shift their cultural orientation towards the create culture as pre-COVID strong compete firms increased their level of that create culture by 22%, while pre-COVID strong control firms increased their level of create culture by 44% over COVID. Consistent with my prior results, I find that during the COVID-19 period firms with particularly strong corporate cultures have tended to lean towards the collaborate and create cultural orientations and they seek greater levels of flexibility.

[Insert Table 3.12 Here]

[8] For instance, strong collaborate would score high (decile 9 or above) in collaborate culture and load low (decile 2 or lower) in the compete culture. Similarly, strong create would load high on create culture but low in the control corporate cultural type. Conversely, strong control would have high in control culture and low in the collaborate culture. Meanwhile, strong control would load high on control and low on create corporate culture.

In Table 3.13, I report changes in culture during the COVID period by Fama and French 12 industry classifications. I note, in a similar fashion to my prior results, that on average, during the COVID-19 period, firms across different industries are moving away from both the compete and control cultures and towards greater flexibility dimension cultures, namely, collaborate and create cultural types. In particular, I find more emphasis being placed on the collaborate culture by firms in the Chemicals and Allied Products and Consumer Durables industries as they increase their orientation toward the collaborate culture by approximately 18%. Likewise, I note that firms in the finance and shop industries increased their orientation towards create by 25% and 19%, respectively. I observe the lowest level of movement towards the collaborate and create cultures among those firms in the Energy and the healthcare industries.

[Insert Table 3.13 Here]

3.5.2 Application to Interfering Business Performance

Finally, I conduct heterogeneity analysis to better understand the type of firms that are moving towards greater collaborate and create cultural orientation. To do this, I first compute the variables $\Delta COLLABORATE\%$ and $\Delta CREATE\%$, as the respective differences between post- and pre- covid collaborate and create cultures divided by pre-covid collaborate and create cultures and then I regress these variables on factors known to capture various firm specific characteristics. To do this, I estimate the following regression model:

$$\begin{aligned}\Delta CULTURE\%_i \; = \; & \alpha_1 + \alpha_2 OPERATING\_PROFIT_{i,\,2018} + \alpha_3 ASSET\_TURNOVER_{i,\,2018} \\ & + \alpha_4 R\&D_{i,\,2018} + \alpha_5 CASH_{i,\,2018} + \alpha_6 LEVERAGE_{i,\,2018}(LT) \\ & + \alpha_7 SIZE_{i,\,2018} + \alpha_8 EMP_{i,\,2018} + \gamma_{s,\,2018} + \varepsilon_{i,\,2018} \qquad (3.2)\end{aligned}$$

where, the variable $\Delta\, CULTURE\ \%_i$ is measured by one of $\Delta\, COLLABORATE\ \%_i$ or $\Delta CREATE\%_i$. For independent variables: $OPERATING\_PROFIT_{i,2008}$ (= [revenue - cost of goods sold - reported sales, general, and administrative expenses]/ total assets); total sales scaled by total assets, $ASSET\_TURNOVER_{i,2008}$; natural logarithm of 1 plus research and development expenses, $R\&D_{i,2008}$; cash and short-term investments by total current liabilities, $CASH_{i,2008}$; firm's long-term debt scaled by total current liabilities, $LEVERAGE_{i,2008}(LT)$; the natural logarithm of firm's total assets, $SIZE_{i,2008}$, and the number of employees scaled by total assets, $EMP_{i,2008}$. All other variables are as previously defined, and industry fixed effect(γ_s) is considered in the regression.

I find a positive and significant relationship between $R\&D_{i,2008}$ and $\Delta COLLABORATE\%_i$, $LEVERAGE_{i,2008}\ (LT)$ and $\Delta COLLABORATE\%_i$, and between $EMP_{i,2008}$ and $\Delta COLLABORATE\%_i$. These results indicate that firms investing more heavily in R&D, those with higher levels of long-term debt, and those with larger workforces tend to shift toward the collaborate culture. This cultural shift reflects the importance of collaboration in fostering innovation, enhancing financial resilience, and managing organizational complexity, particularly in larger firms. Conversely, a negative and significant relationship is observed between $ASSET\_TURNOVER_{i,2008}$ and $\Delta COLLABORATE\%_i$, suggesting that firms with lower operational efficiency (as measured by asset turnover) may prioritize collaboration to enhance internal alignment and long-term performance. As it relates to $\Delta CREATE\%_i$, I find a negative and significant relationship with $R\&D_{i,2008}$, alongside positive relationships with $SIZE_{i,2008}$ and $EMP_{i,2008}$. These results suggest that firms with larger sizes and a greater number of employees tend to adopt create culture traits such as adaptability and flexibility, likely to address external demands in dynamic market environments. The negative relationship between $R\&D_{i,2008}$ and $\Delta CREATE\%_i$ further supports the observation that pure innovation-driven firms may shift focus from risk-taking and flexibility (attributes of create culture) toward teamwork and collaboration, as evidenced by their concurrent movement toward collaborate culture. This finding aligns with observations in Table 3.11 Panel B, which demonstrate that firms with high create culture scores often rebalance toward collaborate culture over time.,

[Insert Table 3.14 Here]

3.6 Conclusion

In this study, I develop and validate a novel methodology for measuring organizational culture using textual analysis of 10-K filings, incorporating the Organizational Culture Assessment Instrument (OCAI) and natural language processing techniques. This approach addresses key limitations of traditional survey-based methods by enabling longitudinal and cross-industry analysis through publicly available data, providing robust and scalable insights into organizational culture.

This study contributes to the literature on the Competing Values Framework (CVF) and OCAI by extending their applicability beyond static, internal survey tools. Traditional methods have been constrained by their reliance on confidential and time-specific data, limiting their use for longitudinal analysis or external evaluation. By leveraging textual analysis of corporate disclosures, this study provides a scalable methodology that allows researchers and practitioners to objectively assess cultural dynamics over time and across industries. This accessibility not only enhances the utility of cultural insights for internal management but also provides external stakeholders, such as investors and policymakers, with a deeper understanding of organizational behavior.

The validity of this methodology is established through rigorous testing, including content, reliability, external, dimensionality, and predictive validity. These validation procedures ensure the robustness of the measurement tool, addressing longstanding concerns about the reliability of textual analysis in cultural research. The methodological rigor of this study provides a strong foundation for future applications of textual analysis in organizational studies, offering researchers and practitioners a reliable framework for assessing cultural attributes.

By examining cultural shifts during the COVID-19 pandemic, this study also highlights the dynamic and adaptive nature of organizational culture. The results demonstrate significant transitions toward more flexible cultural dimensions, particularly collaborate and create cultures, in response to external shocks. These findings underscore the importance of fostering adaptability and resilience within organizations, offering empirical evidence that firms with such cultural traits are better equipped to navigate crises.

The implications of this research are significant for both policy and practice. For policymakers, the results emphasize the need to incentivize cultural adaptability and resilience, particularly in innovation-driven and highly leveraged industries. For managers, the methodology provides a practical tool to monitor and realign organizational culture to balance flexibility with stability, ensuring long-term sustainability and competitiveness. By bridging theoretical, methodological, and practical perspectives, this study not only advances the academic discourse on organizational culture but also provides actionable insights for navigating the complexities of an evolving business environment.

Tables and Figure

Table 3.1: 10-X Variants Used

This table presents the 10-X variants used in this thesis.

```
f_10K = ['10-K', '10-K405', '10KSB', '10-KSB', '10KSB40']
f_10KA = ['10-K/A', '10-K405/A', '10KSB/A', '10-KSB/A', '10KSB40/A']
f_10KT = ['10-KT', '10KT405', '10-KT/A', '10KT405/A']
f_10Q = ['10-Q', '10QSB', '10-QSB']
f_10QA = ['10-Q/A', '10QSB/A', '10-QSB/A']
f_10QT = ['10-QT', '10-QT/A']
```

Table 3.2: 10-K Sample Creation Process

The is the 10-K sample creation process. I download 10-X filings of publicly listed firms whose filing dates are in the range of 1994 and 2021 from the EDGAR website. All tables for Chapter 3 are included at the end of this chapter. The original 10-X variants (see Table 3.1) data includes 10-K, 10-KA, 10-Q, 10-QA, 10-KT and 10-QT. After filtering out duplicates and retaining only the 10-K filings 10-K, 10-KSB, 10-K405 and 10-KSB40, my sample size decreased from 1,140,486 to 265,560. Most studies using textual analysis focus mainly on the textual content of the document, while a substantial portion of an original EDGAR text filing's content consists of HTML code, embedded PDFs, jpg and other artefacts not typically of interest. I parse the original data sources associated with 10-K filings and then extract extraneous materials. After filtering, the files exclude markup tags, ASCII-encoded graphics, and tables, which are usually not the focus of textual analysis. Furthermore, acronyms, proper nouns, all numbers, and single letters should be removed from my analysis so it will be easier to identify and count the collection of characters as words in the analysis. I delete files with less than 2,000 words in analysis, reducing the sample size to 259,189. Lastly, I only keep filings whose fiscal years are between 1994 and 2021 and those that can be classified into Fama French 48 Industry Classification, thus obtaining the sample to 251,707 firm-year observations.

Filtering steps	Sample size
Full 10-X Document	
EDGAR 10-X documents filing date between 1994 and 2021, complete sample	1,140,486
Retaining the 10-K file types, 10-K, 10-KSB, 10-K405 and 10-KSB40 between1994 and 2021 (excluding 10-KA, 10-Q, 10-QA, 10-KT and 10-QT)	265,560
Excluding 10-K files with total number of words < 2000	259,189
Retaining 10-K files within the fiscal year between 1994 and 2021	256,294
Excluding filings of firms not classified in Fama French Industry Classification	253,803
Excluding duplicate filings of the same firm in the same fiscal year	251,707
Final firm-year sample	251,707

Table 3.3: Stop Indicators Used in Textual Analysis.

This table presents the four types of stop indicators (end of sentence) used in the process of textual analysis.

<table>
<tr><td>1. Stop symbols = [‘@’, ‘#’, ‘$’, ‘%’, ‘^’, ‘&’, ‘*’, ‘(‘, ‘)’, ‘{‘, ‘}’, ‘[‘, ‘]’, ‘\’, ‘|’, ‘;’, ‘‘’, ‘,’, ‘.’, ‘/’, ‘:’, ‘”’, ‘<’, ‘>’, ‘?’]</td></tr>
<tr><td>2. Stop words = ['ourselves', 'hers', 'between', 'yourself', 'but', 'again', 'there', 'about', 'once', 'during', 'out', 'very', 'having', 'with', 'they', 'own', 'an', 'be', 'some', 'for', 'do', 'its', 'yours', 'such', 'into', 'most', 'itself', 'other', 'off', 'is', 'am', 'or', 'who', 'as', 'from', 'him', 'each', 'the', 'themselves', 'until', 'below', 'are', 'these', 'your', 'his', 'through', 'nor', 'me', 'were', 'her', 'more', 'himself', 'this', 'down', 'should', 'our', 'their', 'while', 'above', 'both', 'up', 'to', 'ours', 'had', 'she', 'all', 'no', 'when', 'at', 'any', 'before', 'them', 'same', F'and', 'been', 'have', 'in', 'will', 'on', 'does', 'yourselves', 'then', 'that', 'because', 'what', 'over', 'why', 'so', 'can', 'did', 'not', 'now', 'under', 'he', 'you', 'herself', 'has', 'just', 'where', 'too', 'only', 'myself', 'which', 'those', 'after', 'few', 'whom', 'being', 'if', 'theirs', 'my', 'against', 'by', 'doing', 'it', 'how', 'further', 'was', 'here', 'than', 'us', 'of', 'we']</td></tr>
<tr><td>3. Any number</td></tr>
<tr><td>4. Any word which length equals to 1</td></tr>
</table>

Table 3.4: OCAI Bag of Words

This table reports the OCAI bag of words with synonyms that best describe the four corporate cultures (compete, create, collaborate, and control) of the competing value framework (CVF). Words ending with "*" indicate that this study utilizes all suffixes for those words to count as many words as possible with a close meaning.

OCAI Bag of Words			
(A) Collaborate	(B) Create	(C) Compete	(D) Control
mentor*, coaching, counsel*, nurture*, foster*, train*, teamwork, cooperatively, consensus*, participate*, integrity, trustworthy, commitment, openness, impartial*, transparent*	dynamic*, progression*, entrepreneurial*, talent*, innovate*, invent*, modernize*, avant-garde, ground-breaking*, trend-setter*, flexible*, opportunity*, unique*, breakthrough, pioneered*, originally, develop*, advancements, cutting-edge, forefront, leading-edge, spearheaded*, brand-new, contemporary*, state-of-the-art, novel, ultra-modern, create*, designer*, launch*	succeed*, accomplish*, achieve*, compete*, strive*, vying, ambitious*, cut-throat*, rival*, aggressive*, energetically, vigorously, zealously, goal*, target*, win*, dominant*, surpass*, outdo, outshine*	controllable*, oversee*, supervise*, superintend*, orderly, structure*, methodical*, systematic*, protocol*, rigidly, unbending, curb, coordinate*, organize*, efficient*, competency, obey*, stability, solidity, steadfast*, policy*, dependable*, reliable*

continued on the next page

Wordlist

A (Collaborate)
mentor* = [mentored, mentoring, mentors, mentorship]
coaching = [coaching]
counsel* = [counsel, counseled, counseling, counsels]
nurture* = [nurture, nurtured, nurtures, nurturing]
foster* = [fostered, fostering, fosters]
train* = [train, training]
teamwork = [teamwork]
cooperatively = [cooperatively]
consensus* = [consensual, consensus, consensuses]
participate* = [participate, participated, participates, participating, participation]
integrity = [integrity]
trustworthy = [trustworthy]
commitment = [commitment]
openness = [openness]
impartial* = [impartial, impartiality, impartially]
transparent* = [transparency, transparent, transparently]

B (Create)
dynamic* = [dynamic, dynamically]
progression* = [progression, progressive]
entrepreneurial* = [entrepreneurial, entrepreneurism]
talent* = [talent, talented, talents]
innovate* = [innovate, innovated, innovating, innovation, innovational, innovative, innovatively, innovativeness, innovators, innovator]
invent* = [invent, invented, inventing, invention, inventions, inventive, inventively, inventiveness, inventor, inventors, invents]
modernize* = [modernist, modernization, modernize, modernized, modernizing]
avant-garde = [avant-garde]
ground-breaking* = [ground-breaking, groundbreaking]
trend-setter* = [trend-setter, trend-setting, trendsetter, trendsetting]
flexible* = [flexible, flexibly]
opportunity* = [opportunity, opportunistic]
unique* = [unique, uniquely, uniqueness]
breakthrough = [breakthrough]
pioneered* = [pioneered, pioneering, pioneers]
originally = [originally]
develop* = [develop, developed, developing, developmentally, develops, developments]
advancements = [advancements]
cutting-edge = [cutting-edge]
forefront = [forefront]
leading-edge = [leading-edge]
spearheaded* = [spearheaded, spearheading, spearheads]
brand-new = [brand-new]
contemporary* = [contemporary, contemporize, contemporized, contemporizing]
state-of-the-art = [state-of-the-art]
novel = [novel]
ultra-modern = [ultra-modern]
create* = [create, creates, creating, creative, creatively, creativeness, creatively, creator, creators]
designer* = [designer, designers, designs]
launch* = [launch, launched, launches, launching]

C (Compete)
succeed* = [succeed, success, successful, successfully]
accomplish* = [accomplish, accomplishable, accomplished, accomplishes, accomplishing, accomplishment, accomplishments]
achieve* = [achieve, achieved, achievement, achievements, achieves, achieving]
compete* = [compete, competed, competes, competing, competition, competitive, competitively, competitiveness, competitor, competitors]
strive* = [strive, strives, striving]
vying = [vying]
ambitious* = [ambitious, ambitiously]
cut-throat* = [cut-throat, cutthroat]
rival* = [rival, rivaled, rivaling, rivalry, rivals]
aggressive* = [aggressive, aggressively, aggressiveness]
energetically = [energetically]
vigorously = [vigorously]
zealously = [zealously]
goal* = [goal, goals]
target* = [target, targeted, targeting, targets]
win* = [win, winning, wins, won]
dominant* = [dominant, dominate, dominated, dominates, dominating]
surpass* = [surpass, surpassed, surpasses, surpassing]
outdo = [outdo]
outshine* = [outshine, outshines]

D (Control)
controllable* = [controllable, controlling]
oversee* = [oversaw, oversee, overseeing, overseen, oversees]
supervise* = [supervise, supervised, supervises, supervising, supervision, supervisor, supervisors, supervisory]
superintend* = [superintend, superintendent, superintendents, superintending]
orderly = [orderly]
structure* = [structure, structurally]
methodical* = [methodical, methodically]
systematic* = [systematic, systematically, systematization, systematize, systematized, systematizing]
protocol* = [protocol, protocols]
rigidly = [rigidly]
unbending = [unbending]
curb = [curb]
coordinate* = [coordinate, coordinated, coordinates, coordinating, coordination]
organize* = [organize, organizes, organizing]
efficient* = [efficiencies, efficiency, efficient, efficiently]
competency = [competency]
obey* = [obey, obeyed, obeying, obeys]
stability = [stability]
solidity = [solidity]
steadfast* = [steadfast, steadfastly, steadfastness]
policy* = [policy, policies]
dependable* = [dependable, dependably]
reliable* = [reliability, reliable, reliably]

Table 3.5: External Validity: Discriminating across Industries for the Four Cultures

These table present the mean, median, standard deviation and number of firms in the sample across industries for the period 1994-2021 (excluding the industry classification 'Other/Almost Nothing'). The industries are sorted according to the mean culture score and the rank of the industry for the competing culture (collaborate vs. compete; create vs. control) are reported in the final column.

Panel A: Sort according to *COLLABORATE.*

Industry	Number	Mean	Median	Std.	Rank of *COLLABORATE*	Rank of *COMPETE*
Personal Services	2535	0.2315	0.1832	0.1660	1	45
Transportation	4094	0.1969	0.1778	0.1143	2	35
Printing and Publishing	1732	0.1938	0.1429	0.1529	3	31
Healthcare	3738	0.1922	0.1808	0.1073	4	42
Restaraunts, Hotels, Motels	4244	0.1826	0.1638	0.1078	5	24
Insurance	5908	0.1813	0.1154	0.2135	6	47
Shipbuilding, Railroad Equipment	364	0.1795	0.1612	0.1022	7	38
Utilities	7769	0.1791	0.1633	0.0983	8	44
Petroleum and Natural Gas	10653	0.1661	0.1429	0.1114	9	39
Coal	414	0.1654	0.1490	0.0848	10	36
Steel Works Etc	1896	0.1644	0.1355	0.1146	11	10
Shipping Containers	503	0.1642	0.1455	0.0974	12	13
Tobacco Products	239	0.1618	0.1373	0.1104	13	4
Fabricated Products	573	0.1608	0.1287	0.1170	14	16
Real Estate	8845	0.1607	0.1250	0.1456	15	43
Business Supplies	1428	0.1607	0.1333	0.1137	16	20
Wholesale	7022	0.1594	0.1333	0.1140	17	12
Candy & Soda	288	0.1572	0.1206	0.1168	18	15
Textiles	674	0.1570	0.1244	0.1165	19	33
Aircraft	767	0.1566	0.1420	0.0944	20	26
Retail	8747	0.1558	0.1333	0.1064	21	6
Construction	2171	0.1551	0.1333	0.1044	22	37
Entertainment	4497	0.1526	0.1290	0.1091	23	23
Trading	21772	0.1519	0.1284	0.1188	24	40
Construction Materials	2794	0.1516	0.1228	0.1147	25	27
Food Products	2779	0.1468	0.1212	0.1108	26	7
Beer & Liquor	884	0.1436	0.1148	0.1104	27	9
Rubber and Plastic Products	1739	0.1436	0.1148	0.1123	28	29
Automobiles and Trucks	2641	0.1422	0.1159	0.0963	29	22
Banking	23988	0.1403	0.1207	0.0966	30	46
Machinery	5041	0.1372	0.1084	0.1025	31	19
Defense	328	0.1351	0.1250	0.0846	32	30
Apparel	1954	0.1349	0.1027	0.1060	33	18
Chemicals	3995	0.1314	0.1097	0.0962	34	28
Business Services	28219	0.1304	0.1066	0.0975	35	17
Consumer Goods	2886	0.1285	0.1010	0.1002	36	21
Agriculture	838	0.1279	0.1071	0.1006	37	32
Communication	7043	0.1266	0.1018	0.0950	38	1
Electrical Equipment	2224	0.1254	0.0960	0.1042	39	25
Precious Metals	1575	0.1235	0.0968	0.0969	40	41
Non-Metallic and Industrial Metal Mining	3837	0.1207	0.0986	0.0939	41	34
Computers	6052	0.1206	0.0989	0.0866	42	2
Recreation	1483	0.1206	0.0933	0.0964	43	14
Medical Equipment	6339	0.1143	0.0980	0.0806	44	11
Measuring and Control Equipment	3495	0.1119	0.0889	0.0879	45	8
Electronic Equipment	9553	0.1021	0.0805	0.0824	46	3
Pharmaceutical Products	12111	0.0833	0.0678	0.0624	47	5
Rank Correlation					-0.4507	

continued on the next page

Table 3.5 cont'd.

Panel B: Sort according to *CREATE*.

Industry	Number	Mean	Median	Std.	Rank of *CREATE*	Rank of *CONTROL*
Pharmaceutical Products	12111	0.3373	0.3364	0.0906	1	47
Medical Equipment	6339	0.2935	0.2857	0.0963	2	46
Recreation	1483	0.2811	0.2787	0.1123	3	43
Measuring and Control Equipment	3495	0.2727	0.2667	0.102	4	42
Electronic Equipment	9553	0.272	0.2634	0.1007	5	41
Computers	6052	0.2664	0.2571	0.0982	6	45
Defense	328	0.2614	0.2198	0.155	7	32
Consumer Goods	2886	0.2591	0.2489	0.1244	8	36
Business Services	28219	0.2571	0.2511	0.1158	9	38
Electrical Equipment	2224	0.2529	0.2423	0.1147	10	26
Rubber and Plastic Products	1739	0.2518	0.2593	0.112	11	33
Precious Metals	1575	0.2499	0.2353	0.1248	12	8
Apparel	1954	0.2488	0.2454	0.1067	13	34
Textiles	674	0.244	0.2273	0.12	14	29
Non-Metallic and Industrial Metal Mining	3837	0.2429	0.2267	0.1213	15	11
Entertainment	4497	0.2383	0.2195	0.1209	16	37
Petroleum and Natural Gas	10653	0.2383	0.2412	0.11	17	23
Chemicals	3995	0.2348	0.2192	0.1077	18	14
Tobacco Products	239	0.229	0.2206	0.085	19	44
Printing and Publishing	1732	0.2281	0.2047	0.1133	20	40
Automobiles and Trucks	2641	0.2278	0.2189	0.1028	21	22
Aircraft	767	0.2271	0.2097	0.1127	22	27
Beer & Liquor	884	0.2267	0.2102	0.1001	23	35
Machinery	5041	0.2264	0.2154	0.1055	24	20
Agriculture	838	0.2165	0.2049	0.1214	25	7
Communication	7043	0.2142	0.1932	0.1132	26	39
Candy & Soda	288	0.2104	0.1923	0.1011	27	25
Shipbuilding, Railroad Equipment	364	0.2092	0.2065	0.0953	28	16
Personal Services	2535	0.209	0.1868	0.1146	29	31
Construction	2171	0.209	0.188	0.1135	30	10
Shipping Containers	503	0.2077	0.1933	0.096	31	30
Business Supplies	1428	0.2074	0.1919	0.1044	32	21
Healthcare	3738	0.202	0.1775	0.1162	33	13
Fabricated Products	573	0.2003	0.1863	0.1026	34	19
Trading	21772	0.1991	0.1729	0.131	35	5
Coal	414	0.1972	0.1947	0.073	36	9
Construction Materials	2794	0.1969	0.18	0.1099	37	12
Restaraunts, Hotels, Motels	4244	0.1962	0.1827	0.0968	38	28
Retail	8747	0.194	0.1785	0.1032	39	24
Wholesale	7022	0.1915	0.1728	0.1107	40	18
Food Products	2779	0.1899	0.1754	0.0972	41	15
Steel Works Etc	1896	0.1816	0.1679	0.0974	42	17
Real Estate	8845	0.1539	0.125	0.1377	43	3
Transportation	4094	0.1518	0.1333	0.096	44	6
Utilities	7769	0.1515	0.1412	0.0722	45	4
Insurance	5908	0.11	0.1053	0.0677	46	1
Banking	23988	0.1087	0.0979	0.0673	47	2
Rank Correlation					-0.7481	

continued on the next page

Table 3.5 cont'd.

Panel C: Sort according to *COMPETE.*

Industry	Number	Mean	Median	Std.	Rank of *COMPETE*	Rank of *COLLABORATE*
Communication	7043	0.4675	0.4766	0.1413	1	38
Computers	6052	0.4385	0.4444	0.1156	2	42
Electronic Equipment	9553	0.4382	0.4444	0.1143	3	46
Tobacco Products	239	0.4347	0.4180	0.1063	4	13
Pharmaceutical Products	12111	0.4323	0.4423	0.0921	5	47
Retail	8747	0.4297	0.4318	0.1299	6	21
Food Products	2779	0.4294	0.4267	0.1289	7	26
Measuring and Control Equipment	3495	0.4285	0.4324	0.1096	8	45
Beer & Liquor	884	0.4236	0.4212	0.1315	9	27
Steel Works Etc	1896	0.4223	0.4161	0.1330	10	11
Medical Equipment	6339	0.4177	0.4215	0.1054	11	44
Wholesale	7022	0.4176	0.4231	0.1375	12	17
Shipping Containers	503	0.4141	0.4194	0.1087	13	12
Recreation	1483	0.4138	0.4118	0.1252	14	43
Candy & Soda	288	0.4123	0.4186	0.1203	15	18
Fabricated Products	573	0.4099	0.4095	0.1325	16	14
Business Services	28219	0.4094	0.4155	0.1266	17	35
Apparel	1954	0.4094	0.4167	0.1230	18	33
Machinery	5041	0.4087	0.4103	0.1196	19	31
Business Supplies	1428	0.4083	0.4103	0.1245	20	16
Consumer Goods	2886	0.4070	0.4035	0.1231	21	36
Automobiles and Trucks	2641	0.4068	0.4025	0.1151	22	29
Entertainment	4497	0.4034	0.4026	0.1349	23	23
Restaraunts, Hotels, Motels	4244	0.4034	0.4096	0.1308	24	5
Electrical Equipment	2224	0.4031	0.4083	0.1183	25	39
Aircraft	767	0.3991	0.3962	0.1161	26	20
Construction Materials	2794	0.3980	0.4000	0.1312	27	25
Chemicals	3995	0.3979	0.3981	0.1129	28	34
Rubber and Plastic Products	1739	0.3950	0.3925	0.1297	29	28
Defense	328	0.3921	0.3848	0.1148	30	32
Printing and Publishing	1732	0.3891	0.3946	0.1408	31	3
Agriculture	838	0.3883	0.3826	0.1416	32	37
Textiles	674	0.3834	0.3842	0.1268	33	19
Non-Metallic and Industrial Metal Mining	3837	0.3815	0.3889	0.1402	34	41
Transportation	4094	0.3780	0.3735	0.1209	35	2
Coal	414	0.3777	0.3862	0.1004	36	10
Construction	2171	0.3776	0.3750	0.1281	37	22
Shipbuilding, Railroad Equipment	364	0.3751	0.3795	0.1214	38	7
Petroleum and Natural Gas	10653	0.3725	0.3661	0.1278	39	9
Trading	21772	0.3671	0.3529	0.1757	40	24
Precious Metals	1575	0.3634	0.3636	0.1418	41	40
Healthcare	3738	0.3570	0.3500	0.1208	42	4
Real Estate	8845	0.3529	0.3333	0.1814	43	15
Utilities	7769	0.3511	0.3457	0.1139	44	8
Personal Services	2535	0.3452	0.3333	0.1304	45	1
Banking	23988	0.3251	0.3232	0.1076	46	30
Insurance	5908	0.2269	0.2273	0.1205	47	6
Rank Correlation					-0.4507	

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Table 3.5 cont'd.

Panel D: Sort according to *CONTROL*.

Industry	Number	Mean	Median	Std.	Rank of *CONTROL*	Rank of *CREATE*
Insurance	5908	0.4781	0.5040	0.1947	1	46
Banking	23988	0.4227	0.4313	0.1277	2	47
Real Estate	8845	0.3304	0.3077	0.1919	3	43
Utilities	7769	0.3177	0.3083	0.1122	4	45
Trading	21772	0.2792	0.2609	0.1605	5	35
Transportation	4094	0.2731	0.2647	0.1083	6	44
Agriculture	838	0.2673	0.2565	0.1272	7	25
Precious Metals	1575	0.2601	0.2500	0.1232	8	12
Coal	414	0.2597	0.2412	0.0988	9	36
Construction	2171	0.2582	0.2450	0.1066	10	30
Non-Metallic and Industrial Metal Mining	3837	0.2546	0.2444	0.1237	11	15
Construction Materials	2794	0.2517	0.2400	0.1045	12	37
Healthcare	3738	0.2489	0.2433	0.1066	13	33
Chemicals	3995	0.2357	0.2273	0.1021	14	18
Food Products	2779	0.2339	0.2222	0.1069	15	41
Shipbuilding, Railroad Equipment	364	0.2334	0.2285	0.0852	16	28
Steel Works Etc	1896	0.2317	0.2282	0.0963	17	42
Wholesale	7022	0.2303	0.2204	0.1103	18	40
Fabricated Products	573	0.2290	0.2222	0.1015	19	34
Machinery	5041	0.2278	0.2198	0.1017	20	24
Business Supplies	1428	0.2236	0.2143	0.0973	21	32
Automobiles and Trucks	2641	0.2232	0.2182	0.0889	22	21
Petroleum and Natural Gas	10653	0.2227	0.2169	0.1068	23	17
Retail	8747	0.2205	0.2121	0.0993	24	39
Candy & Soda	288	0.2201	0.2108	0.0992	25	27
Electrical Equipment	2224	0.2186	0.2062	0.1083	26	10
Aircraft	767	0.2172	0.2118	0.0967	27	22
Restaraunts, Hotels, Motels	4244	0.2169	0.2055	0.1027	28	38
Textiles	674	0.2155	0.2075	0.0936	29	14
Shipping Containers	503	0.2140	0.2080	0.0858	30	31
Personal Services	2535	0.2138	0.1985	0.1166	31	29
Defense	328	0.2114	0.1894	0.1222	32	7
Rubber and Plastic Products	1739	0.2096	0.1951	0.0931	33	11
Apparel	1954	0.2069	0.1935	0.0963	34	13
Beer & Liquor	884	0.2060	0.2052	0.0958	35	23
Consumer Goods	2886	0.2054	0.1944	0.0970	36	8
Entertainment	4497	0.2051	0.1913	0.1077	37	16
Business Services	28219	0.2028	0.1818	0.1152	38	9
Communication	7043	0.1914	0.1810	0.0906	39	26
Printing and Publishing	1732	0.1890	0.1721	0.1007	40	20
Electronic Equipment	9553	0.1878	0.1765	0.0900	41	5
Measuring and Control Equipment	3495	0.1870	0.1769	0.0863	42	4
Recreation	1483	0.1839	0.1727	0.1009	43	3
Tobacco Products	239	0.1745	0.1667	0.0704	44	19
Computers	6052	0.1744	0.1667	0.0903	45	6
Medical Equipment	6339	0.1742	0.1613	0.0858	46	2
Pharmaceutical Products	12111	0.1472	0.1333	0.0751	47	1
Rank Correlation					-0.7481	

Table 3.6: Dimensionality Validity: Correlations between Cultures

This table presents the average Pearson correlations between culture scores according to Fama and French 48 industry classification (excluding the industry classification 'Other/Almost Nothing') for the period 1994 to 2021. T-statistics have been conducted and *, ** and *** indicate 10%, 5%, and 1% levels of significance, respectively.

	COLLABORATE	*CREATE*	*COMPETE*	*CONTROL*
COLLABORATE	1***			
CREATE	-0.3184***	1***		
COMPETE	-0.4705***	-0.2580***	1***	
CONTROL	-0.1113***	-0.3575***	-0.4163***	1***

Table 3.7: Dimensionality Validity: Overlap of Champions (Top 10% of Firms) from Each Culture

This table presents overlap of champions (the highest 10% of firms according to culture score) for each culture, for the sample period 1994-2021 (excluding the industry classification ‘Other/Almost Nothing’).

	Champions in *COLLABORATE* (1)	Champions in *CREATE* (2)	Champions in *COMPETE* (3)	Champions in *CONTROL* (4)
Champions in *COLLABORATE*	100%	1.8094%	0.5716%	2.8237%
Champions in *CREATE*	1.8094%	100%	0.4642%	0.5072%
Champions in *COMPETE*	0.5716%	0.4642%	100%	0.0000%
Champions in *CONTROL*	2.8237%	0.5072%	0.0000%	100%

Table 3.8: Dimensionality Validity: Decile Sorting

These table reports decile sorting of firms based on their average culture scores from 1994-2021 (excluding the industry classification 'Other/Almost Nothing') in the first columns of each panel. Columns (2)-(4) report average culture scores for the firms within the deciles formed in Column (1). T-statistics have been conducted to test the significance of the difference in mean culture scores between the 10th and 1st deciles, and *, ** and *** indicate 10%, 5%, and 1% levels of significance, respectively.

Panel A: Sort according to *COLLABORATE.*

	COLLABORATE (1)	*COMPETE* (2)	*CREATE* (3)	*CONTROL* (4)
1 (lowest)	0.0205	0.2650	0.4561	0.2500
2	0.0502	0.2600	0.4506	0.2392
3	0.0705	0.2435	0.4373	0.2488
4	0.0896	0.2295	0.4217	0.2592
5	0.1093	0.2182	0.4100	0.2626
6	0.1306	0.2106	0.3942	0.2646
7	0.1557	0.2019	0.3777	0.2648
8	0.1875	0.1902	0.3553	0.2669
9	0.2350	0.1770	0.3277	0.2603
10 (highest)	0.3610	0.1445	0.2615	0.2330
Diff (10 – 1)	0.3405	-0.1205	-0.1946	-0.0171
t-test	20.4379***	-21.2751***	-24.9175***	-2.5247**

Panel B: Sort according to *CREATE.*

	CREATE (1)	*CONTROL* (2)	*COLLABORATE* (3)	*COMPETE* (4)
1 (lowest)	0.0459	0.3945	0.1728	0.3785
2	0.0945	0.3522	0.1689	0.3843
3	0.1261	0.3085	0.1729	0.3926
4	0.1547	0.2788	0.1701	0.3965
5	0.1845	0.2523	0.1567	0.4065
6	0.2164	0.2314	0.1426	0.4096
7	0.2501	0.2125	0.1301	0.4072
8	0.2882	0.1942	0.1150	0.4027
9	0.3376	0.1744	0.1004	0.3876
10 (highest)	0.4404	0.1511	0.0823	0.3262
Diff (10 – 1)	0.3945	-0.2434	-0.0904	-0.0523
t-test	42.7110***	-33.7834***	-12.0102***	-7.3058***

Panel C: Sort according to *COMPETE.*

	COMPETE (1)	*COLLABORATE* (2)	*CREATE* (3)	*CONTROL* (4)
1 (lowest)	0.1522	0.2269	0.2084	0.4042
2	0.2538	0.1970	0.2089	0.3402
3	0.3022	0.1740	0.2173	0.3065
4	0.3402	0.1563	0.2240	0.2795
5	0.3737	0.1409	0.2307	0.2547
6	0.4060	0.1285	0.2338	0.2316
7	0.4394	0.1166	0.2314	0.2127
8	0.4759	0.1056	0.2238	0.1948
9	0.5217	0.0934	0.2081	0.1768
10 (highest)	0.6244	0.0727	0.1538	0.1491
Diff (10 – 1)	0.4722	-0.1542	-0.0546	-0.2551
t-test	46.0136***	-13.0138***	-8.3756***	-41.8029***

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Table 3.8 cont'd.

Panel D: Sort according to *CONTROL*.

	CONTROL (1)	*CREATE* (2)	*COLLABORATE* (3)	*COMPETE* (4)
1 (lowest)	0.0786	0.3047	0.1261	0.4823
2	0.1258	0.2847	0.1269	0.4625
3	0.1556	0.2629	0.1394	0.4422
4	0.1826	0.2442	0.1465	0.4267
5	0.2101	0.2261	0.1542	0.4096
6	0.2407	0.2082	0.1577	0.3935
7	0.2766	0.1941	0.1562	0.3732
8	0.3252	0.1737	0.1537	0.3474
9	0.3998	0.1421	0.1419	0.3162
10 (highest)	0.5525	0.0999	0.1089	0.2387
Diff (10 – 1)	0.4739	-0.2049	-0.0172	-0.2436
t-test	53.8663***	-28.1712***	-2.0772**	-48.0307***

(* $p<0.1$; ** $p<0.05$; *** $p<0.01$)

Table 3.9: Transition Matrices

These table presents the average transition matrices from year t to year t+1 in the period of 1994-2021 (excluding the industry classification 'Other/Almost Nothing') The matrices show the average probabilities of a company, initially ranked in a specific decile based on its culture score in year t, transitioning to each of the 10 deciles in year t+1.

Panel A: Transition matrix for *COLLABORATE.*

			$COLLABORATE_{t+1}$									
			1	2	3	4	5	6	7	8	9	10
$COLLABORATE_t$	Lowest	1	**0.5675**	0.1579	0.0753	0.0533	0.0365	0.0284	0.0259	0.0191	0.0188	0.0166
		2	0.1754	**0.3493**	0.1721	0.0912	0.0619	0.0427	0.0322	0.0286	0.0221	0.0239
		3	0.0797	0.1920	**0.2658**	0.1634	0.0989	0.0692	0.0461	0.0322	0.0273	0.0247
		4	0.0490	0.0966	0.1686	**0.2341**	0.1566	0.1021	0.0703	0.0486	0.0387	0.0347
		5	0.0318	0.0603	0.1058	0.1596	**0.2239**	0.1570	0.1009	0.0697	0.0506	0.0397
		6	0.0250	0.0429	0.0713	0.1034	0.1632	**0.2250**	0.1591	0.0974	0.0621	0.0498
		7	0.0218	0.0321	0.0470	0.0687	0.0993	0.1615	**0.2400**	0.1661	0.0986	0.0641
		8	0.0165	0.0276	0.0369	0.0545	0.0693	0.1001	0.1638	**0.2586**	0.1768	0.0954
		9	0.0175	0.0208	0.0300	0.0364	0.0495	0.0654	0.0974	0.1827	**0.3185**	0.1811
	Highest	10	0.0150	0.0198	0.0264	0.0348	0.0403	0.0480	0.0636	0.0964	0.1858	**0.4758**

Panel B: Transition matrix for *CREATE.*

			$CREATE_{t+1}$									
			1	2	3	4	5	6	7	8	9	10
$CREATE_t$	Lowest	1	**0.6733**	0.1944	0.0584	0.0281	0.0150	0.0076	0.0075	0.0050	0.0047	0.0054
		2	0.2072	**0.4242**	0.2032	0.0794	0.0394	0.0183	0.0113	0.0088	0.0036	0.0039
		3	0.0567	0.2212	**0.3534**	0.1949	0.0904	0.0398	0.0208	0.0112	0.0067	0.0043
		4	0.0250	0.0857	0.2139	**0.3183**	0.1903	0.0898	0.0396	0.0202	0.0109	0.0057
		5	0.0143	0.0359	0.0928	0.2029	**0.3040**	0.1867	0.0908	0.0407	0.0212	0.0101
		6	0.0076	0.0177	0.0391	0.0901	0.1982	**0.3034**	0.1976	0.0912	0.0387	0.0158
		7	0.0057	0.0095	0.0199	0.0465	0.0860	0.2022	**0.3128**	0.2043	0.0838	0.0287
		8	0.0028	0.0055	0.0104	0.0218	0.0453	0.0922	0.2102	**0.3428**	0.2040	0.0644
		9	0.0033	0.0036	0.0051	0.0114	0.0211	0.0387	0.0805	0.2127	**0.4271**	0.1958
	Highest	10	0.0034	0.0016	0.0033	0.0060	0.0098	0.0207	0.0283	0.0625	0.1986	**0.6716**

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Table 3.9 cont'd.

Panel C: Transition matrix for *COMPETE*.

			COMPETE$_{t+1}$								
			1	2	3	4	5	6	7	8	9	10
COMPETE$_t$	Lowest	1	**0.6236**	0.1641	0.0666	0.0407	0.0295	0.0235	0.0167	0.0130	0.0108	0.0109
		2	0.1702	**0.3699**	0.1913	0.0939	0.0588	0.0383	0.0294	0.0211	0.0154	0.0111
		3	0.0667	0.1979	**0.2854**	0.1744	0.0987	0.0622	0.0439	0.0310	0.0228	0.0163
		4	0.0378	0.0902	0.1885	**0.2514**	0.1746	0.1024	0.0627	0.0439	0.0297	0.0181
		5	0.0264	0.0547	0.1020	0.1777	**0.2345**	0.1736	0.1012	0.0703	0.0367	0.0222
		6	0.0241	0.0424	0.0594	0.1037	0.1752	**0.2274**	0.1742	0.1031	0.0621	0.0277
		7	0.0156	0.0294	0.0382	0.0629	0.1061	0.1769	**0.2438**	0.1836	0.0999	0.0429
		8	0.0130	0.0231	0.0288	0.0439	0.0613	0.1054	0.1812	**0.2710**	0.1940	0.0777
		9	0.0107	0.0160	0.0222	0.0306	0.0392	0.0584	0.0990	0.1898	**0.3424**	0.1911
	Highest	10	0.0113	0.0117	0.0169	0.0200	0.0215	0.0311	0.0472	0.0725	0.1857	**0.5879**

Panel D: Transition matrix for *CONTROL*.

			CONTROL$_{t+1}$								
			1	2	3	4	5	6	7	8	9	10
CONTROL$_t$	Lowest	1	**0.6136**	0.1821	0.0764	0.0413	0.0272	0.0198	0.0158	0.0118	0.0064	0.0049
		2	0.2024	**0.3909**	0.1867	0.0923	0.0495	0.0308	0.0225	0.0146	0.0067	0.0029
		3	0.0725	0.2140	**0.3165**	0.1882	0.0945	0.0495	0.0305	0.0196	0.0103	0.0037
		4	0.0393	0.0951	0.1980	**0.2864**	0.1820	0.0965	0.0542	0.0281	0.0136	0.0061
		5	0.0236	0.0480	0.1005	0.1926	**0.2751**	0.1917	0.0954	0.0472	0.0188	0.0065
		6	0.0173	0.0284	0.0546	0.0979	0.1925	**0.2811**	0.1940	0.0920	0.0323	0.0092
		7	0.0132	0.0188	0.0311	0.0561	0.1055	0.1982	**0.3068**	0.1927	0.0624	0.0145
		8	0.0090	0.0115	0.0205	0.0277	0.0478	0.0899	0.2001	**0.3688**	0.1846	0.0394
		9	0.0056	0.0071	0.0102	0.0124	0.0184	0.0331	0.0649	0.1861	**0.4886**	0.1729
	Highest	10	0.0029	0.0033	0.0047	0.0044	0.0068	0.0088	0.0152	0.0384	0.1756	**0.7459**

Table 3.10: Performance of Firms during COVID-19 Period

This table reports the quarterly DID regressions from the March 01, 2019, to February 28, 2021 (four quarters before and after the onset of the pandemic), where the independent time dummy $COVID_t$ captures the quarters after March 2020, which marks the beginning of the pandemic as per the World Health Organization. Strong culture ($STRONG\_CULTURE_{i,\ t}$) is defined as firms with 3-year average scores scoring a decile rank of 10 in one culture and a low decile rank of 1 in the opposing culture within the competing values framework (collaborate vs. compete; create vs. control) in pre-COVID period from 2016 to 2018. The OLS estimates for firm performance ($OPERATING\_PROFIT_{i,\ t}$, $TOBINQ_{i,t}$, $ASSET\_TURNOVER_{i,t}$ and $CASH\_TURNOVER_{i,t}$) are presented from columns (1) to (4), respectively. Furthermore, the control variables include $CASH_{i,t}$, $LEVERAGE_{i,t}$ *(ST)*, and $SIZE_{i,t}$. All variables are defined in Table 3.15. In addition. The estimates include the firm fixed effect. All models include a constant (not shown) and the standard errors are clustered at the firm level. T-statistics are given in parentheses and *, ** and *** indicate 10%, 5%, and 1% levels of significance, respectively.

	$OPERATING\_PROFIT_{i,t}$	$TPBINQ_{i,t}$	$ASSET\_TURNOVER_{i,t}$	$CASH\_TURNOVER_{i,t}$
	(1)	(2)	(3)	(4)
$COVID_t$	-0.113***	-0.030***	-0.114***	-0.192***
	(7.17)	(3.54)	(14.83)	(10.12)
$COVID_t$ *$STRONG\_CULTURE_{i,t}$	0.084**	0.060**	0.078***	0.120***
	(2.19)	(2.04)	(3.91)	(4.19)
$CASH_{i,t}$	-0.122***	-0.012	-0.117***	-0.103***
	(4.72)	(0.70)	(9.51)	(5.85)
$LEVERAGE_{i,t}(ST)$	-0.101***	-0.018**	-0.057***	-0.023
	(5.98)	(2.24)	(6.82)	(0.78)
$SIZE_{i,t}$	0.783***	-0.163*	-0.662***	0.224
	(5.74)	(1.94)	(9.46)	(1.25)
FIRM FE	Yes	Yes	Yes	Yes
Adj. R^2	0.76	0.92	0.94	0.73
N	13,536	13,545	13,545	13,523

(* p<0.1; ** p<0.05; *** p<0.01)

Table 3.11: Change in Culture during the COVID-19 Period

These table reports the changes in culture (from pre-COVID period 2016-2018 to post-COVID period 2020-2021) sorted according to cultures in pre-COVID period. Particularly, the variables *PRE_COLLABORATE*, *PRE_CREATE*, *PRE_COMPETE* and *PRE_CONTROL* are defined as the three-year average pre-COVID corporate culture scores for the respective cultural orientations while the variables *POST_COLLABORATE*, *POST_CREATE*, *POST_COMPETE* and *POST_CONTROL* represent the two-year post-COVID average corporate culture scores. In addition, the variables *ΔCOLLABORATE%*, *ΔCREATE%*, *ΔCOMPETE%*, and *ΔCONTROL%*, are computed as the difference between post- and pre-COVID corporate culture cultures scaled by pre-COVID cultures. These tables present the mean values for *ΔCOLLABORATE%*, *ΔCREATE%*, *ΔCOMPETE%*, and *ΔCONTROL%*, sorted based on firms from 1st (lowest/Contenders) to 10th (highest/Champions) decile rank of *PRE_COLLABORATE*, *PRE_CREATE*, *PRE_COMPETE* and *PRE_CONTROL* in Panels A, B, C and D.

Panel A: Sort according to *PRE_COLLABORATE.*

Rank and mean *PRE_COLLABORATE*		*Mean ΔCOLLABORATE%*	*Mean ΔCREATE%*	*Mean ΔCOMPETE%*	*Mean ΔCONTROL%*
1 (lowest) - Contenders	0.0367	57.26%	8.68%	-5.83%	3.36%
2	0.0559	27.78%	10.41%	-3.12%	-0.45%
3	0.0703	21.48%	9.15%	-1.34%	-2.52%
4	0.0832	11.49%	12.45%	-0.35%	-3.94%
5	0.0965	8.38%	14.18%	-1.43%	-4.52%
6	0.1114	0.50%	13.81%	0.98%	-3.43%
7	0.1287	0.13%	13.91%	1.45%	-3.00%
8	0.1497	-3.81%	17.58%	2.28%	-4.77%
9	0.1816	-7.66%	18.09%	2.62%	-3.06%
10 (highest)- Champions	0.2607	-18.14%	26.24%	6.66%	-0.46%

continued on the next page

Table 3.11 cont'd.

Panel B: Sort according to *PRE_CREATE.*

Rank and mean *PRE_CREATE*		*Mean ΔCOLLABORATE%*	*Mean ΔCREATE%*	*Mean ΔCOMPETE%*	*Mean ΔCONTROL%*
1 (lowest) - Contenders	0.0766	8.52%	48.32%	-1.68%	-5.24%
2	0.1138	7.26%	31.09%	-0.45%	-5.73%
3	0.1422	10.27%	25.18%	-0.69%	-3.76%
4	0.1691	7.58%	19.45%	-1.73%	-4.46%
5	0.1987	6.31%	13.20%	0.86%	-3.01%
6	0.2272	6.13%	8.20%	0.10%	-2.93%
7	0.2568	8.36%	5.69%	0.44%	-3.91%
8	0.2886	10.65%	2.06%	-0.35%	-0.23%
9	0.3246	9.78%	-1.19%	1.76%	2.13%
10 (highest)- Champions	0.3964	18.48%	-4.99%	3.60%	4.09%

Panel C: Sort according to *PRE_COMPETE.*

Rank and mean *PRE_COMPETE*		*Mean ΔCOLLABORATE%*	*Mean ΔCREATE%*	*Mean ΔCOMPETE%*	*Mean ΔCONTROL%*
1 (lowest) - Contenders	0.1988	-3.28%	15.24%	12.93%	-5.27%
2	0.2876	0.37%	18.02%	5.56%	-6.27%
3	0.3277	5.96%	12.80%	4.75%	-5.92%
4	0.3585	8.27%	15.56%	1.89%	-6.29%
5	0.3863	5.48%	14.62%	0.42%	-4.74%
6	0.4105	8.35%	10.81%	-0.99%	-2.47%
7	0.4368	7.77%	11.33%	-1.04%	-2.40%
8	0.4626	13.44%	11.24%	-3.86%	0.69%
9	0.4957	17.86%	11.63%	-5.47%	1.59%
10 (highest)- Champions	0.5759	29.47%	23.57%	-11.20%	8.49%

continued on the next page

Table 3.11 cont'd.

Panel D: Sort according to *PRE_CONTROL*.

Rank and mean *PRE_CONTROL*		*Mean ΔCOLLABORATE%*	*Mean ΔCREATE%*	*Mean ΔCOMPETE%*	*Mean ΔCONTROL%*
1 (lowest) - Contenders	0.1081	17.19%	3.99%	-4.56%	14.34%
2	0.1495	8.74%	5.73%	-2.47%	5.28%
3	0.1798	7.42%	7.86%	-0.71%	0.05%
4	0.2051	8.04%	9.70%	-1.40%	-1.19%
5	0.2327	8.11%	12.14%	-0.19%	-3.06%
6	0.2625	6.38%	14.14%	0.26%	-6.17%
7	0.2951	8.09%	17.65%	0.24%	-6.83%
8	0.3334	6.07%	19.07%	1.71%	-7.55%
9	0.4007	8.84%	23.42%	4.08%	-8.12%
10 (highest)- Champions	0.5251	14.53%	31.56%	5.21%	-9.06%

Table 3.12: Movement in Strong Cultures during COVID-19 Period

This tables presents the change in firms with strong corporate culture over the COVID-19 period (*STRONG_CULTURE*, defined as firms with 3-year average scores scoring a decile rank of 10 in one culture and a low decile rank of 1 in the opposing culture within the competing values framework (collaborate vs. compete; create vs. control) in pre-COVID period). Specifically, 2016 to 2018 is defined as pre-COVID period and 2020 to 2021 as the post-COVID period. Particularly, *PRE_COLLABORATE*, *PRE_CREATE*, *PRE_COMPETE* and *PRE_CONTROL* are denoted as the three-year average pre-COVID corporate culture scores for the respective cultural orientations while the variables *POST_COLLABORATE*, *POST_CREATE*, *POST_COMPETE* and *POST_CONTROL* represent the two-year post-COVID average corporate culture scores. In addition, the variables *ΔCOLLABORATE%*, *ΔCREATE%*, *ΔCOMPETE%*, and *ΔCONTROL%*, are computed as the difference between my post- and pre-COVID corporate culture cultures scaled by pre-covid cultures. In this table, mean values for *ΔCOLLABORATE%*, *ΔCREATE%*, *ΔCOMPETE%*, and *ΔCONTROL%* are computed for firms with a strong culture in the pre-COVID period.

Firm Types	*Mean ΔCOLLABORATE%*	*Mean ΔCREATE%*	*Mean ΔCOMPETE%*	*Mean ΔCONTROL%*
Firms with strong collaborate culture	-16.43%	20.72%	14.28%	-0.53%
Firms with strong create culture	16.67%	-3.83%	-0.16%	13.41%
Firms with strong compete culture	61.61%	21.77%	-15.70%	16.64%
Firms with strong control culture	12.78%	44.43%	0.71%	-8.34%

Table 3.13: Changes in Culture during the COVID-19 Period across Industries

This table presents the changes in culture during the COVID period by Fama and French 12 industry classifications. Specifically, 2016 to 2018 is defined as pre-COVID period and 2020 to 2021 as the post-COVID period. Particularly, the variables *PRE_COLLABORATE*, *PRE_CREATE*, *PRE_COMPETE* and *PRE_CONTROL* are denoted as the three-year average pre-COVID corporate culture scores for the respective cultural orientations while the variables *POST_COLLABORATE*, *POST_CREATE*, *POST_COMPETE* and *POST_CONTROL* represent the two-year post-COVID average corporate culture scores. In addition, the variables *ΔCOLLABORATE%*, *ΔCREATE%*, *ΔCOMPETE%*, and *ΔCONTROL%*, are computed as the difference between the post- and pre-COVID corporate culture cultures scaled by pre-COVID cultures.

Industry	*Mean ΔCOLLABORATE%*	*Mean ΔCREATE%*	*Mean ΔCOMPETE%*	*Mean ΔCONTROL%*
Consumer NonDurables --Food, Tobacco, Textiles, Apparel, Leather, Toys	10.78%	15.81%	0.03%	-4.29%
Consumer Durables -- Cars, TV's, Furniture, Household Appliances	17.78%	14.36%	-2.37%	-0.77%
Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	9.79%	14.97%	0.49%	-4.84%
Energy --Oil, Gas, and Coal Extraction and Products	3.20%	7.51%	3.75%	-1.78%
Chemicals and Allied Products	17.80%	6.94%	1.94%	-3.47%
Business Equipment --Computers, Software, and Electronic Equipment	14.59%	7.65%	-1.59%	-0.73%
Telecom --Telephone and Television Transmission	10.09%	13.18%	-0.26%	-1.91%
Utilities	0.82%	16.48%	3.11%	-4.96%
Shops --Wholesale, Retail, and Some Services (Laundries, Repair Shops)	-0.25%	18.66%	1.01%	-2.35%
Healthcare, Medical Equipment, and Drugs	9.65%	3.56%	-0.95%	3.13%
Finance	9.55%	24.68%	1.76%	-5.79%
Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	9.53%	16.33%	-1.93%	-1.60%

Table 3.14: Heterogeneity Analysis

This table reports heterogeneity analysis to better understand the type of firms that are moving towards greater collaborate and create cultural orientation. Specifically, 2016 to 2018 is defined as pre-COVID period and 2020 to 2021 as the post-COVID period. The key independent variables $\Delta COLLABORATE\,\%_i$, and $\Delta CREATE\,\%_i$ are computed as the difference between the post- and pre-COVID corporate culture cultures divided by pre-COVID cultures. The OLS estimates for key dependent variables $\Delta COLLABORATE\,\%_i$ and $\Delta CREATE\,\%_i$ are presented from columns (1) to (2), respectively. Furthermore, the independent variables include $OPERATING\_PROFIT_{i,2018}$, $ASSET\_TURNOVER_{i,2018}$, $R\&D_{i,2018}$, $CASH_{i,2018}$, $LEVERAGE_{i,2018}$ *(LT)*, $SIZE_{i,2018}$, and $EMP_{i,2018}$. All variables are defined in Table 3.15. The estimates include the industry fixed effect. All models include a constant (not shown) and the standard errors are clustered at the firm level. The t-statistics are given in parentheses.

	$\Delta COLLABORATE\,\%_i$	$\Delta CREATE\,\%_i$
	(1)	(2)
$OPERATING\_PROFIT_{i,2018}$	-0.003	0.005
	(0.13)	(0.25)
$ASSET\_TURNOVER_{i,2018}$	-0.052*	0.044
	(1.96)	(1.40)
$R\&D_{i,2018}$	0.065**	-0.105***
	(2.20)	(3.96)
$CASH_{i,2018}$	0.012	-0.018
	(0.50)	(1.28)
$LEVERAGE_{i,2018}(LT)$	0.052**	-0.006
	(2.12)	(0.27)
$SIZE_{i,2018}$	0.014	0.147***
	(0.49)	(4.96)
$EMP_{i,2018}$	0.044*	0.061**
	(1.91)	(2.41)
INDUSTRY FE	Yes	Yes
Adj. R^2	0.03	0.09
N	2,661	2,678

(* p<0.1; ** p<0.05; *** p<0.01)

Table 3.15: Definition of Variables for Chapter 3

Symbol		Definitions
Culture variables		
COLLABORATE	=	Firm's relative collaborate culture estimated for each fiscal year using the text-analysis approach and computed as [collaborate words / (collaborate words + create words + compete words + control words)];
CREATE	=	Firm's relative create culture estimated for each fiscal year using the text-analysis approach and computed as [create words/ (collaborate words + create words + compete words + control words)];
COMPETE	=	Firm's relative compete culture estimated for each fiscal year using the text-analysis approach and computed as [compete words/ (collaborate words + create words + compete words + control words)];
CONTROL	=	Firm's relative control culture estimated for each fiscal year using the text-analysis approach and computed as [control words/ (collaborate words + create words + compete words + control words)];
Dependent variables		
OPERATING_PROFIT	=	Total revenues [Compustat item: revtq]-cost of goods sold [Compustat item: cogsq] - selling, general and administrative expenses [Compustat item: xsgaq] + research and development expenses [Compustat item: xrdq] and then scaled by total assets [Compustat item: atq];
TOBINQ	=	Market value of assets (total assets [Compustat item: atq] + market value of common equity [Compustat item: cshoq*prccq] - common equity [Compustat item: ceqq] - deferred taxes [Compustat item: txdbq])/ (0.9*book value of assets [Compustat item: atq] + 0.1*market value of assets);
ASSET_TURNOVER	=	Total sales [Compustat item: saleq] scaled by total assets [Compustat item: atq];
CASH_TURNOVER	=	Total sales [Compustat item: saleq] scaled by cash and short-term investments [Compustat item: cheq];
Independent variables		
COVID	=	An indicator that serves as an interaction term between time and treatment group in a regression model and equals to 1 to capture quarters after March 2020 and equals to 0 otherwise;
STRONG_CULTURE	=	An indicator that equals to 1 if a firms with 3-year average scores scoring a decile rank of 10 in one culture and a low decile rank of 1 in the opposing culture within the Competing Values Framework (collaborate vs. compete; create vs. control) in pre-COVID period from 2016 to 2018.
Control variables		
CASH	=	The cash and short-term investments [Compustat item: cheq] scaled by toal current liabilities [Compustat item: lctq)];
LEVERAGE(ST)	=	The debt in current liabilities [Compustat item: dlcq] scaled by total assets [Compustat item: atq];
SIZE	=	The natural logarithm of total assets [Compustat item: atq];
Culture change variables		
PRE_COLLABORATE	=	Firm's 3-year average collaborate culture scores in pre-COVID period from 2016 to 2018;
PRE_CREATE	=	Firm's 3-year average create culture scores in pre-COVID period from 2016 to 2018;
PRE_COMPETE	=	Firm's 3-year average compete culture scores in pre-COVID period from 2016 to 2018;
PRE_CONTROL	=	Firm's 3-year average control culture scores in pre-COVID period from 2016 to 2018;

Table 3.15 cont'd.

Symbol		Definitions
Culture change variables		
POST_COLLABORATE	=	Firm's 2-year average collaborate culture scores in post-COVID period from 2020 to 2021;
POST_CREATE	=	Firm's 2-year average create culture scores in post-COVID period from 2020 to 2021;
POST_COMPETE	=	Firm's 2-year average compete culture scores in post-COVID period from 2020 to 2021;
POST_CONTROL	=	Firm's 2-year average control culture scores in post-COVID period from 2020 to 2021;
Δ*COLLABORATE%*	=	The difference between post- and pre-COVID average collaborate culture scores scaled by pre-COVID average collaborate culture scores;
Δ*CREATE%*	=	The difference between post- and pre-COVID average collaborate culture scores scaled by pre-COVID average create culture scores;
Δ*COMPETE%*	=	The difference between post- and pre-COVID average collaborate culture scores scaled by pre-COVID average compete culture scores;
Δ*CONTROL%*	=	The difference between post- and pre-COVID average collaborate culture scores scaled by pre-COVID average control culture scores;
Heterogeneity analysis variables		
R&D	=	The natural logarithm of research and development expenses [Compustat item: xrd];
LEVERAGE(LT)	=	The long-term debt [Compustat item: dltt] scaled by total assets [Compustat item: at]; and
EMP	=	The number of employees [Compustat item: emp] scaled by total assets [Compustat item: at].

4 Bank Competition Culture: Meeting and/or Beating Earnings Expectations via Loan Loss Provisioning

4.1 Introduction

Traditionally, since the separation of ownership and control within companies, researchers have been deeply engaged in exploring effective means to (partially) alleviate the detrimental effects of agency problems. Influenced by the compensation mechanism, managers are tempted to manipulate earnings by sacrificing economic value and information quality for the profit and loss (P&L) statement to achieve short-term objectives more effectively, which is often blamed for the several onslaughts of accounting scandals (Beatty and Harris, 1999; Koh and Rajgopal, 2008; Liao et al.,2009; Alhadab and Al-Own 2019).

In the banking sector, these issues are magnified due to the industry's critical role in financial stability and economic health. Banks are unique as they play a central role in ensuring the healthy functioning of the entire financial system and bank regulatory authorities closely monitor whether and how individual banks may trigger systemic risks or pose a threat to the entire financial system as a result of earnings manipulation or other means of risk-taking behavior (Acharya et al., 2010; Hanson et al., 2011; Fiordelisi et al., 2014b; Nguyen et al., 2019; Illueca et al., 2022.), it is necessary to investigate a mechanism for shareholders to coordinate conflicts of interests with bank managers.

During the past years, the banking industry operated in an increasingly competitive landscape (Erler et al., 2017), which may exacerbate the severity of agency problems. Previous deregulation in the US, like the Gramm-Leach-Bliley Act in 1999, allowing commercial banks, investment banks, and insurance companies to engage in more diverse activities, potentially lead to more intense competition. Currently, the emergence of financial technology (fintech) companies has brought forth new competitors in the banking industry, challenging the established market positions of traditional banks and potentially intensifying overall competitiveness.

The competitive environment necessitates banks to enhance efficiency, trim unnecessary costs, and optimize resource allocation to sustain profitability and market share. In this context, the exploration of competition culture holds significant relevance. It can assist banks in responding to external information, adapting to subtle shifts in the market environment, and enhancing efficiency to meet shareholder performance targets more effectively (Thakor, 2015). In a highly competitive environment, a competition culture thrives. Given the mounting external competition and internal performance pressures that bank managers confront, comprehending the role of competition culture in banking management practices can offer fresh perspectives for mitigating agency problems in the present competitive banking landscape.

Building upon the unique combination of Competing Value Framework (CVF) and Organizational Culture Assessment Instrument (OCAI), this study deploys the methodology proposed in the first study to quantify competition culture[9]. This involves conducting a textual analysis of 10–K filings sourced from the SEC's Edgar database. In line with recent research, I posit that firms' documents, such as the 10-K filings, can unveil insights into firms' underlying culture (see, e.g., Fiordelisi and Ricci, 2014; Andreou et al., 2020a; Andreou et al., 2020b; Andreou et al., 2022).

To access managerial performance in a competition culture, this chapter adopts indicator analysts' forecasts as external measures, which have commonly been employed by several scholars in current literature (Barton and Simko, 2002; Cheng and Warfield, 2005;

[9] The terms 'compete culture' and 'competition culture' will be used interchangeably in the second study(Chapter 4) to facilitate better understanding for the readers.

Bhojraj et al., 2009; Jensen and Meckling, 2019). For investors and stakeholders, these analysts' forecasts serve as an internal tool for evaluating performance and offer guidance regarding what to anticipate from a firm's balance sheet in the near future. Furthermore, meeting or beating forecasts can be seen as a sign of effective management and operational efficiency. In contrast, consistently missing forecasts may raise concerns about the firm's ability to achieve its goals. Accordingly, this chapter uses meeting or beating analysts' consensus forecasts as a measurement of managerial performance, and I am motivated to consider the following research question: "*What is the relationship between bank competition culture and the likelihood of meeting or beating analysts' forecasts?*".

Also, I am interested in examining the underlying mechanisms by which highly competitive organisational cultures help banks meet their performance targets. One possible explanation is that through discretionary loan loss provisions as prior evidence suggests that banks can opportunistically exercise the discretion over loan loss provisions to disguise risk, smooth profits, manipulate earnings, or distort balance sheet information quality. [10]

Loan loss provisions are a relatively large accrual for commercial banks and, therefore, significantly impact banks' earnings and regulatory capital (Ahmed et al.,1999). There are two components of the loan loss provisions: the nondiscretionary part and discretionary parts, and this chapter focuses on the discretionary component. Firstly, bank managers can adjust discretionary loan loss provisions to manipulate their reported earnings, offering a higher degree of income smoothing and perceived stability. Secondly, the timing and flexibility inherent in discretionary loan loss provisions give banks significant discretion to adjust earnings as needed. Since loan loss provisions are estimates of future losses, they can be adjusted up or down as economic conditions and expectations change. Moreover, in

[10] A non-exhaustive list of studies on banks' loan loss provision includes Wahlen, 1994; Beatty et al., 1995; Collins et al., 1995; Beaver and Engel, 1996; Kim and Kross, 1998; Liu and Ryan, 2006; Ivashina, and Scharfstein, 2010; Kanagaretnam et al., 2014; Bushman and Williams, 2012; Beck and Narayanamoorthy, 2013; Beatty and Liao, 2011, 2014; Curcio and Hasan 2015; Bushman et al., 2016; Bushman et al., 2018 and Alhadab and Al-Own, 2019.

situations of information asymmetry, banks can use discretionary loan loss provisions to signal confidence in their loan portfolio performance or prudent risk management methods to the market. These signals can impact analysts' expectations and increase the likelihood of meeting or beating them. Additionally, the use of discretionary loan loss provisions helps managers fulfil regulatory capital requirements more effectively. Therefore, I am motivated to consider the following research questions: "*Is bank competition culture related to discretionary loan loss provisioning activity?*" and "*Does bank competition culture propel banks to engage in more or less discretionary loan loss provisioning in order to meet or beat analysts' forecasts?*". I expect to find empirical evidence to demonstrate the mechanism that bank competition culture influences the propensity to meet and/or beat earnings forecasts via (more or less) discretionary use of the loan loss provision.

For my empirical investigation, I use a large sample of US bank-level information from 1994-2021. I follow the methodology proposed in the first study conducting a textual analysis of banks'10–K filings[11] obtained from the SEC's Edgar database. Thus, this chapter includes the following dataset: the 10–K filings for the listed bank (SIC 6000 – 6999) from SEC's Edgar database; the analysts' forecast data from the Institutional Brokers Estimate System (I/B/E/S) and the firm-level financial data from the CRSP /Compustat Merged. Besides, given that bank competition culture is expected and observed to remain constant over time (please see Andreou et al., 2020b, 2022), I employ ordinary least squares (OLS) regressions with year-fixed effect when incorporating this measure as an independent variable in my regression models.[12] In order to mitigate potential endogeneity concerns[13], I

[11] 10-K filings have been identified as a channel for managers to convey useful and important information about distinctive, yet latent, firm traits (Loughran and McDonald, 2009, 2011). 10-K filings are different from annual reports, which include glossary and marketing materials. 10-K filings provide management's disclosure of the company's businesses and operations, including its main products and services, the market environment and conditions, the risk factors and prospects the company faces and so on, thus providing a natural setting for eliciting important information about culture.
[12] The fixed-effects model is used throughout the analysis to account for unobserved, time-invariant heterogeneity, which is critical given the likely correlation between explanatory variables and bank-specific characteristics. This choice ensures robust and unbiased results, aligning with the research objectives.

proceed to re-estimate the main empirical models by application of an instrumental variable (IV) analysis, yielding similar results. Moreover, I conduct robustness tests to verify the reliability of the findings.

According to the empirical results, banks with a higher level of competitive organizational culture are more inclined to meet or beat analyst earnings expectations and exhibit a reduced propensity to engage in discretionary loan loss provisions. It is observed that banking competition culture reduces the discretionary use of loan loss provisions, especially when such use reduces earnings. Consistent with these observations and prior research in this area[14], I argue that as competition culture incentivizes managers to achieve performance goals, it reduces the discretionary use of banks' loan loss provisions, which in turn reduces reported earnings and further undermines the transparency of the banks' information environment. On this basis, I believe that such behavior in turn increases the likelihood of meeting and/or exceeding analysts' consensus earnings forecasts. Furthermore, the robustness check supports my findings as well. All econometric estimates confirm the robustness of my main findings and indicate a strong interrelationship between bank competition culture, the propensity to meet or beat analysts' consensus earnings forecasts and discretionary loan loss provisioning and are not only noteworthy for policy implications but distinct to the present research.

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[13] Specifically, the level of bank competition culture is identified as potentially endogenous. This is due to the possibility that it is influenced by past instances of meeting or beating analysts' earnings expectations or discretionary loan loss provisioning. The simultaneous determination of bank competition culture and these outcome measures creates endogeneity concerns arising from reverse causality or omitted variable bias. For instance, banks with a strong competition culture may be more likely to meet or beat analysts' forecasts, while prior performance outcomes could also shape the competition culture within the bank.

[14] A non-exhaustive list of studies includes Wahlen, 1994; Beatty et al., 1995; Collins et al., 1995; Beaver and Engel, 1996; Kim and Kross, 1998; Liu and Ryan, 2006; Kanagaretnam et al., 2014; Bushman and Williams, 2012; Beck and Narayanamoorthy, 2013; Beatty and Liao, 2014; Curcio and Hasan 2015; Bushman et al., 2016 and Alhadab and Al-Own, 2019.

Extensive literature exhibits a predominantly acceptance when it comes to acknowledging the influence of culture in elucidating economic outcomes at the firm level. [15] Furthermore, prior research has extensively explored the intrinsic logic chain within organizational culture and earnings manipulation in nonfinancial firms. [16] However, there is limited focus on the importance of organizational culture, especially competition culture in explaining economic phenomena in the US banking industry. Furthermore, according to findings in my first study (see Table 3.6), which rank the Fama French 48 industry classifications for different cultures, the banking industry ranks second, just below the insurance industry in control culture; in collaborate culture, the banking industry ranks in the middle, while in create and compete cultures, it ranks at the bottom. Currently, the compete culture does not hold a dominant position in the banking industry, although it is suitable for the current competitive environment. Therefore, studying the role the competitio culture plays in the banking industry is meaningful for managerial in steering the firm's development direction.

This chapter contributes to the existing literature in organizational culture and banking sectors. Firstly, previous studies have suggested that corporate culture will influence bank managers' propensity to engage in marginal lending and other risk-taking activities (see e.g., Fiordelisi et al., 2014b; Thakor, 2015, 2020; Nguyen et al., 2019; Barth and Mansouri, 2021 and Luu et al., 2023), however, there is limited evidence regarding the effects of bank competition culture on the probability to meet or beat analysts' earnings forecasts or discretionary loan loss provisioning activity. This chapter seeks to bridge these research gaps by providing empirical evidence to demonstrate the mechanism that bank competition culture

[15] A non-exhaustive list of studies includes Deal and Kennedy (1982), Kotter and Heskett (1992) , Andrew (1998), Grieves (2000), Hellriegel et al. (2001), Cameron and Quinn (2011), Campbell et al. (2011), Cameron et al., (2022), Hogan and Coote (2014), Graham et al. (2017), Andreou et al. (2020a, 2020b, 2022), Li et al. (2020), Gorton et al. (2022), and Luu et al. (2023).

[16] A non-exhaustive list of literature that focuses on organizational culture and earnings manipulation includes Elias, 2004; Doupnik, 2008; Geiger and Smith., 2010; Abernethy et al., 2017; Paredes and Wheatley, 2017; Jarne-Jarne et al., 2022 and Luu et al.,2023.

influences the propensity to meet and/or beat earnings forecasts via (more or less) discretionary use of the loan loss provision.

Secondly, this chapter contributes to the broad literature on agency theory. Agency problems emerge as managers are incentivized to manipulate firm performance by sacrificing economic value and information quality for their own sake (Beatty and Harris, 1999; Koh and Rajgopal, 2008; Liao et al.,2009; Alhadab and Al-Own 2019). Researchers have been trying to coordinate conflicts of interest between management and shareholders (Bebchuk and Fried, 2003; D'Mello and Miranda, 2010; Chen and Sougiannis, 2012). In this chapter, I interpret a mechanism that effectively coordinates conflicts of interest with bank managers between shareholders and bank managers. By adopting a high level of competition culture, managers are more likely to meet performance requirements, reducing the inclination of manipulation of accruals. These findings add a new dimension to my understanding of how cultural aspects can mitigate agency conflicts in banking.

Finally, my findings provide practical implications for senior bank executives and board members as they contemplate the significance of bank culture in strategic decision-making. As underscored by Federal Reserve Bank of New York President William Dudley in 2014, banks need to develop strong cultures to eliminate ethical shortcomings. Failing to do so could lead to regulatory intervention. My study lends credence to this statement by empirically demonstrating the influence of a competition culture on financial reporting practices and managerial behaviors. Consequently, my research serves as a valuable guide for senior executives and regulators as they aim to foster a culture that aligns with regulatory norms and ethical banking practices.

This chapter is structured as follows. Section 4.2 provides the literature review; Section 4.3 details the data and summary statistics; Section 4.4 presents the empirical results and robustness check, and Section 4.5 concludes.

4.2 Literature Review and Hypotheses Development

4.2.1 Literature Review

4.2.1.1 Bank Competition Culture

Organizational culture is a crucial and complex issue that plays a significant role in shaping a firm's identity by establishing its beliefs and operational philosophy (Schein, 1990). In measuring corporate culture, many researchers have relied on the competing values framework (CVF), which is a theory developed by Quinn and Rohrbaugh (1983) and emerging from studies of the factors that account for highly effective organizational performance (Cameron et al., 2022). The CVF has been tested and validated in different organizations from various aspects over 30 years (Cameron and Quinn, 1983; Quinn and Rohrbaugh, 1983; Berrio, 2003; Cameron and Quinn, 2011; Hartnell et al., 2011; Schneider et al., 2013; Cameron et al., 2022; Fiordelisi and Ricci, 2014a; Fiordelisi et al., 2019). There are two main dimensions--internal focus versus external focus and stability versus flexibility--thereby dividing culture into four types (see Figure 2.1): Clan (collaborate), Adhocracy (create), Market (compete), and Hierarchy (control), creating a robust taxonomy for studying organizational practices and outcomes (Cameron and Quinn, 2011). For a detailed literature review on organizational culture, please refer to Chapter 2 of this thesis.

This chapter focuses on the bank's competition culture. Firms with a compete-dominant culture can be characterized as a combination of those attitudes and norms that focusing on rapid responses to external information and sensitive to subtle changes in market conditions (Hartnell et al., 2011; Fiordelisi et al., 2014b; Thakor, 2015), which are conducive to the adaptation of the intense competitive environment for banks. Furthermore, competitive organizations prioritize customers and clients, monitor feedback from the marketplace and strive to provide excellent customer. In the banking industry, these traits will prompt banks to improve response speed and better problem-solving and develop customer-oriented products to achieve differentiation, which can help improve financial services, develop financial technology (fintech) and modernize banking operations. Additionally, competitive strategies concentrate on delivering short-term profitability for shareholders, enabling the firm to have a strong position among investors by creating a remarkable reputation for its superior short-term financial performance. However, an aggressive competition culture can accelerate distrust among employees, lead to individualistic pursuit of self-serving goals and induce risk-taking activities like expanding working capital, manipulating provisions, acquiring other firms to win the market share (HHI) radically and giving birth to irrational competition (Narver and Slater, 1990 and 1994; Hurley et al., 1998; Hartnell et al., 2011).

Previous studies have suggested that corporate culture will influence bank managers' propensity to engage in marginal lending and other risk-taking activities (see e.g., Fiordelisi et al., 2014b; Thakor, 2015, 2020; Nguyen et al., 2019; Barth and Mansouri, 2021 and Luu et al., 2023), however, there is limited focus on the importance of competition culture in explaining economic phenomena in the US banking industry. According to findings in my first study (see Table 3.6), which rank the Fama French 48 industry classifications for different cultures, the banking industry ranks at the bottom in competition culture, which means the competition culture does not hold a dominant position in the banking industry, although it is suitable for the current competitive environment. This chapter focuses on the banks' competition culture of banks and expects to provide a fresh perspective on culture development in banks.

4.2.1.2 Meeting/ Beating Analysts' Forecasts

Extensive research underlines the critical role of meeting or beating analysts' forecasts in managerial decision-making. Surveys indicate that many CFOs regard meeting or beating these benchmarks as a top priority, emphasizing its importance in corporate strategies

(Graham et al., 2005). For the firm, the indicator can be regarded as a communication tool with the market. Companies often provide earnings guidance to analysts, indicating what they expect their earnings to be. Meeting or beating these forecasts can demonstrate management's competence and provide reassurance to investors (Matsunaga and Park, 2001; Bartov et al., 2002). In addition, in some cases, meeting or beating earnings forecasts can have regulatory implications. Companies may face legal challenges or scrutiny if they consistently miss earnings expectations, leading to potential investigations or shareholder lawsuits.

Analysts' forecasts acting as external measures to access managerial performance have commonly been widely adopted (O'Brien,1988; Barton and Simko, 2002; Farrell and Whidbee, 2003; Cheng and Warfield, 2005; Bhojraj et al., 2009; Mande and Son 2012; Jensen and Meckling,2019). For investors and stakeholders, the analysts' forecasts are an effective tool for evaluating performance and offer guidance regarding what to anticipate from a firm's balance sheet in the near future. Firms that consistently meet or beat forecasts are rewarded with higher market valuations, demonstrating the market's favourable response to financial reliability (Bartov et al., 2002; Kasznik and McNichols, 2002; Beaver et al., 2008). Conversely, those who fail to meet forecasts see adverse market reactions, underscoring the high stakes involved (Skinner and Sloan, 2002).

4.2.1.3 Discretionary Bank Loan Loss Provisioning

Bank Loan Loss Provisioning is a critical metric for assessing a bank's risk management, financial stability, and its ability to absorb credit losses. It plays a vital role in promoting transparency, instilling confidence in the financial system, and protecting the interests of stakeholders (Beatty and Liao, 2014). In principle, bank loan loss provisions is aim to set aside a portion of their profits to create a reserve or provision for potential losses arising from loans that may default or become non-performing. In other words, it is the amount of money that a bank sets aside to cover expected credit losses on its loan portfolio.

Besides, loan loss provisioning involves estimating the potential credit losses on different categories of loans based on historical data, economic conditions, and the credit quality of borrowers. Therefore, the indicator provides valuable insights into a bank's financial health and risk management practices (Ahmed et al.,1999).

The bank loan loss provisions are composed of two parts: nondiscretionary and discretionary components. Prior evidence suggests that banks can opportunistically exercise discretion over loan loss provisions to disguise risk, smooth profits, manipulate earnings, or distort balance sheet information quality(Wahlen, 1994; Beatty et al., 1995; Collins et al., 1995; Beaver and Engel, 1996; Kim and Kross, 1998; Liu and Ryan, 2006; Kanagaretnam et al., 2014; Bushman and Williams, 2012; Beck and Narayanamoorthy, 2013; Beatty and Liao, 2014; Curcio and Hasan 2015; Bushman et al., 2016 and Alhadab and Al-Own, 2019). First of all, bank managers can adjust discretionary loan loss provisions to manipulate their reported earnings, offering a higher degree of income smoothing and perceived stability. Specifically, banks can decrease discretionary loan loss provisions in periods where they might fail to meet forecasts to enhance reported earnings or increase discretionary loan loss provisions during profitable periods to create a buffer for future earnings challenges. Secondly, the timing and flexibility inherent in discretionary loan loss provisions give banks significant discretion to adjust earnings as needed. Since loan loss provisions are estimates of future losses, they can be adjusted up or down as economic conditions and expectations change. This makes them a precious tool for managing earnings and meeting analysts' forecasts. Moreover, in situations of information asymmetry, banks can use discretionary loan loss provisions to signal confidence in their loan portfolio performance or prudent risk management methods to the market. These signals can impact analysts' expectations and increase the likelihood of meeting or beating them. Additionally, the use of discretionary loan loss provisions helps managers fulfil regulatory capital requirements more effectively. By strategically adjusting provisions, banks can optimize their regulatory capital ratios, potentially eliciting positive responses from analysts and the market (Chang et al.,2008; Tran rt al., 2020).

In this chapter, I employ a rigorous two-stage approach to measure the discretionary loan loss provisioning. With regulatory requirements and accounting standards, the level of loan loss provisioning should be included in the financial statements and must obligate to certain minimum provisioning levels based on the type of loans and the bank's portfolio's risk profile. Hence, in calculation of discretionary loan loss provisioning, I follow Beatty and Liao (2014) to estimate the nondiscretionary component of banks' loan loss provisions first and then take the remaining portion. This method ensures a comprehensive and accurate assessment of the discretionary component, enhancing the reliability of my findings.

4.2.2 Hypotheses Development

According to Nguyen et al. (2019), banks with high competition cultureare associated with risky lending practices – higher loan approval rate, lower borrower quality and fewer covenant requirements. For the banking industry, most banks are dominated by control culture (Andreou et al., 2020b), which will place significant importance on rigorous credit analysis, risk-minimization, post-lending monitoring of adherence to covenants and a low tolerance for default risk. Tight control of guidelines and procedures may sacrifice growth for prudence and safety, leading to missed performance benchmark. Agency problems emerge as influenced by the compensation mechanism, managers are incentive to promote the probability of manipulating firm performance by sacrificing economic value and balance sheet information quality in order to more effectively achieve short-term objectives, which is often blamed for the several onslaughts of accounting scandals (Beatty and Harris, 1999; Koh and Rajgopal, 2008; Liao et al.,2009; Alhadab and Al-Own 2019). Furthermore, agency problems may intensify in the increasingly competitive financial environment setting. Thus, it is meaningful to investigate the influence and possible mechanism of competition culture on bank performance to help managers direct the banks and adapt to the external environment more effectively.

In this chapter, I adopt analysts' forecasts as an external benchmark to evaluate managerial performance, release signals and effectively communicate with stakeholders (Barton and Simko, 2002; Cheng and Warfield, 2005; Bhojraj et al., 2009; Jensen and Meckling, 2019). My aim is to investigate the relationship between bank competition culture and the achievement of performance targets. I hypothesize that banks with a high competition culture are more likely to meet or beat analysts' forecasts. This is because banks dominated by competition culture are often driven to "compete hard, move fast, and play to win" to achieve desired outcomes, such as profits, market share, and shareholder value (Thakor, 2015). My hypothesis is as follows:

Hypothesis 1: *Banks with higher competition culture will have higher likelihood of meeting or beating analysts' forecasts.*

Building on the foundation established in Hypothesis 1, I now delve deeper into the mechanisms through which competition culture influences specific managerial behaviors and reporting practices. One possible explanation is the use of discretionary loan loss provisions. Discretionary loan loss provisions provide managers with significant flexibility to manipulate reported financial performance. By adjusting these provisions, managers can smooth earnings, manage balance sheet volatility, or strategically align financial results with market expectations. For instance, during periods of financial underperformance, managers may decrease discretionary loan loss provisions to inflate reported earnings, while in times of profitability, they may increase provisions to create reserves for future uncertainties. These practices are well-documented in the literature as tools for earnings management (e.g., Beatty & Liao, 2014; Fiordelisi et al., 2014).

However, in a highly competitive cultural environment, banks face strong incentives to prioritize transparency and align managerial practices with shareholder interests. Competition culture, with its emphasis on performance excellence and accountability, may discourage the opportunistic use of discretionary loan loss provisions. Instead, it fosters managerial behaviors that reduce earnings manipulation, improve information quality, and enhance long-term financial stability (Graham et al., 2005; Chen et al., 2022). Accordingly, I hypothesize the following:

Hypothesis 2: *Bank competition culture is negatively related to discretionary loan loss provisioning.*

In competitive cultural settings, the emphasis on sustainable performance and shareholder alignment further shapes these behaviors. Banks with a strong competition culture are likely to prioritize transparent and credible reporting practices over short-term earnings manipulation. This reduces their reliance on discretionary loan loss provisioning as a tool to meet or beat analysts' forecasts, thereby aligning managerial behavior with long-term shareholder value and regulatory expectations. Based on these considerations, I propose the following:

Hypothesis 3: *Bank competition culture propel banks to engage in less discretionary loan loss provisioning to meet or beat analysts' forecasts.*

4.3 Data, Variables and Summary Statistics

4.3.1 Data

For the data period 1994 – 2021, three main data sets serve to construct the sample with the required data: the listed bank (SIC 6000 – 6999) competition culture metrics (followed Andreou et al., 2020b) derived from 10–K filings in the SEC's Edgar database; the annually analysts' forecast data from the Institutional Brokers Estimate System (I/B/E/S), which provided by the Thomson Reuters Corporation and the bank-level financial data from the CRSP /Compustat Merged. In supporting to measure certain main variables, this chapter will utilize some macroeconomic data (e.g., GDP) from the Federal Reserve Economic Data (FRED) database.

Before proceeding with the data analyses, I took several steps to ensure the quality and reliability of my data. Firstly, I removed observations with missing values on the key variables of interest. Next, I addressed the potential influence of outliers by winsorizing all continuous variables at the upper and lower one percentile of their distributions. I also retained banks that became inactive or were acquired during the study period in my sample to mitigate distortions caused by survivorship bias. The definitions of the variables used in this chapter are presented in Table 4.9.

[Insert Table 4.9 Here]

4.3.2 Measuring Bank Competition Culture

This chapter aims to shed light on whether the banks competition culture is efficient in restraining managerial forms arbitrary manipulation of the balance sheet. To quantify competition culture, I review the extensive literature on this area. Traditionally, as constrained by limited access to large amount of promptly public archivable data, scholars rely on small sample of interviews or point-in-time surveys (Sheridan (1992), Hartmann (2006), Ke and Wei (2008), Kotter (2008), Cameron et al. (2011), Graham et al. (2016) and Graham et al. (2022)). However, surveys or interviews, accompanied by high time and economic costs, are often internal documents and must maintain a narrow focus to be effective (Graham et al., 2022). In addition to employing survey-based methodologies, with the advancement of technology and the continuous increase in regulatory and disclosure requirements, there has been a growing trend in utilizing textual analysis techniques to assess different dimensions of corporate culture quantitatively. This approach has gained popularity in recent years, as evidenced by the works of Fiordelisi and Ricci (2014a), Fiordelisi et al. (2014b), Loughran and McDonald (2011, 2016), Fiordelisi et al. (2019), Grennan (2019), Andreou et al. (2020a, 2022), and Luu et al. (2023).

Based on the combination of Competing Value Framework (CVF) and Organizational Culture Assessment Instrument (OCAI), I implement the methodology proposed in the first study to quantify competition culture by conducting a textual analysis of 10–K filings obtained from the SEC's Edgar database. In keeping with recent work, I assume that firms' documents (e.g., the 10–K filings) can reveal information concerning firms underlying culture (see e.g., Fiordelisi and Ricci, 2014a; Nguyen et al., 2019; Andreou et al., 2022; Luu et al., 2023).

To compute the measurement, I follow a rigorous process. Firstly, I select words from the OCAI questionnaire and identify their corresponding synonyms from Princeton University WorldNet lexical database and Harvard IV-4 psychosocial dictionary. I then consider whether all the variants (of selected words and related synonyms) have specific cultural meanings, retaining only those with a certain semantic meaning. I check the contextual words captured before and after the variants in the 10-K filings to understand whether the usage of these variants is meaningful in the financial area. Finally, I only take these variants as keywords which are consistently appearing to capture only the semantic cultural meaning in 10-K filings and form a bag of words(89 word-roots and retain 261 keywords).[17] Following necessary pre-processing steps, I then produce the measure of competition culture, *COMP*, by counting the frequencies of lexical tokens describing the competition culture together and then dividing by the total number of lexical tokens for all

[17] Please see Table 3.4 for further details on the bag of words used to capture the cultures of the competing values framework.

types of CVF cultures appear in a bank's 10-K filings. In simple terms, I apply the simple word count algorithm to estimate banks competition culture:[18]

$$COMP = \frac{Number\ of\ lexical\ tokens\ describing\ the\ Competition\ Culture}{Total\ number\ of\ lexical\ tokens\ for\ all\ types\ of\ CVF\ cultures} \tag{4.1}$$

For a detailed quantification process of the methodology and measurement of the organizational culture score, please refer to Chapter 3 of this thesis.

4.3.3 Measuring Meeting/ Beating Earnings Forecasts

Analysts' forecasts act as external measures for evaluating a firm's performance. These forecasts are formulated by financial experts who analyze the firm's financial records, industry trends, and macroeconomic influences (Barton and Simko, 2002; Cheng and Warfield, 2005; Bhojraj et al., 2009). Financial markets often respond to whether a firm meets, beats, or falls short of analysts' earnings predictions. Meeting or beating expectations can lead to positive market sentiment while missing forecasts can trigger negative responses that affect the movement of stock prices. Comparing a firm's actual earnings with these forecasts offers an unbiased evaluation of its performance.

To comprehensively capture firms' tendencies to meet or beat analysts' earnings expectations, I adopt a multi-proxy approach based on analysts' forecasts, following Cheng and Warfield (2005). Specifically, I compare the I/B/E/S actual EPS for the current fiscal year with the most recent consensus analysts' forecasts made within three months prior to the earnings announcement. This approach accounts for the possibility of varying thresholds at which firms may aim to meet or beat earnings expectations.

The four proxies, *MBEAT_2*, *MBEAT_3*, *MBEAT_4,* and *MBEAT_5*, represent incremental thresholds for meeting or beating analysts' forecasts by up to 2, 3, 4, or 5 cents,

[18] While conducting the count, I exclude negation of the lexical tokens by ignoring occasions when the word is preceded by "no", "non", "not", "less", "few" or "limited" by three or fewer words before or after keywords.

respectively. For instance, if actual earnings meet or beat the consensus forecast by at most 2 cents, the indicator variable *MBEAT*_2 is assigned a value of one, and zero otherwise. Similarly, *MBEAT*_3, *MBEAT*_4, and *MBEAT*_5 are defined for thresholds of 3, 4, and 5 cents, respectively. This multi-proxy framework offers a more nuanced analysis, capturing the varying degrees to which firms strive to meet or exceed market expectations.

Employing multiple thresholds reduces reliance on any single metric and ensures robustness, as consistent findings across multiple proxies provide stronger evidence of the underlying patterns. This methodology aligns with established practices in the literature, including Cheng and Warfield (2005), who emphasize the importance of using diverse metrics to reflect the multifaceted nature of financial performance and earnings management. By incorporating multiple proxies, this study not only enhances the granularity of the analysis but also increases its reliability and applicability across varied contexts.

4.3.4 Measuring Bank Loan Loss Provisioning

In principle, the purpose of bank loan loss provisions is to set aside a portion of their profits to create a buffer, which will assist in absorbing potential losses from loans that borrowers may not repay. The rationale is to ensure that banks are financially prepared to deal with credit losses and maintain financial stability. Therefore, to a certain extent, the loan loss provisioning helps safeguard the bank's capital adequacy and ensures that it can continue operating smoothly even in adverse economic conditions (Ozili and Outa, 2017). However, managers also have the incentives to use loan loss provisions to manipulate earnings and regulatory capital (Ahmed et al.,1999; Alhadab and Al-Own, 2019).

I employ a two-stage approach based on prior theoretical insights (e.g., Beatty and Liao, 2014). As discretionary loan loss provisions are estimated by decomposing total loan loss provisions into non-discretionary and discretionary components, I first estimate the nondiscretionary component of banks' loan loss provision using the empirical models listed below. Then, I determine the discretionary loan loss provisions are the absolute values of the residuals generated from estimating Equation (4.2a):

$$LLP_{i,t} = \alpha_1 + \alpha_2 \Delta NPA_{i,\,t+1} + \alpha_3 \Delta NPA_{i,\,t} + \alpha_4 \Delta NPA_{i,\,t-1} + \alpha_5 \Delta NPA_{i,\,t-2} + \alpha_6 SIZE_{i,\,t-1} + \alpha_7 \Delta LOAN_{i,\,t} + \alpha_8 \Delta GDP_{i,\,t} + \alpha_9 CSRET_{i,\,t} + \alpha_{10} \Delta UNEMP_{i,\,t} + \nu_t + \varepsilon_{i,\,t} \qquad (4.2a)$$

where, I denote the variable $LLP_{i,t}$, represents a bank's loan loss provision scaled by lagged total loans; the discretionary loan loss provision variable $DLLP_{i,t}$, the residuals from Eq.'s (4.2a); the variable $|DLLP_{i,t}|$, the absolute value of $DLLP_{i,t}$; $\Delta NPA_{i,t}$, the change in bank's non-performing assets divided by lagged total loans (The inclusion of $\Delta NPA_{i,t+1}$, $\Delta NPA_{i,t}$, $\Delta NPA_{i,t-1}$ and $\Delta NPA_{i,t-2}$ reflects the dynamic relationship between non-performing assets (NPA) and loan loss provisions (LLP), capturing both backward- and forward-looking considerations in provisioning decisions)[19]; $SIZE_{i,t}$, the natural log of bank total assets[20]; the variable $\Delta Loan$, the change in total loans scaled by lagged total loans; $\Delta GDP_{i,t}$, the change in county-level GDP over the year; $CSRET_{i,t}$, the return on the Case-Shiller Real Estate Index over the year; $\Delta UNEMP_{i,t}$, the change in county-level unemployment rates over the year[21]; ν_t, the time fixed effect and $\varepsilon_{i,\,t}$, the residual and the main variable of interest, which reflects discretionary loan loss provisions beyond those accounted for by the regressors included in

[19] In Equation 4.2a, *NPA* variables are included for multiple time periods (t+1, t, t−1, t−2) to capture the dynamic impact of loan performance on LLP. This approach reflects the practical reality that banks consider historical $NPA_{i,t-1}$ and $NPA_{i,t-2}$ to account for long-term trends in credit quality, while forward-looking $NPA_{i,t+1}$ represent expectations of future loan defaults, which influence current provisioning decisions. While the inclusion of $\Delta NPA_{i,\,t+1}$ may raise concerns about endogeneity, it serves as a proxy for banks' forward-looking assessments of credit risk. Robust estimation techniques are employed to mitigate potential endogeneity and validate the reliability of the results. This practice aligns with prior literature emphasizing the anticipatory nature of *LLP* decisions (e.g., Beaver and Engel, 1996; Beatty & Liao, 2014;Bushman and Williams, 2012).

[20] Consistent with prior research (Beck and Narayanmoorth, 2013; Kim and Kross, 1998; Bushman and Williams, 2012; Beatty and Liao, 2014), the $Size$ variable is lagged to mitigate endogeneity concerns. Firm size, represented as the natural logarithm of total assets, is a critical determinant of provisioning behavior, influencing banks' operational capacity and risk management strategies. By using the lagged value (t−1), the model ensures that the variable is predetermined relative to the dependent variable, reducing simultaneity bias and enhancing the validity of the estimated relationships.

[21] The use of county-level GDP and unemployment rates captures regional economic heterogeneity that national-level data may obscure. This allows for a more precise analysis of how local economic conditions influence bank provisioning decisions.

Equation (4.2a). Given that the residual can be positive or negative, I take the absolute value of the residual to capture the magnitude of discretionary loan loss provisions.

Prior research suggests that such use, whether income-increasing or income-decreasing, results in a deterioration of banks' information quality, it is plausible that earnings management through the discretionary loan loss provision, results in financial reports that significantly diverge from banks' actual level of profitability and provisioning for risk. This in turn has been argued to undermine the transparency of banks' information environment and the accuracy of analysts' forecasts. Therefore, it is meaningful for us to investigate $|DLLP_{i,t}|$, the absolute value of the discretionary component of the loan loss provision. Additionally, I examine both the positive components ($Pos\_DLLP_{i,t}$) and the absolute value of the negative components ($Neg\_DLLP_{i,t}$) of discretionary loan loss provisioning.

In most cases, in pursuit of higher profits, bank managers are more likely to be incentivized to reduce the loan loss provision by decreasing the discretionary part. Therefore, I expect that managerial opportunism and career concerns at banks that are more orientated towards the competition culture will generally drive and reward them to engage in less income-decreasing discretionary use of banks' loan loss provisions. Additionally, when measuring the relationship between bank competition culture and discretionary loan loss provisioning, this study employs more emphasis on the positive (income-decreasing) components of the discretionary loan loss provisioning measures. Accordingly, managers at high competition banks should be more inclined to follow accounting practices that help them meet or beat analysts' forecasts (Payne and Robb, 2000; Cheng and Warfield, 2005; Doupnik, 2008).

My research methodology is robust and thorough. I define the variable alternative discretionary loan loss provisions $DLLP^{A}_{i,t}$ for my robustness tests. Compared with the variable $|DLLP_{i,t}|$, the variable $|DLLP^{A}_{i,t}|$ takes loan loss allowance[22] into consideration and are the absolute values of the residuals generated from estimating Equation (4.2b):

$$LLP_{i,\,t} = \alpha_1 + \alpha_2 \Delta NPA_{i,\,t+1} + \alpha_3 \Delta NPA_{i,\,t} + \alpha_4 \Delta NPA_{i,\,t-1} + \alpha_5 \Delta NPA_{i,\,t-2} + \alpha_6 SIZE_{i,t-1} + \alpha_7 \Delta LOAN_{i,\,t} + \alpha_8 \Delta GDP_{i,\,t} + \alpha_9 CSRET_{i,\,t} + \alpha_{10} \Delta UNEMP_{i,\,t} + \alpha_{11} ALW_{i,\,t-1} + \nu_t + \varepsilon_{i,\,t} \quad (4.2b)$$

where, I denote the variables $DLLP^{A}_{i,t}$, the residuals from Eq.'s (4.2b); the alternative discretionary loan loss provision variables $|DLLP^{A}_{i,t}|$, the absolute value of $DLLP^{A}_{i,t}$; the variable $ALW_{i,t}$, the loan loss allowance divided by total loans.[23] All other variables are as previously defined.

4.3.5 Control Variables

The previous literature has documented a list of factors that could impact the discretionary loan loss provisions of banks (see, e.g., Beatty and Liao, 2014). To account for these influences, I include a comprehensive array of control variables to statistically capture bank-specific attributes and contextual factors.

In particular, I include *CAP*1, the bank's tier 1 risk-adjusted capital ratio at the beginning of the fiscal year, divided by 100. A higher *CAP*1 reflects a stronger capital position, which may reduce the need for earnings management through discretionary provisions; I also include $\Delta CAP1$, the change in *CAP*1 of the fiscal year to capture adjustments in capital adequacy, which could influence provisioning behavior as banks

[22] Compared with Equation 4.2a, Equation 4.2b introduces the Allowance for Loan Losses (*ALW)* as an additional explanatory variable. This variable is critical because it reflects the bank's prior provisioning decisions and its existing capacity to absorb future losses. Including *ALW* in the model accounts for the path dependency of provisioning decisions, where past provisioning behavior influences current and future provisioning levels. By incorporating *ALW*, Equation 4.2b provides a more comprehensive view of how banks manage their loan loss reserves over time.

[23] According to literature(e.g., Beatty et al., 1995; Beatty & Liao, 2014; Beaver and Engel, 1996; Beck and Narayanamoorthy, 2013;Collins et al., 1995), the rationale of controlling for past allowance is that if banks recognize sufficiently high provision in the past, then the current provision may be lower. However, if past allowance reflects the overall credit quality of the bank's clients, then lagged allowance and provision may be positively correlated.

respond to regulatory requirements. Both variables are expected to exhibit a negative relationship with discretionary provisions, as better-capitalized banks are generally less motivated to engage in earnings manipulation (Beatty and Liao, 2014); Δ*UNEMP*, the change in the employment rate over the fiscal year, higher unemployment typically signals increased credit risk, which may lead to higher loan loss provisions. Therefore, Δ *UNEMP* is expected to have a positive relationship with discretionary provisions (Bushman and Williams, 2012); *DEPOSITS*, the lagged total deposits divided by total assets, is included to control for funding structure. Banks with a higher proportion of deposits relative to assets are typically more stable and may exhibit less discretionary behavior. Hence, *DEPOSITS* is expected to show a negative relationship with discretionary provisions; *SIZE*, the natural logarithm of bank's total assets, is included to capture the scale effects on provisioning decisions. Larger banks may have more resources and sophisticated risk management practices, leading to lower discretionary provisions (Kim and Kross, 1998).

I also control for cultural factors by including *COLLAB*, *CREATE* and *CONTROL*, by counting the frequencies of lexical tokens describing the collaborate, create, and control culture, respectively, divided by the total number of lexical tokens for all types of CVF cultures appear in a bank's 10-K filings. The calculation is similar to *COMP* in Equation (4.1).

Furthermore, I have incorporated additional variables as controls in the main regression models. They include: *AGE*, the number of years since the bank was first included in the CRSP /Compustat Merged database. Older banks are likely to have more stable operational practices, potentially leading to less discretionary behavior; *AUDIT_BIG4*, a binary variable set to 1 if the bank is audited by one of the Big 4 accounting firms (i.e. KPMG, PWC, Deloitte, and E&Y) and is 0 otherwise. Big 4 auditors typically enforce stricter reporting standards, reducing discretionary provisions (Francis et al., 1999); Similarly, *AUDIT_TENURE*, the number of years the bank is audited by the same accounting firm, accounts for auditor familiarity, which could either mitigate or exacerbate earnings management, depending on the context; *DIV_YIELD*, banks' annual dividend yield. Higher dividends may indicate stronger financial health but could also incentivize earnings management to maintain payout levels (Skinner and Sloan, 2002); and *MODIFIED*, an indicator variable equal to 1 if the bank's auditor issues a modified audit opinion, captures the impact of negative audit signals on managerial behavior. Modified opinions may prompt banks to adjust provisions to align with regulatory expectations.

Further, I include controls that are likely to be correlated with earning management activity and meeting and/or beating analysts' forecasts (Cheng and Warfield, 2005). I include net operating assets, *NOA*, as Barton and Simko (2002) find that firms with higher beginning-of-period net operating assets are less likely to meet analysts' forecasts. I also include controls for the number of analysts, *NUMEST*; number of analysts who revise forecasts upwards, *NUMUP*; and the number of analysts who revise their forecasts downwards, *NUMDOWN*. These variables are included because it has been argued that incentives to meet analysts forecast increase according to the number of analysts following the firm and the consensus of their estimates (Payne and Robb, 2000). Finally, *REV_GROWTH*, revenue growth, is included as higher growth firms often face greater pressure to meet analysts' expectations, making discretionary provisions more likely. Consistent with Skinner and Sloan (2002), I expect *REV_GROWTH* to exhibit a positive relationship with discretionary provisions..

By including these controls and justifying their selection based on prior literature, this model provides a robust framework for analyzing discretionary loan loss provisions in the banking sector.

4.3.6 Summary Statistics and Correlations

All tables for Chapter 4 are included at the end of this chapter and the entire time span is from 1994 to 2021. Table 4.1 provides summary statistics of the variables used in my empirical analysis.[24] In particular, the mean value of my bank competition culture variable, *COMP*, is 0.327, the mean values of the meeting and beating analysts' forecasts variables, *MBEAT*_2, *MBEAT*_3, *MBEAT*_4, and *MBEAT*_5 are 0.275, 0.332, 0.374, and 0.383, respectively. The mean values of my discretionary loan loss provisioning measures |*DLLP*| and |$DLLP^A$|, are 0.291 and 0.286, respectively. I observe that the descriptive statistics on the variables are broadly comparable to the values reported in previous studies using these data (see, e.g., Beatty et al., 1995; Cheng and Warfield, 2005; Betty and Liao, 2014; Bushman et al., 2016; Nguyen et al., 2019; Fiordelisi et al., 2019; Andreou et al., 2016, 2022; Barth and Mansouri, 2021; Luu et al., 2023).

[Insert Table 4.1 here]

Further, in this chapter, for the data period 1994 – 2021, Pearson correlation was employed to assess the linear relationships between variables, aligning with the linear modeling techniques used throughout the analysis. The selection of Pearson correlation reflects the assumption that the variables under consideration exhibit linear dependencies, which are central to evaluating the relationships relevant to this study. Given the structured nature of financial and organizational data in this chapter, Pearson correlation provides an effective measure to validate the relationships prior to further regression analyses. I report the Pearson correlation in Table 4.2. Some of the more interesting correlations include the relation between *COMP*, |*DLLP*| and |$DLLP^A$|, where I find a negative and significant correlation between *COMP* and |*DLLP*| (correlation = -0.081), and a negative and significant

[24] To mitigate the effects of outliers, all continuous variables are winsorized at the 1% and 99% levels.

correlation between *COMP* and $|DLLP^A|$ (correlation = -0.068). Additionally, I find negative and significant correlations between $|DLLP|$ and *MBEAT*_2 (correlation = -0.044), $|DLLP|$ and *MBEAT*_3 (correlation = -0.053), $|DLLP|$ and *MBEAT*_4 (correlation = -0.056), and $|DLLP|$ and *MBEAT*_5 (correlation = -0.058). Similarly, I find negative and significant correlations between $|DLLP^A|$ and *MBEAT*_2 (correlation = -0.059), $|DLLP^A|$ and *MBEAT*_3 (correlation = -0.068), $|DLLP^A|$ and *MBEAT*_4 (correlation = -0.071), and $|DLLP^A|$ and *MBEAT*_5 (correlation = -0.071). These results are consistent with my expectations that bank competition culture can serve to diminish income-decreasing discretionary (i.e., abnormal) loan loss provisioning activity, and that there is a negative relationship between banks' discretionary use of the loan loss provision and meeting and/or beating analysts' earnings expectations.

[Insert Table 4.2 here]

4.4 Empirical Results

4.4.1 Bank Competition Culture and Meeting/ Beating Earnings Forecasts

Firstly, I aim to investigate the first research question: *"What is the relationship between bank competition culture and the likelihood of meeting or beating analysts' forecasts?"* (Hypothesis 1). Hence, I test whether competition culture is positively related to analysts' consensus forecasts for the data period 1994 to 2021. To do this, I estimate the following regression models:

$$\begin{aligned} ANALYST_{i,t} \;=\; & \alpha_1 + \boldsymbol{\alpha_2 COMP_{i,t}} + \alpha_3 AGE_{i,t} + \alpha_4 AUDIT\_BIG4_{i,t} \\ & + \alpha_5 AUDIT\_TENURE_{i,t} + \alpha_6 CAP1_{i,t} + \alpha_7 \Delta UNEMP_{i,t} + \alpha_8 DEPOSITS_{i,t-1} \\ & + \alpha_9 DIV\_YIELD_{i,t} + \alpha_{10} \Delta CAP1_{i,t} + \alpha_{11} MODIFIED_{i,t} + \alpha_{12} NOA_{i,t} \end{aligned}$$

$$+ \alpha_{13}NUMEST_{i,t} + \alpha_{14}NUMUP_{i,t} + \alpha_{15}NUMDOWN_{i,t}$$
$$+ \alpha_{16}REV\_GROWTH_{i,t} + \alpha_{17}SIZE_{i,t-1} + \nu_t + \varepsilon_{i,t}, \tag{4.3a}$$

where, the key independent variable of interest, $COMP_{i,t}$ represents a measure of bank competition culture; the variable $ANALYST_{i,t}$ is measured by one of the $MBEAT\_2_{i,t}$, $MBEAT\_3_{i,t}$, $MBEAT\_4_{i,t}$, or $MBEAT\_5_{i,t}$. To ensure that the impact of competition culture on banks' inclination to meet and/ or beat analysts' consensus forecasts is not attributed to other factors, I incorporate $NUMEST_{i,t}$, $NUMUP_{i,t}$, and $NUMDOWN_{i,t}$ as additional control variables that account for bank-specific attributes known to strongly relate to banks' propensity to meet and/or beat analysts' forecasts (please see Cheng and Warfield, 2005). All other variables are as previously defined. In addition, I include year dummies to control for unobserved time-invariant year factors in this and all subsequent models.

The results from the estimation of Equation (4.3a) are presented in Table 4.3 (columns 1 to 4). Specifically, the coefficient estimates for the key variable of interest, $COMP_{i,t,}$ are 0.011, 0.015, 0.016, and 0.018 in columns (1), (2), (3), and (4), respectively, all of which are statistically significant. These results indicate that higher levels of competition culture within banks are positively associated with the likelihood of meeting or exceeding analysts' profitability expectations.

[Insert Table 4.3 here]

To account for potential confounding effects of other cultural dimensions, I extend the analysis by incorporating additional control variables:,$COLLAB_{i,t}$, $CREATE_{i,t}$ and $CONTROL_{i,t}$ as specified in Equation (4.3b). These control variables measure other CVF cultural dimensions that could influence banks' performance outcomes. I estimate the following new regression models:

$$ANALYST_{i,t} = \alpha_1 + \boldsymbol{\alpha_2 COMP_{i,t}} + \alpha_3 AGE_{i,t} + \alpha_4 AUDIT\_BIG4_{i,t} + \alpha_5 AUDIT\_TENURE_{i,t}$$

$$+ \alpha_6 CAP1_{i,t} + \alpha_7 \Delta UNEMP_{i,t} + \alpha_8 DEPOSITS_{i,t-1} + \alpha_9 DIV\_YIELD_{i,t}$$
$$+ \alpha_{10} \Delta CAP1_{i,t} + \alpha_{11} MODIFIED_{i,t} + \alpha_{12} NOA_{i,t} + \alpha_{13} NUMEST_{i,t}$$
$$+ \alpha_{14} NUMUP_{i,t} + \alpha_{15} NUMDOWN_{i,t} + \alpha_{16} REV\_GROWTH_{i,t}$$
$$+ \alpha_{17} SIZE_{i,t-1} + \alpha_{18} COLLAB_{i,t} + \alpha_{19} CREATE_{i,t} + \alpha_{20} CONTROL_{i,t}$$
$$+ \nu_t + \varepsilon_{i,t}, \tag{4.3b}$$

The results of these extended OLS regressions are presented in Table 4.3 (columns 5 to 8). The coefficients for $COMP_{i,t}$ in this extended model are 0.251, 0.236, 0.255, and 0.246 in columns (5), (6), (7), and (8), respectively. These estimates remain positive and statistically significant, further reinforcing the robustness of the relationship between bank competition culture and the propensity to meet or beat analysts' forecasts. When examining the signs and significance of the newly included control variables, $COLLAB_{i,t}$, $CREATE_{i,t}$ and $CONTROL_{i,t}$, I observe that all three variables exhibit positive and strongly significant coefficients. This suggests that, apart from competition culture, collaborative, creative, and control-oriented cultures also positively influence the likelihood of banks meeting or beating analysts' forecasts. For instance, a collaborative culture may foster teamwork and effective communication, which enhances operational efficiency and aids in meeting performance targets. Similarly, a creative culture may encourage innovative strategies to achieve profitability benchmarks. Lastly, a control-oriented culture may enforce disciplined risk management and operational practices that align with performance expectations.

In terms of economic significance, the coefficients suggest that banks with stronger competition culture ($COMP_{i,t}$) and the additional cultural dimensions ($COLLAB_{i,t}$, $CREATE_{i,t}$ and $CONTROL_{i,t}$) jointly play a critical role in shaping managerial decisions and performance outcomes. For every unit increase in $COMP_{i,t}$, the probability of meeting or beating analysts' forecasts increases by approximately 0.2 to 0.3. Similarly, the positive coefficients on

$COLLAB_{i,t}$, $CREATE_{i,t}$ and $CONTROL_{i,t}$ highlight the complementary roles of these cultural dimensions in driving banks' performance.

Overall, the results in Table 4.3 strongly support Hypothesis 1, as the positive and significant coefficients on COMP across all columns demonstrate that a stronger competition culture is positively associated with an increased likelihood of meeting or beating analysts' forecasts. This finding is consistent with the argument that competition culture incentivizes managers to align performance with market expectations.

4.4.2 Bank Competition Culture and Loan Loss Provisioning

Prior evidence suggests that the bank managers can adjust discretionary loan loss provisions to manipulate their reported earnings, signal confidence in their loan portfolio performance or prudent risk management and optimize their regulatory capital ratios to potentially elicit positive responses from analysts and the market. Therefore, I am motivated to consider the following research questions; "*Is bank competition culture related to discretionary loan loss provisioning activity?*" (Hypothesis 2) and "*Does bank competition culture propel banks to engage in more or less discretionary loan loss provisioning in order to meet or beat analysts' forecasts?*" (Hypothesis 3). For Hypothesis 2, I expect to observe that managers at banks with greater levels of the competition culture are more likely to achieve analysts' earnings forecasts by avoiding making income-decreasing discretionary use of the loan loss.

I estimate models to examine the relationship between lagged values and differences in bank competition culture and my discretionary loan loss provisioning measures for the span from 1994 to 2021. Notably, I estimate the following empirical models:

$$\begin{aligned} DLLP_{i,t} \;=\; & \alpha_1 + \boldsymbol{\alpha_2 COMP_{i,t}} \\ & + \alpha_3 AGE_{i,t} + \alpha_4 AUDIT\_BIG4_{i,t} + \alpha_5 AUDIT\_TENURE_{i,t} + \alpha_6 CAP1_{i,t} \\ & + \alpha_7 \Delta UNEMP_{i,t} + \alpha_8 DEPOSITS_{i,t-1} + \alpha_9 DIV\_YIELD_{i,t} + \alpha_{10} \Delta CAP1_{i,t} \end{aligned}$$

$$+ \alpha_{11}MODIFIED_{i,t} + \alpha_{12}NOA_{i,t} + \alpha_{13}REV\_GROWTH_{i,t} + \alpha_{14}SIZE_{i,t-1} + \alpha_{15}COLLAB_{i,t} + \alpha_{16}CREATE_{i,t} + \alpha_{17}CONTROL_{i,t} + \nu_t + \varepsilon_{i,t}, \quad (4.4)$$

where, the key independent variable of interest, $COMP_{i,t}$ represents a measure of bank competition culture and the variable $DLLP_{i,t}$ is measured by one of the $|DLLP_{i,t}|$, $Pos\_DLLP_{i,t}$ or $Neg\_DLLP_{i,t}$. Specifically, $|DLLP_{i,t}|$ denotes the absolute value of the residual from the equation (4.2a); $Pos\_DLLP_{i,t}$, is defined as the positive components of the discretionary loan loss provisions; while $Neg\_DLLP_{i,t}$, represents the absolute value of the negative components of discretionary loan loss provisioning. All other variables are as previously defined.

Table 4.4 presents the results of ordinary least squares (OLS) regressions designed to examine the relationship between bank competition culture ($COMP_{i,t}$) and discretionary loan loss provisioning ($DLLP_{i,t}$), including its positive ($Pos\_DLLP_{i,t}$) and negative components ($Neg\_DLLP_{i,t}$). Column (1) reports overall $DLLP_{i,t}$, while columns (2) and (3) focus on $Pos\_DLLP_{i,t}$ and $Neg\_DLLP_{i,t}$, respectively. The coefficient for $COMP_{i,t}$ in column (2) is -0.445 (p-value < 0.01), indicating a significant negative relationship between competition culture and income-increasing provisions($Pos\_DLLP_{i,t}$). This suggests that banks with stronger competition culture are less likely to use discretionary provisions to inflate reported earnings. Columns (1) and (3) show no significant relationship between $COMP_{i,t}$ and overall or income-decreasing provisions, reinforcing the idea that competition culture discourages opportunistic financial behavior.

Control variables provide additional context. For instance, $DEPOSITS_{i,t}$ and $NOA_{i,t}$ exhibit consistent negative and significant coefficients, aligning with prior studies that associate greater financial stability with reduced discretionary behavior. Conversely, $SIZE_{i,t-1}$, measured as the natural logarithm of total assets, has a positive and significant coefficient in column (1). While larger banks are typically associated with sophisticated risk management practices (Kim and Kross, 1998), the observed positive coefficient may reflect their greater flexibility in provisioning decisions within this sample. Overall, these findings highlight the role of competition culture in fostering disciplined financial reporting and align with prior literature, enhancing the robustness of the specification.

[Insert Table 4.4 here]

The findings in Table 4.4 lend support to Hypothesis 2, as the negative and significant coefficient on COMP in column (2) indicates that banks with stronger competition culture are less likely to engage in income-decreasing discretionary loan loss provisioning. This result underscores the role of competition culture in discouraging discretionary practices that compromise reported earnings.

4.4.3 Instrumental Variable Regressions

It is possible that the level of bank competition culture is influenced by past instances of meeting/beating analysts' earnings expectations or discretionary loan loss provisioning; therefore, the choice of instrumental variable (IV) in my analysis is motivated by the need to address potential endogeneity concerns that arise from the simultaneous determination of bank competition culture and the measures of meeting or beating analysts' forecasts and discretionary loan loss provisioning. I take this into consideration by estimating the following two-stage least squares (2SLS) instrumental variable (IV) models to better protect against potential endogeneity in the relation between bank competition culture and my measures of meeting/beating analysts' forecasts and discretionary loan loss provisioning for the data period 1994 – 2021:

$$\begin{aligned} COMP_{i,t} = {} & u_1 + \boldsymbol{\delta_1 COMP\_STATE_{i,t}} + \beta_1 AGE_{i,t} + \beta_2 CAP1_{i,t} \\ & + \beta_3 \Delta UNEMP_{i,t} + \beta_4 DEPOSITS_{i,t-1} + \beta_5 \Delta CAP1_{i,t} + \beta_6 SIZE_{i,t-1} \\ & + \alpha_7 COLLAB_{i,t} + \alpha_8 CREATE_{i,t} + \alpha_9 CONTROL_{i,t} + \nu_t + \varepsilon_{i,t}, \qquad (4.5a) \end{aligned}$$

$$
\begin{aligned}
ANALYST_{i,t} = {} & \alpha_1 + \boldsymbol{\alpha_2 \widehat{COMP}_{i,t}} + \alpha_3 AGE_{i,t} + \alpha_4 AUDIT\_BIG4_{i,t} \\
& + \alpha_5 AUDIT\_TENURE_{i,t} + \alpha_6 CAP1_{i,t} + \alpha_7 \Delta UNEMP_{i,t} \\
& + \alpha_8 DEPOSITS_{i,t-1} + \alpha_9 DIV\_YIELD_{i,t} + \alpha_{10} \Delta CAP1_{i,t} \\
& + \alpha_{11} MODIFIED_{i,t} + \alpha_{12} NOA_{i,t} + \alpha_{13} NUMEST_{i,t} \\
& + \alpha_{14} NUMUP_{i,t} + \alpha_{15} NUMDOWN_{i,t} + \alpha_{16} REV\_GROWTH_{i,t} \\
& + \nu_t + \varepsilon_{i,t},
\end{aligned}
\tag{4.5b}
$$

$$
\begin{aligned}
DLLP_{i,t} = {} & \alpha_1 + \boldsymbol{\alpha_2 \widehat{COMP}_{i,t}} + \alpha_3 AGE_{i,t} + \alpha_4 AUDIT\_BIG4_{i,t} + \alpha_5 AUDIT\_TENURE_{i,t} \\
& + \alpha_6 CAP1_{i,t} + \alpha_7 \Delta UNEMP_{i,t} + \alpha_8 DEPOSITS_{i,t-1} + \alpha_9 DIV\_YIELD_{i,t} \\
& + \alpha_{10} \Delta CAP1_{i,t} + \alpha_{11} MODIFIED_{i,t} + \alpha_{12} NOA_{i,t} + \alpha_{13} REV\_GROWTH_{i,t} \\
& + \alpha_{14} SIZE_{i,t-1} + \alpha_{15} COLLAB_{i,t} + \alpha_{16} CREATE_{i,t} + \alpha_{17} CONTROL_{i,t} \\
& + \nu_t + \varepsilon_{i,t},
\end{aligned}
\tag{4.5c}
$$

where the variable $COMP\_STATE_{i,t}$ represents the mean competition culture measured for the bank's state for the fiscal year. I adopt this variable as my instrument for competition culture, $COMP_{i,t}$. All other variables are as previously defined.

The rationale for using $COMP\_STATE_{i,t}$ as an instrument is grounded in its theoretical and empirical relevance. The state-level competition culture reflects broader socio-economic and regulatory environments that influence individual banks' competitive behaviors, yet it is plausibly exogenous to the specific bank-level outcomes I am examining, such as meeting or beating analysts' forecasts and discretionary loan loss provisioning. This instrument captures regional variations in competitive practices that are likely to affect individual bank's competition culture but are unlikely to be directly correlated with the idiosyncratic factors driving the specific financial outcomes of individual banks, thus satisfying the relevance and exogeneity criteria for a valid instrument. Additionally, using state-level variables as instruments is a common practice in the literature when dealing with potential endogeneity issues in firm-level analyses (Flammer and Kacperczyk, 2016; French and Popovici, 2011; Geczy et al., 2015; Gibson et al.,2021 and Tosun and Moon, 2024).

The results of the 2SLS IV estimates are provided in Table 4.5, the sign and significance of the fitted values of $COMP_{i,t}$ are consistent with those presented in my previous analysis, according to which I find positive and significant relations between competition culture and my analysts' forecasts measures. What's more, consistent with my prior results, I find a negative and significant relationship between competition culture and discretionary loan loss provisioning, which is driven particularly by the positive (income-decreasing) component of the discretionary loan loss provision. Indeed, these instrumental variable results provide evidence in support of the relationship between bank competition culture and my measures of meeting/beating analysts' forecasts and discretionary loan loss provisioning, as I can also take into account the possibility that endogeneity affects the results.

To ensure that the 2SLS IV results are valid I conduct several diagnostic tests. Mainly, I conduct Hausman's (1978) tests to assess the endogeneity of the first stage of the 2SLS IV estimates; my results suggest that I should reject the null hypotheses that my competition culture, discretionary loan loss provision and meeting and/or beating analysts' forecasts measures are exogenous. In addition, the Stock and Yogo's (2005) test for weak instruments suggest that my choice of instrument is appropriate. Furthermore, the Hansen J-statistics indicate that the instrument used in my analyses is uncorrelated with the disturbance process of the models and this satisfies the exclusion principle.

[Insert Table 4.5 here]

4.4.4 Dynamic Model for Bank Competition Culture and Loan Loss Provisioning

Additionally, I estimate dynamic models to examine the relationship between lagged values and changes in bank competition culture and discretionary loan loss provisioning measures for the data period 1994–2021. By including lagged competition culture variables, I capture both immediate and long-term effects, addressing the persistence of cultural influences over time. These dynamic regressions serve two key purposes. First, they reveal whether the relationship between competition culture and discretionary provisioning extends beyond a single period. Second, they mitigate simultaneity concerns by examining long-run relationships, providing evidence of causality. For instance, a negative relationship between competition culture and discretionary provisioning over two years suggests that competition culture drives provisioning decisions rather than the reverse. The decomposition of competition culture into lagged and change components further distinguishes the effects of cultural shifts from sustained attributes. This approach provides a nuanced understanding of how competition culture shapes financial reporting practices.[25] Notably, I estimate the following empirical models to test these relationships:

$$\begin{aligned} DLLP_{i,t} = {} & \alpha_1 + \boldsymbol{\alpha_2 \Delta COMP_{i,t}} + \boldsymbol{\alpha_3 COMP_{i,t-1}} \\ & + \alpha_4 AGE_{i,t} + \alpha_5 AUDIT\_BIG4_{i,t} + \alpha_6 AUDIT\_TENURE_{i,t} + \alpha_7 CAP1_{i,t} \\ & + \alpha_8 \Delta UNEMP_{i,t} + \alpha_9 DEPOSITS_{i,t-1} + \alpha_{10} DIV\_YIELD_{i,t} + \alpha_{11} \Delta CAP1_{i,t} \\ & + \alpha_{12} MODIFIED_{i,t} + \alpha_{13} NOA_{i,t} + \alpha_{14} REV\_GROWTH_{i,t} + \alpha_{15} SIZE_{i,t-1} \end{aligned}$$

[25] The choice to use dynamic models for loan loss provisions but not for meeting or beating analysts' forecasts is guided by the distinct characteristics of these variables. *LLP* are accumulative and reflect both past and expected future credit risks, requiring a dynamic model to capture their persistence over time. This approach aligns with prior literature emphasizing the role of historical provisioning in understanding current and future decisions (e.g., Beatty and Liao, 2014; Bushman and Williams, 2012).Conversely, meeting or beating analysts' forecasts is episodic and typically driven by contemporaneous managerial decisions and specific economic conditions at the time of reporting. Given its less accumulative nature, a static model is sufficient to capture the immediate relationships between competition culture and firms' performance outcomes. This is consistent with established practices in the literature (e.g., Cheng and Warfield, 2005; Bhojraj et al., 2009)

$$+ \alpha_{16}COLLAB_{i,t} + \alpha_{17}CREATE_{i,t} + \alpha_{18}CONTROL_{i,t} + \nu_t + \varepsilon_{i,t}, \quad (4.6a)$$

$$DLLP_{i,t} = \alpha_1 + \boldsymbol{\alpha_2 \Delta COMP_{i,t}} + \boldsymbol{\alpha_3 \Delta COMP_{i,t-1}} + \boldsymbol{\alpha_4 COMP_{i,t-2}}$$
$$+ \alpha_5 AGE_{i,t} + \alpha_6 AUDIT\_BIG4_{i,t} + \alpha_7 AUDIT\_TENURE_{i,t} + \alpha_8 CAP1_{i,t}$$
$$+ \alpha_9 \Delta UNEMP_{i,t} + \alpha_{10} DEPOSITS_{i,t-1} + \alpha_{11} DIV\_YIELD_{i,t} + \alpha_{12} \Delta CAP1_{i,t}$$
$$+ \alpha_{13} MODIFIED_{i,t} + \alpha_{14} NOA_{i,t} + \alpha_{15} REV\_GROWTH_{i,t} + \alpha_{16} SIZE_{i,t-1}$$
$$+ \alpha_{17}COLLAB_{i,t} + \alpha_{18}CREATE_{i,t} + \alpha_{19}CONTROL_{i,t} + \nu_t + \varepsilon_{i,t}, \quad (4.6b)$$

where, the key independent variables of interest, $\Delta COMP_{i,t}$, $COMP_{i,t\text{-}1}$, $\Delta COMP_{i,t\text{-}1}$, and $COMP_{i,t\text{-}2}$, represent lagged levels and differences in the relative measure of bank competition culture. All other variables are as previously defined.

The ordinary least squared (OLS) regression estimates for the above specifications are reported in Table 4.6. For $|DLLP_{i,t}|$, I find for Eq. (4.6b) that the coefficient terms -0.094, -0.091 and -0.116 on the $\Delta COMP_{i,t}$, $\Delta COMP_{i,t\text{-}1}$ and $COMP_{i,t\text{-}2}$ variables in column (2) are significant. For $Pos\_DLLP_{i,t}$, the positive (income-decreasing) component of the discretionary loan loss provisioning measures produced via Eq. (4.2a), I find according to (4.6a) the coefficient terms are -0.407 and -0.525 on the $\Delta COMP_{i,t}$ and $COMP_{i,t\text{-}1}$ variables in column (3), respectively, thereby indicating a significant negative relation between the change and lagged level of competition culture and the positive components of the discretionary loan loss provisioning ($Pos\_DLLP_{i,t}$) at 1 percent level. Besides, based on Eq. (4.6b), the coefficients of $\Delta COMP_{i,t}$, $\Delta COMP_{i,t\text{-}1}$ and $COMP_{i,t\text{-}2}$, are negative and significant at the 1 percent level with coefficient terms of -0.372, -0.378 and -0.500, respectively.

Additionally, for the absolute value of negative components ($Neg\_DLLP_{i,t}$) of discretionary loan loss provisioning, no significant results are provided in columns (5) and (6). I conclude that the negative relationship between the changes and lagged levels of competition culture and discretionary loan loss provisioning previously observed is driven exclusively by the positive component of the discretionary loan loss provision, which aligns with my expectations.

[Insert Table 4.6 here]

4.4.5 Bank Competition Culture, Loan Loss Provisioning and Meeting/ Beating Analysts' Forecasts

For the third research question "*Does bank competition culture propel banks to engage in more or less discretionary loan loss provisioning in order to meet or beat analysts' forecasts?*" (Hypothesis 3), I investigate the interplay between bank competition culture, discretionary loan loss provisioning, and the likelihood of meeting or beating analysts' forecasts over the data span from 1994 to 2021. My findings suggest that bank competition culture significantly increases the likelihood of meeting or beating analysts' earnings expectations. Additionally, I find that competition culture reduces the discretionary use of loan loss provisions, particularly when such provisions would directly lower reported earnings.

Consistent with these observations and prior research (e.g., Beatty and Liao, 2014; Bushman and Williams, 2012; Kanagaretnam et al., 2010), I argue that competition culture incentivizes managers to prioritize performance objectives, fostering disciplined financial reporting practices. This reduction in discretionary provisioning, especially when income-decreasing, not only aligns with shareholder interests but also preserves the transparency of the bank's information environment. By minimizing income-decreasing discretionary provisioning, managers are better positioned to achieve earnings benchmarks, thereby increasing the likelihood of meeting or beating analysts' forecasts. This argument highlights the dual role of competition culture in curbing earnings manipulation through discretionary provisioning while simultaneously enhancing performance outcomes aligned with market expectations.

To explore this, I conduct further empirical analyses for full and subsamples of the available data that are sorted into groups of High and Low bank competition culture. I define a subsample group as High (Low) if it is above (below) the yearly median of my bank competition culture measure. To be clear, if competition culture serves the purpose that I describe, I would expect to observe that the relationship between meeting and/or beating analysts' forecasts and discretionary loan loss provisioning is stronger for those banks with above yearly median $COMP_t$ (i.e., High $COMP_t$) compared with below yearly median subsample. I expect this because a significant presence of a competition culture is likely to pressure managers to avoid discretionary use of the loan loss provision, specifically the positive (income-decreasing) component, which in turn leads to higher instances of meeting and/or beating analysts' earnings expectations. Furthermore, I extend the analysis to a series of binary variables that denote the individual years before meeting/beating analysts' forecasts. Particularly, I estimate the following empirical model:

$$\begin{aligned} DLLP_{i,t} = {} & \alpha_1 + \boldsymbol{\alpha_2 MBEAT\_3Y\_PRIOR_{i,t}} + \boldsymbol{\alpha_3 MBEAT\_2Y\_PRIOR_{i,t}} \\ & + \boldsymbol{\alpha_4 MBEAT\_1Y\_PRIOR_{i,t}} + \boldsymbol{\alpha_5 MBEAT\_YEAR_{i,t}} + \alpha_6 AGE_{i,t} \\ & + \alpha_7 AUDIT\_BIG4_{i,t} + \alpha_8 AUDIT\_TENURE_{i,t} + \alpha_9 CAP1_{i,t} \\ & + \alpha_{10} \Delta UNEMP_{i,t} + \alpha_{11} DEPOSITS_{i,t-1} + \alpha_{12} DIV\_YIELD_{i,t} \\ & + \alpha_{13} \Delta CAP1_{i,t} + \alpha_{14} MODIFIED_{i,t} + \alpha_{15} NOA_{i,t} \\ & + \alpha_{16} REV\_GROWTH_{i,t} + \alpha_{17} SIZE_{i,t-1} + \nu_t + \varepsilon_{i,t} \end{aligned} \tag{4.7}$$

where the variables $MBEAT\_3Y\_PRIOR_{i,t}$, is equal to one for three years before meeting/ beating analysts' earnings forecasts, and zero otherwise. $MBEAT\_2Y\_PRIOR_{i,t}$, is equal to one for two years prior to meeting/ beating analysts' earnings forecasts and is zero otherwise.

$MBEAT\_1Y\_PRIOR_{i,t}$, is equal to one for one year prior to meeting/ beating analysts' earnings forecasts and is zero otherwise. $MBEAT\_YEAR_{i,t}$ is equal to one for the year of meeting/ beating analysts' earnings forecasts and is zero otherwise.

Table 4.7 Panel A provides the OLS estimates of Eq. (4.7) where $Pos\_DLLP_{i,t}$, indicates the positive (income-decreasing) components of the discretionary loan loss provisioning measure produced from Eq. (4.2a). I find that for the full sample of banks (columns 1 to 4) managers avoid discretionary use of the loan loss provision up to one years before ($MBEAT\_1Y\_PRIOR_{i,t}$) and in the same year that they meet/beat analysts' forecasts ($MBEAT\_YEAR_{i,t}$). Further, I find that for the subsample of banks with above median bank competition culture (High *COMP*) (columns 5 to 8) output the similar results. Meanwhile, I observe no meaningful relation between before (up to three years) meeting/ beating analysts' forecasts and discretionary loan loss provisioning for the subsample group of banks with below median bank competition culture (Low *COMP*) (columns 9 to 12). In addition, Panel B provides the OLS estimates of Eq. (4.7) where $Neg\_DLLP_{i,t}$, indicates the absolute value of the negative (income-increasing) components of the discretionary loan loss provisioning measure produced from Eq. (4.2a). As what I expected, I haven't observed any significant results.

[Insert Table 4.7 here]

The results in Table 4.7 support Hypothesis 3, demonstrating that the relationship between bank competition culture and discretionary loan loss provisioning varies depending on the competitive environment. The findings indicate that banks with higher competition culture reduce their reliance on income-decreasing discretionary provisioning, which aligns with their objective to meet or beat analysts' forecasts. This evidence highlights the interplay between competition culture, discretionary practices, and financial reporting objectives.

4.4.6 Robustness Check: Alternative Specification for Discretionary Loan Loss Provisions

As a robustness check, I adopt an alternative specification $|DLLP^{A}_{i,t}|$ to estimate discretionary loan loss provisions by adding loan loss allowance (Beatty and Liao, 2014). I use $|DLLP^{A}_{i,t}|$, the absolute value of the residual from the equation (4.2b); $Pos\_DLLP^{A}_{i,t}$, the positive components of $DLLP^{A}_{i,t}$ and $Neg\_DLLP^{A}_{i,t}$, the absolute value of the negative components of $DLLP^{A}_{i,t}$ as the dependent variable in Equation (4.4a), (4.6a) and (4.6b).

The results, presented in Table 4.8, indicate that the negative relationship between the changes and lagged levels of competition culture and alternative discretionary loan loss provisioning observed in columns (2) and (3) is exclusively driven by the positive component of discretionary loan loss provisioning, consistent with the baseline findings. Since all prior results align with expectations, I tentatively attribute the negative significance (at the 10 percent level, ttt-value = 1.81) observed in column (7) to a statistical anomaly, which does not alter the conclusions of the study.

[Insert Table 4.8 Here]

In conclusion, the results in Section 4.4 validate all three hypotheses. Hypothesis 1 is supported by the positive relationship between competition culture and the likelihood of meeting or beating analysts' forecasts (Table 4.3). Hypothesis 2 is affirmed by the negative association between competition culture and income-decreasing discretionary loan loss provisioning (Table 4.4). Hypothesis 3 is substantiated by the findings in Table 4.7, which show that competition culture reduces reliance on discretionary provisioning to meet earnings targets. A robustness check further confirms the consistency of these results, highlighting the critical role of competition culture in shaping financial reporting practices.

4.5 Conclusion

This chapter makes three key contributions. Firstly, it extends the literature on organizational culture and financial reporting by focusing on the banking sector. Previous studies (e.g., Kanagaretnam et al., 2004; Beatty and Liao, 2014; Bushman and Williams, 2012) have extensively examined earnings manipulation in nonfinancial firms and the broader influence of organizational culture. However, limited attention has been paid to how competition culture specifically shapes financial reporting practices in banks. By examining the role of competition culture in influencing the use of discretionary loan loss provisions to meet or beat analysts' forecasts, this chapter addresses a significant gap in the literature and provides new insights into the cultural determinants of financial decision-making in banks.

Secondly, this chapter contributes to agency theory by illustrating how competition culture serves as an effective mechanism for mitigating conflicts of interest between shareholders and managers. The results demonstrate that banks with a stronger competition culture exhibit a higher propensity to achieve performance goals while simultaneously reducing their reliance on accrual manipulation. These findings suggest that fostering a competition culture can enhance managerial alignment with shareholder interests, improve financial reporting quality, and strengthen governance mechanisms in the banking sector.

Thirdly, the findings offer significant policy and managerial implications. For policymakers and regulators, the research highlights the critical role of competition culture in promoting disciplined financial reporting and aligning managerial behaviors with long-term regulatory and performance objectives. Bank executives can leverage competition culture as a tool to enhance operational efficiency and reporting credibility, fostering trust among stakeholders and optimizing financial performance. Additionally, the findings underscore the importance of designing regulatory frameworks that encourage a healthy competition culture while ensuring compliance with financial reporting standards.

Future research could explore how recent regulatory developments, such as ASC 326 and IFRS 9, and the ongoing impact of the COVID-19 pandemic affect the relationship between competition culture, discretionary loan loss provisioning, and performance outcomes. Furthermore, examining the role of bank competition culture in influencing systemic risk, stock price crash risk, and other outcomes like CEO tenure, compensation structures, and M&A decisions could provide valuable extensions to this work. Finally, while this study focuses on the U.S. banking industry, future research could expand the analysis to other countries, offering a more global perspective on how competition culture shapes financial decision-making in banks.

Tables and Figure

Table 4.1: Summary Statistics

This table presents the mean, median, 25th percentile, 75th percentile, minimum value, maximum value, standard deviation and the number of observations for all variables used in this chapter.

Variable	Obs	Mean	S.D.	Min	0.25	Mdn	0.75	Max
COMP	6,865	0.327	0.078	0.117	0.274	0.325	0.380	0.599
$\|DLLP\|$	6,865	0.291	0.353	0.001	0.091	0.190	0.362	3.113
$\|DLLP^{A}\|$	6,865	0.286	0.351	0.001	0.086	0.185	0.353	3.398
*MBEAT*_2	5,600	0.275	0.446	0	0	0	1	1
*MBEAT*_3	5,600	0.332	0.472	0	0	0	1	1
*MBEAT*_4	5,600	0.374	0.484	0	0	0	1	1
*MBEAT*_5	5,600	0.383	0.486	0	0	0	1	1
AGE	8,810	2.978	0.578	0.693	2.639	3.091	3.367	4.078
*AUDIT_BIG*4	6,865	0.229	0.420	0	0	0	0	1
AUDIT_TENURE	6,865	3	3.747	0	0	1	5	15
*CAP*1	6,865	0.119	0.033	0.043	0.098	0.116	0.136	0.310
Δ*UNEMP*	6,865	-0.021	1.013	-1.200	-0.500	-0.400	0.200	4.400
DEPOSITS	6,865	0.758	0.092	0.237	0.706	0.777	0.825	0.910
DIV_YIELD	6,865	0.024	0.018	0	0.0120	0.0230	0.0330	0.207
Δ*CAP*1	6,865	-0.061	1.625	-8.60	-0.780	-0.010	0.630	7.930
MODIFIED	6,865	0.047	0.212	0	0	0	0	1
NOA	6,865	0.994	1.034	-5.164	0.485	0.947	1.567	5.124
NUMEST	5,600	5.398	5.652	1	2	3	6	37
NUMUP	5,600	1.952	3.078	0	0	1	3	24
NUMDOWN	5,600	1.573	2.731	0	0	1	2	20
REV_GROWTH	6,865	0.078	0.168	-0.560	-0.025	0.053	0.146	1.341
COLLAB	6,865	7.573	1.536	4.143	6.486	7.247	8.419	14.339
CREATE	6,865	0.129	0.069	0	0.080	0.116	0.162	0.441
CONTROL	6,865	0.099	0.042	0	0.071	0.094	0.123	0.303
SIZE	6,865	0.444	0.081	0.175	0.392	0.444	0.500	0.691

Table 4.2: Pearson Correlation Matrix

This table presents the Pearson correlation coefficients for the main variables used in the empirical analyses. T-statistics have been conducted and *, ** and *** indicate 10%, 5%, and 1% levels of significance, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
COMP	(1)	1												
|DLLP|	(2)	-0.081***	1											
|DLLP^A|	(3)	-0.068***	0.858***	1										
MBEAT_2	(4)	0.0030	-0.044**	-0.059***	1									
MBEAT_3	(5)	0.0080	-0.053***	-0.068***	0.870***	1								
MBEAT_4	(6)	0.0110	-0.056***	-0.071***	0.792***	0.910***	1							
MBEAT_5	(7)	0.0140	-0.058***	-0.071***	0.774***	0.890***	0.978***	1						
AGE	(8)	-0.074***	0.026*	0.023*	0.081***	0.075***	0.061***	0.061***	1					
*AUDIT_BIG*4	(9)	-0.038***	0.034**	0.0130	0.00400	-0.0160	-0.0190	-0.031*	0.305***	1				
AUDIT_TENURE	(10)	-0.028**	-0.082***	-0.083***	-0.0140	-0.0190	-0.0230	-0.031*	0.113***	0.319***	1			
*CAP*1	(11)	0.037***	-0.023*	0.040***	0.0140	0.0120	0.0110	0.00100	-0.074***	-0.024*	0.154***	1		
Δ*UNEMP*	(12)	-0.039***	0.287***	0.268***	-0.123***	-0.137***	-0.136***	-0.137***	-0.035***	-0.103***	-0.212***	-0.050***	1	
DEPOSITS	(13)	0.068***	-0.172***	-0.103***	-0.024*	-0.0110	-0.00500	-0.00400	-0.088***	-0.101***	0.169***	0.056***	-0.035***	1
DIV_YIELD	(14)	-0.039***	0.126***	0.107***	-0.0270	-0.039**	-0.044**	-0.044**	0.142***	0.096***	-0.031**	0.00400	0.207***	-0.170***
Δ*CAP*1	(15)	-0.0130	0.0120	-0.00700	0.00300	0.00300	-0.00500	0	0.074***	0.031**	0.026*	-0.436***	0.039***	0.074***
MODIFIED	(16)	0.0150	0.084***	0.076***	-0.051***	-0.061***	-0.068***	-0.071***	0.0180	0.119***	-0.0210	-0.029**	0.109***	-0.040***
NOA	(17)	0.043***	-0.106***	-0.118***	0.048***	0.034**	0.035**	0.031*	-0.068***	0.157***	0.326***	0.167***	-0.127***	-0.110***
NUMEST	(18)	-0.167***	0.049***	0.034*	0.091***	0.083***	0.064***	0.056***	0.402***	0.375***	0.135***	-0.175***	-0.068***	-0.219***
NUMUP	(19)	-0.109***	0.039**	0.041**	0.026*	0.033**	0.031**	0.026*	0.249***	0.338***	0.211***	-0.0150	0.080***	-0.0240
NUMDOWN	(20)	-0.074***	0.062***	0.046***	-0.0220	-0.040***	-0.063***	-0.072***	0.219***	0.308***	0.159***	-0.090***	-0.041***	-0.120***
REV_GROWTH	(21)	0.099***	-0.035**	-0.052***	-0.00700	-0.00600	0.00500	-0.00100	-0.084***	-0.032**	-0.063***	-0.084***	-0.181***	0.0190
COLLAB	(22)	-0.116***	0.054***	0.0140	0.059***	0.047***	0.028**	0.0150	0.509***	0.508***	0.269***	-0.161***	0.0150	-0.228***
CREATE	(23)	-0.467***	0.076***	0.070***	-0.033**	-0.038***	-0.040***	-0.039***	0.061***	0.00200	-0.140***	-0.125***	0.076***	-0.155***
CONTROL	(24)	-0.130***	-0.029**	-0.0210	-0.041***	-0.027*	-0.0160	-0.0140	0.056***	0.038***	-0.00100	-0.076***	0.063***	-0.063***
SIZE	(25)	-0.481***	0.025*	0.0140	0.049***	0.041***	0.035**	0.030**	-0.0100	0.0150	0.149***	0.112***	-0.060***	0.098***

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Table 4.2 cont'd.

		(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
DIV_YIELD	(14)	1											
Δ*CAP*1	(15)	-0.039***	1										
MODIFIED	(16)	0.064***	0.00200	1									
NOA	(17)	0.103***	-0.101***	-0.025*	1								
NUMEST	(18)	0.0170	0.032**	-0.0150	-0.034*	1							
NUMUP	(19)	-0.054***	0.039***	-0.0240	0.067***	0.518***	1						
NUMDOWN	(20)	0.119***	0.0200	0.080***	0.060***	0.467***	0.031**	1					
REV_GROWTH	(21)	-0.194***	-0.071***	-0.00400	0.046***	-0.0220	-0.055***	-0.0210	1				
COLLAB	(22)	0.060***	0.096***	0.038***	0.088***	0.807***	0.519***	0.483***	0.00700	1			
CREATE	(23)	0.122***	0.024**	0.00900	-0.089***	0.143***	0.026*	0.044***	-0.097***	0.100***	1		
CONTROL	(24)	-0.030**	0.018*	-0.00500	-0.131***	0.167***	0.097***	0.065***	0.045***	0.171***	-0.00400	1	
SIZE	(25)	-0.052***	-0.018*	-0.0190	0.104***	-0.055***	0.028*	-0.00200	-0.034**	-0.063***	-0.403***	-0.387***	1

(* p<0.1; ** p<0.05; *** p<0.01)

Table 4.3: Relationship between Bank Competition Culture and Meet/Beat Analysts' Expectations

This table presents ordinary least squared (OLS) regression to investigate the relationship between bank competition culture and the propensity to meeting/beating analyst expectations for the data period 1994 – 2021. The estimates include year fixed effect. All variables are defined in Table 4.9 and all models include a constant (not shown) and the standard errors are clustered at the firm level. The *t*-statistics are given in parentheses.

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Table 4.3 cont'd.

	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$COMP_{i,t}$	0.011*	0.015**	0.016**	0.018**	0.251***	0.236***	0.255***	0.246***
	(1.76)	(2.06)	(2.31)	(2.57)	(4.58)	(4.48)	(4.71)	(4.91)
$AGE_{i,t}$	0.030***	0.030***	0.029***	0.032***	0.029***	0.029***	0.028***	0.031***
	(3.52)	(3.34)	(3.19)	(3.43)	(3.44)	(3.25)	(3.12)	(3.37)
$AUDIT\_BIG4_{i,t}$	0.022	0.004	0.017	0.017	0.023	0.005	0.017	0.017
	(1.02)	(0.18)	(0.73)	(0.73)	(1.09)	(0.22)	(0.74)	(0.73)
$AUDIT\_TENURE_{i,t}$	-0.020*	-0.026**	-0.031**	-0.030**	-0.021*	-0.027**	-0.032***	-0.031**
	(1.79)	(2.12)	(2.55)	(2.50)	(1.85)	(2.17)	(2.63)	(2.58)
$CAP1_{i,t}$	0.015*	0.012	0.010	0.005	0.013	0.010	0.008	0.003
	(1.85)	(1.47)	(1.17)	(0.62)	(1.61)	(1.23)	(0.93)	(0.38)
$\Delta UNEMP_{i,t}$	-0.122	-0.095	-0.075	-0.051	-0.114	-0.085	-0.064	-0.040
	(1.31)	(0.99)	(0.77)	(0.52)	(1.22)	(0.88)	(0.66)	(0.41)
$DEPOSITS_{i,t-1}$	0.012	0.013	0.016*	0.017*	0.010	0.012	0.015*	0.015*
	(1.41)	(1.55)	(1.86)	(1.91)	(1.21)	(1.36)	(1.72)	(1.78)
$DIV\_YIELD_{i,t}$	-0.007	-0.012**	-0.014**	-0.014**	-0.008	-0.013**	-0.014**	-0.015**
	(1.16)	(1.97)	(2.13)	(2.15)	(1.36)	(2.14)	(2.29)	(2.29)
$\Delta CAP1_{i,t}$	0.011	0.009	0.005	0.005	0.010	0.008	0.005	0.004
	(1.56)	(1.31)	(0.78)	(0.66)	(1.43)	(1.19)	(0.69)	(0.58)
$MODIFIED_{i,t}$	-0.025	-0.032	-0.048*	-0.049*	-0.023	-0.030	-0.047*	-0.048*
	(1.10)	(1.29)	(1.83)	(1.87)	(1.01)	(1.22)	(1.78)	(1.84)
$NOA_{i,t}$	0.035***	0.036***	0.038***	0.037***	0.033***	0.034***	0.037***	0.037***
	(4.43)	(3.94)	(4.22)	(4.18)	(4.15)	(3.76)	(4.13)	(4.11)
$NUMEST_{i,t}$	0.067***	0.066***	0.057***	0.054***	0.066***	0.065***	0.056***	0.052***
	(4.47)	(4.28)	(3.70)	(3.42)	(4.43)	(4.25)	(3.63)	(3.35)
$NUMUP_{i,t}$	-0.019**	-0.009	-0.005	-0.002	-0.019**	-0.009	-0.004	-0.001
	(2.03)	(0.98)	(0.47)	(0.16)	(2.02)	(0.95)	(0.44)	(0.12)
$NUMDOWN_{i,t}$	-0.041***	-0.041***	-0.048***	-0.047***	-0.041***	-0.041***	-0.048***	-0.048***
	(4.40)	(4.33)	(5.21)	(5.12)	(4.43)	(4.37)	(5.24)	(5.17)
$REV\_GROWTH_{i,t}$	0.001	-0.003	0.000	-0.001	0.002	-0.002	0.001	-0.001
	(0.15)	(0.41)	(0.06)	(0.14)	(0.26)	(0.33)	(0.11)	(0.09)
$SIZE_{i,t-1}$	0.001	0.000	0.005	0.001	0.007	0.006	0.010	0.006
	(0.06)	(0.02)	(0.30)	(0.04)	(0.41)	(0.35)	(0.61)	(0.34)
$COLLAB_{i,t}$					0.214***	0.195***	0.212***	0.201***
					(4.15)	(3.88)	(4.11)	(4.21)
$CREATE_{v}$					0.122***	0.115***	0.130***	0.125***
					(4.08)	(3.94)	(4.35)	(4.51)
$CONTROL_{i,t}$					0.275***	0.254***	0.273***	0.260***
					(4.63)	(4.41)	(4.62)	(4.78)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.06	0.06	0.07	0.07	0.06	0.07	0.07	0.07
N	5,600	5,600	5,600	5,600	5,600	5,600	5,600	5,600

(* p<0.1; ** p<0.05; *** p<0.01)

Table 4.4: Relationship between Bank Competition Culture and Discretionary Loan Loss Provisioning

This table presents ordinary least squared (OLS) regression estimates for the relationship between bank competition culture and the discretionary loan loss provisioning from 1994 to 2021. The key independent variable of interest, $COMP_{i,t}$, represents a contemporaneous measure of bank competition culture. Besides, $|DLLP_{i,t}|$, denotes the absolute value of the residual from the equation (4.2a); $Pos\_DLLP_{i,t}$, is defined as the positive components of the discretionary loan loss provisions; while $Neg\_DLLP_{i,t}$, represents the absolute value of the negative components of discretionary loan loss provisioning. All other variables are defined in Table 4.9. The estimates include the year fixed effect. All models include a constant (not shown) and the standard errors are clustered at the firm level. The t-statistics are given in parentheses.

	$\|DLLP_{i,t}\|$	$Pos\_DLLP_{i,t}$	$Neg\_DLLP_{i,t}$
	(1)	(2)	(3)
$COMP_{i,t}$	-0.129	-0.455***	-0.138
	(1.14)	(3.61)	(0.85)
$AGE_{i,t}$	-0.021*	-0.045***	-0.019
	(1.85)	(3.02)	(1.05)
$AUDIT\_BIG4_{i,t}$	0.020	-0.020	0.034
	(0.58)	(0.42)	(0.69)
$AUDIT\_TENURE_{i,t}$	-0.005	0.023	-0.021
	(0.30)	(1.21)	(0.90)
$CAP1_{i,t}$	-0.013	-0.092***	0.019
	(1.05)	(5.43)	(0.97)
$\Delta UNEMP_{i,t}$	-0.002	0.000	0.003
	(0.08)	(0.01)	(0.07)
$DEPOSITS_{i,t-1}$	-0.091***	-0.219***	-0.054**
	(5.46)	(5.29)	(2.36)
$DIV\_YIELD_{i,t}$	0.005	0.030	-0.022
	(0.37)	(1.57)	(1.05)
$\Delta CAP1_{i,t}$	0.003	-0.067***	0.043**
	(0.24)	(4.79)	(2.35)
$MODIFIED_{i,t}$	0.114	0.015	0.167
	(1.63)	(0.28)	(1.62)
$NOA_{i,t}$	-0.076***	-0.109***	-0.065***
	(5.96)	(6.44)	(3.21)
$REV\_GROWTH_{i,t}$	0.014	-0.012	0.034
	(0.85)	(0.59)	(1.25)
$SIZE_{i,t-1}$	0.041***	0.015	0.079***
	(2.70)	(0.91)	(3.07)
$COLLAB_{i,t}$	-0.118	-0.403***	-0.140
	(1.19)	(3.67)	(0.98)
$CREATE_{i,t}$	-0.078	-0.223***	-0.102
	(1.27)	(3.35)	(1.18)
$CONTROL_{i,t}$	-0.079	-0.296**	-0.153
	(0.67)	(2.32)	(0.91)
YEAR FE	Yes	Yes	Yes
Adj. R^2	0.25	0.29	0.32
N	6,865	2,181	4,687

(* p<0.1; ** p<0.05; *** p<0.01)

Table 4.5: Instrumental Variable Regressions of Bank Competition Culture, Meet/Beat Analysts' Expectations and Loan Loss Provisioning

This table presents instrumental variable (IV) regression estimates to investigate the relationships between bank competition culture, the propensity to meeting/beating analyst expectations and discretionary loan loss provisioning for the data range 1994 to 2021. I present first stage OLS in column 1 and second stage regression estimates in columns 2 to 7. The variable $Pos\_DLLP_{i,t}$, is defined as the positive components of the of the residual from the equation (4.2a); while $Neg\_DLLP_{i,t}$, represents the absolute value of the negative components of the residual from the equation (4.2a). All other variables are defined in Table 4.9. The regressions include year fixed effect, and the standard errors are clustered by firm. The *t*-statistics are given in parentheses.

	1st stage $COMP_{i,t}$	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$	Pos_$DLLP_{i,t}$	Neg_$DLLP_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$COMP\_STATE_{i,t}$	0.004***						
	(3.51)						
$COMP_{i,t}$		0.392***	0.319**	0.271	0.276	-0.402***	-0.183
		(2.95)	(2.03)	(1.59)	(1.63)	(2.77)	(0.90)
$AGE_{i,t}$	0.002	0.026*	0.029*	0.031**	0.031**	-0.041***	-0.032*
	(1.50)	(1.79)	(1.95)	(2.03)	(1.97)	(2.91)	(1.92)
$AUDIT\_BIG4_{i,t}$		0.002	-0.023	-0.009	-0.012	-0.035	0.024
		(0.07)	(0.79)	(0.31)	(0.42)	(0.90)	(0.55)
$AUDIT\_TENURE_{i,t}$		-0.010	-0.015	-0.018	-0.016	0.015	-0.010
		(0.59)	(0.84)	(1.07)	(0.92)	(1.00)	(0.51)
$CAP1_{i,t}$	-0.000	0.008	0.005	0.004	-0.001	-0.050***	0.054***
	(0.34)	(0.62)	(0.40)	(0.36)	(0.05)	(3.50)	(2.68)
$\Delta UNEMP_{i,t}$	-0.001	-0.073**	-0.085**	-0.054	-0.058	0.004	-0.013
	(1.31)	(2.02)	(2.27)	(1.12)	(1.19)	(0.12)	(0.35)
$DEPOSITS_{i,t-1}$	-0.001	0.006	0.007	0.010	0.011	-0.163***	-0.058***
	(1.02)	(0.49)	(0.63)	(0.88)	(0.94)	(4.14)	(2.72)
$DIV\_YIELD_{i,t}$		-0.005	-0.007	-0.006	-0.006	0.038**	0.019
		(0.50)	(0.73)	(0.66)	(0.61)	(2.08)	(0.88)
$\Delta CAP1_{i,t}$	-0.000	0.010	0.008	0.011	0.008	-0.048***	0.027
	(0.18)	(0.92)	(0.66)	(0.95)	(0.73)	(4.02)	(1.37)
$MODIFIED_{i,t}$		-0.025	-0.035	-0.047	-0.048	-0.008	0.179
		(0.68)	(0.88)	(1.19)	(1.20)	(0.14)	(1.52)
$NOA_{i,t}$		0.039***	0.036***	0.039***	0.040***	-0.093***	-0.056***
		(3.50)	(2.90)	(3.20)	(3.27)	(6.06)	(3.11)
$NUMEST_{i,t}$		0.079***	0.066***	0.061***	0.059***		
		(3.88)	(2.98)	(2.82)	(2.76)		
$NUMUP_{i,t}$		-0.019	-0.006	-0.005	-0.003		
		(1.56)	(0.46)	(0.35)	(0.19)		
$NUMDOWN_{i,t}$		-0.042***	-0.043***	-0.052***	-0.052***		
		(3.57)	(3.42)	(4.29)	(4.32)		
$REV\_GROWTH_{i,t}$		-0.006	-0.008	0.000	-0.004	0.025	0.095***
		(0.55)	(0.64)	(0.02)	(0.35)	(1.19)	(3.46)
$SIZE_{i,t-1}$	-0.001	0.005	0.011	0.010	0.007	0.029**	0.099***
	(0.56)	(0.20)	(0.46)	(0.41)	(0.32)	(2.12)	(4.22)
$COLLAB_{i,t}$	-0.849***	-0.012	-0.016*	-0.015	-0.017*	0.009	-0.005
	(376.95)	(1.33)	(1.65)	(1.55)	(1.78)	(0.53)	(0.30)
$CREATE_{i,t}$	-0.512***	-0.031***	-0.024**	-0.016	-0.014	0.008	-0.033*
	(329.41)	(2.96)	(2.20)	(1.41)	(1.28)	(0.72)	(1.94)
$CONTROL_{i,t}$	-1.006***	0.007	0.006	0.010	0.008	0.137***	0.000
	(435.11)	(0.55)	(0.50)	(0.80)	(0.67)	(7.07)	(0.01)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	1.00	0.06	0.06	0.07	0.07	0.24	0.29
N	5,519	3,309	3,309	3,309	3,309	1,758	3,763

(* $p<0.1$; ** $p<0.05$; *** $p<0.01$)

Table 4.6: Dynamic Model: Relationship between Bank Competition Culture and Discretionary Loan Loss Provisioning

This table presents ordinary least squared (OLS) regression estimates for the relationship between bank competition culture and the discretionary loan loss provisioning for the data period 1994 – 2021. The key independent variables of interest $\Delta COMP_{i,t}$, $COMP_{i,t\text{-}1}$, $\Delta COMP_{i,t\text{-}1}$, and $COMP_{i,t\text{-}2}$, represent lagged levels and differences in my relative measure of bank competition culture. Besides, $|DLLP_t|$, denotes the absolute value of the residual from the equation (4.2a); $Pos\_DLLP_{i,t}$, is defined as the positive components of the discretionary loan loss provisions; while $Neg\_DLLP_{i,t}$, represents the absolute value of the negative components of discretionary loan loss provisioning. All other variables are defined in Table 4.9. The estimates include the year fixed effect. All models include a constant (not shown) and the standard errors are clustered at the firm level. The t-statistics are given in parentheses.

	$\|DLLP_{i,t}\|$	$\|DLLP_{i,t}\|$	$Pos\_DLLP_{i,t}$	$Pos\_DLLP_{i,t}$	$Neg\_DLLP_{i,t}$	$Neg\_DLLP_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta COMP_{i,t}$	-0.047	-0.094**	-0.407***	-0.372***	0.019	-0.016
	(0.71)	(2.05)	(5.01)	(6.82)	(0.19)	(0.22)
$COMP_{i,t-1}$	-0.051		-0.525***		0.035	
	(0.59)		(4.88)		(0.27)	
$\Delta COMP_{i,t-1}$		-0.091*		-0.378***		-0.014
		(1.94)		(6.64)		(0.19)
$COMP_{i,t-2}$		-0.116*		-0.500***		-0.003
		(1.90)		(6.75)		(0.03)
$AGE_{i,t}$	-0.021*	-0.021*	-0.046***	-0.048***	-0.019	-0.019
	(1.87)	(1.87)	(3.06)	(3.16)	(1.06)	(1.05)
$AUDIT\_BIG4_{i,t}$	0.021	0.020	-0.019	-0.015	0.034	0.034
	(0.59)	(0.58)	(0.40)	(0.32)	(0.69)	(0.70)
$AUDIT\_TENURE_{i,t}$	-0.005	-0.005	0.024	0.025	-0.021	-0.021
	(0.30)	(0.30)	(1.22)	(1.31)	(0.91)	(0.91)
$CAP1_{i,t}$	-0.014	-0.014	-0.092***	-0.093***	0.018	0.018
	(1.07)	(1.06)	(5.47)	(5.55)	(0.93)	(0.93)
$\Delta UNEMP_{i,t}$	-0.001	-0.001	-0.000	-0.002	0.004	0.004
	(0.05)	(0.06)	(0.01)	(0.07)	(0.10)	(0.12)
$DEPOSITS_{i,t\text{-}1}$	-0.091***	-0.091***	-0.221***	-0.221***	-0.054**	-0.054**
	(5.47)	(5.48)	(5.36)	(5.39)	(2.36)	(2.36)
$DIV\_YIELD_{i,t}$	0.005	0.005	0.030	0.028	-0.023	-0.023
	(0.35)	(0.36)	(1.54)	(1.47)	(1.09)	(1.09)
$\Delta CAP1_{i,t}$	0.003	0.003	-0.067***	-0.069***	0.043**	0.043**
	(0.23)	(0.23)	(4.86)	(4.91)	(2.35)	(2.35)
$MODIFIED_{i,t}$	0.115	0.114	0.013	0.008	0.168	0.168
	(1.64)	(1.63)	(0.24)	(0.14)	(1.62)	(1.63)
$NOA_{i,t}$	-0.076***	-0.076***	-0.110***	-0.110***	-0.064***	-0.064***
	(5.95)	(5.95)	(6.53)	(6.55)	(3.19)	(3.19)
$REV\_GROWTH_{i,t}$	0.013	0.013	-0.013	-0.015	0.034	0.033
	(0.82)	(0.81)	(0.62)	(0.74)	(1.24)	(1.23)
$SIZE_{i,t\text{-}1}$	0.041***	0.041***	0.014	0.014	0.079***	0.079***
	(2.73)	(2.73)	(0.90)	(0.86)	(3.09)	(3.11)
$COLLAB_{i,t}$	-0.051	-0.104**	-0.457***	-0.420***	0.009	-0.026
	(0.69)	(2.10)	(5.06)	(6.95)	(0.09)	(0.32)
$CREATE_{i,t}$	-0.036	-0.069**	-0.254***	-0.233***	-0.011	-0.032
	(0.81)	(2.18)	(4.69)	(6.10)	(0.16)	(0.65)
$CONTROL_{i,t}$	0.003	-0.060	-0.356***	-0.312***	0.026	-0.015
	(0.04)	(1.03)	(3.51)	(4.54)	(0.20)	(0.16)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.25	0.25	0.29	0.29	0.32	0.32
N	6,865	6,865	2,181	2,181	4,687	4,687

(* p<0.1; ** p<0.05; *** p<0.01)

Table 4.7: Relationship between Meet/Beat Analysts' Expectations and Loan Loss Provisioning

This table presents ordinary least squared (OLS) regression estimates for the relationship between discretionary loan loss provisioning and the meet/beat analysts' forecasts measures for the time span from 1994 to 2021. In this table, the variables $MBEAT\_3Y\_PRIOR_t$, is equal to one for three years before meeting/ beating analysts' earnings forecasts, and zero otherwise; $MBEAT\_2Y\_PRIOR_{i,t}$, is equal to one for two years prior to meeting/ beating analysts' earnings forecasts and is zero otherwise. $MBEAT\_1Y\_PRIOR_{i,t}$, is equal to one for one year prior to meeting/ beating analysts' earnings forecasts and is zero otherwise; and $MBEAT\_YEAR_{i,t}$ is equal to one for the year of meeting/ beating analysts' earnings forecasts and is zero otherwise. I present results for full sample of banks in columns 1 to 4, subsample of banks with above yearly median $COMP_t$ (i.e., High $COMP_t$) in columns 5 to 8 and subsample of banks with below yearly median $COMP_t$ (i.e., Low $COMP_t$) in columns 9 to 12. All other variables are defined in Table 4.9 and the estimates include year fixed effect. All models include a constant (not shown) and the standard errors are clustered at the firm level. The t-statistics are given in parentheses.

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Table 4.7 cont'd.

Panel A. Meeting/beating analyst expectations and the positive component of discretionary loan loss provisioning.

	$Pos\_DLLP_{i,t}$				$Pos\_DLLP_{i,t}$ in banks with High *COMP*				$Pos\_DLLP_{i,t}$ in banks with Low *COMP*			
	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$MBEAT\_3Y\_PRIOR_{i,t}$	-0.055	-0.045	-0.052	-0.058	-0.033	-0.017	-0.016	-0.025	-0.102	-0.091	-0.109	-0.114
	(1.35)	(1.14)	(1.35)	(1.48)	(0.76)	(0.44)	(0.42)	(0.66)	(1.23)	(1.16)	(1.39)	(1.46)
$MBEAT\_2Y\_PRIOR_{i,t}$	-0.042	-0.045	-0.032	-0.035	-0.017	-0.027	-0.039	-0.040	-0.052	-0.056	-0.020	-0.019
	(0.98)	(1.14)	(0.84)	(0.93)	(0.49)	(0.79)	(1.21)	(1.26)	(0.67)	(0.76)	(0.28)	(0.28)
$MBEAT\_1Y\_PRIOR_{i,t}$	-0.043	-0.064**	-0.065**	-0.063*	-0.040	-0.073**	-0.070**	-0.070**	-0.054	-0.042	-0.046	-0.033
	(1.31)	(1.97)	(2.04)	(1.95)	(1.20)	(2.40)	(2.29)	(2.31)	(0.86)	(0.73)	(0.78)	(0.57)
$MBEAT\_YEAR_{i,t}$	-0.075**	-0.072**	-0.092***	-0.091***	-0.081***	-0.077***	-0.087***	-0.081***	-0.094	-0.095*	-0.129**	-0.136**
	(2.52)	(2.55)	(3.34)	(3.25)	(2.61)	(2.65)	(3.20)	(2.98)	(1.57)	(1.72)	(2.34)	(2.44)
$AGE_{i,t}$	-0.049**	-0.050**	-0.049**	-0.047**	-0.042**	-0.043**	-0.043**	-0.041*	-0.056	-0.058	-0.055	-0.052
	(2.11)	(2.16)	(2.12)	(2.04)	(2.01)	(2.08)	(2.02)	(1.93)	(1.20)	(1.24)	(1.17)	(1.12)
$AUDIT\_BIG4_{i,t}$	-0.033	-0.031	-0.029	-0.029	-0.074	-0.072	-0.071	-0.070	0.026	0.028	0.031	0.028
	(0.59)	(0.56)	(0.53)	(0.54)	(1.65)	(1.63)	(1.61)	(1.60)	(0.24)	(0.26)	(0.30)	(0.27)
$AUDIT\_TENURE_{i,t}$	0.021	0.020	0.019	0.019	0.006	0.006	0.006	0.005	0.040	0.037	0.037	0.038
	(0.81)	(0.76)	(0.74)	(0.75)	(0.33)	(0.31)	(0.31)	(0.28)	(0.94)	(0.91)	(0.88)	(0.92)
$CAP1_{i,t}$	-0.062**	-0.061**	-0.061**	-0.062**	-0.067***	-0.068***	-0.066***	-0.068***	-0.035	-0.033	-0.033	-0.035
	(2.33)	(2.34)	(2.33)	(2.37)	(2.68)	(2.78)	(2.69)	(2.74)	(0.84)	(0.80)	(0.81)	(0.84)
$\Delta UNEMP_{i,t}$	-0.007	-0.014	-0.013	-0.015	-0.140	-0.303	-0.284	-0.313	0.017	0.017	0.019	0.017
	(0.21)	(0.47)	(0.44)	(0.50)	(0.41)	(0.94)	(0.87)	(0.95)	(0.29)	(0.29)	(0.31)	(0.29)
$DEPOSITS_{i,t-1}$	-0.255***	-0.254***	-0.253***	-0.252***	-0.158***	-0.158***	-0.157***	-0.157***	-0.331***	-0.328***	-0.328***	-0.327***
	(4.86)	(4.88)	(4.91)	(4.92)	(5.18)	(5.23)	(5.23)	(5.22)	(3.64)	(3.65)	(3.71)	(3.73)
$DIV\_YIELD_{i,t}$	0.020	0.019	0.018	0.019	-0.001	-0.002	-0.003	-0.002	0.039	0.038	0.038	0.038
	(0.79)	(0.74)	(0.73)	(0.75)	(0.04)	(0.13)	(0.17)	(0.15)	(0.81)	(0.78)	(0.78)	(0.79)
$\Delta CAP1_{i,t}$	-0.023	-0.022	-0.021	-0.021	-0.046**	-0.048**	-0.045**	-0.046**	0.009	0.013	0.015	0.015
	(1.12)	(1.09)	(1.03)	(1.03)	(2.45)	(2.56)	(2.44)	(2.46)	(0.26)	(0.36)	(0.42)	(0.42)
$MODIFIED_{i,t}$	-0.073	-0.076	-0.075	-0.076	-0.048	-0.054	-0.051	-0.052	-0.138	-0.134	-0.135	-0.136
	(1.11)	(1.15)	(1.15)	(1.17)	(0.77)	(0.88)	(0.83)	(0.85)	(1.17)	(1.13)	(1.14)	(1.16)
$NOA_{i,t}$	-0.080***	-0.080***	-0.081***	-0.081***	-0.066***	-0.066***	-0.067***	-0.067***	-0.090***	-0.092***	-0.093***	-0.093***
	(5.06)	(5.06)	(5.11)	(5.10)	(3.24)	(3.17)	(3.30)	(3.28)	(3.54)	(3.65)	(3.68)	(3.68)
$REV\_GROWTH_{i,t}$	0.006	0.005	0.007	0.006	-0.029	-0.032*	-0.030*	-0.031*	0.029	0.030	0.033	0.032
	(0.25)	(0.20)	(0.27)	(0.25)	(1.58)	(1.81)	(1.71)	(1.75)	(0.67)	(0.70)	(0.75)	(0.75)
$SIZE_{i,t-1}$	0.010	0.011	0.009	0.007	0.046*	0.045*	0.044*	0.042*	-0.021	-0.018	-0.023	-0.024
	(0.42)	(0.44)	(0.35)	(0.30)	(1.81)	(1.78)	(1.72)	(1.67)	(0.53)	(0.47)	(0.58)	(0.61)
$COLLAB_{i,t}$	0.015	0.016	0.016	0.016	-0.013	-0.010	-0.010	-0.011	0.080	0.080	0.078	0.079
	(0.67)	(0.69)	(0.67)	(0.70)	(0.50)	(0.40)	(0.41)	(0.44)	(1.45)	(1.47)	(1.42)	(1.44)
$CREATE_{i,t}$	0.020	0.020	0.020	0.020	-0.014	-0.014	-0.014	-0.014	0.078*	0.077*	0.079*	0.078*
	(1.02)	(1.02)	(1.06)	(1.04)	(0.65)	(0.65)	(0.63)	(0.66)	(1.91)	(1.91)	(1.95)	(1.94)
$CONTROL_{i,t}$	0.212***	0.211***	0.211***	0.210***	0.125***	0.124***	0.124***	0.122***	0.328***	0.327***	0.327***	0.326***
	(6.64)	(6.66)	(6.66)	(6.65)	(4.07)	(4.12)	(4.10)	(4.03)	(4.26)	(4.27)	(4.27)	(4.26)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.30	0.30	0.31	0.31	0.31	0.32	0.32	0.32	0.35	0.35	0.35	0.35
N	1,202	1,202	1,202	1,202	651	651	651	651	551	551	551	551

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Table 4.7 cont'd.

Panel B. Meeting/beating analyst expectations and the negative component of discretionary loan loss provisioning.

	$Neg\_DLLP_{i,t}$				$Neg\_DLLP_{i,t}$ in banks with High *COMP*				$Neg\_DLLP_{i,t}$ in banks with Low *COMP*			
	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$	$MBEAT\_2_{i,t}$	$MBEAT\_3_{i,t}$	$MBEAT\_4_{i,t}$	$MBEAT\_5_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$MBEAT\_3Y\_PRIOR_{i,t}$	-0.041	-0.010	0.002	-0.002	-0.088	-0.015	0.008	0.003	-0.011	-0.018	-0.019	-0.022
	(0.99)	(0.25)	(0.04)	(0.05)	(1.44)	(0.26)	(0.15)	(0.05)	(0.20)	(0.35)	(0.38)	(0.44)
$MBEAT\_2Y\_PRIOR_{i,t}$	0.011	-0.019	-0.016	-0.020	0.016	-0.021	-0.039	-0.036	0.007	-0.012	0.010	0.003
	(0.31)	(0.52)	(0.45)	(0.56)	(0.29)	(0.39)	(0.74)	(0.71)	(0.13)	(0.24)	(0.21)	(0.06)
$MBEAT\_1Y\_PRIOR_{i,t}$	-0.021	-0.031	-0.033	-0.031	-0.039	-0.030	-0.046	-0.045	-0.005	-0.028	-0.016	-0.017
	(0.74)	(1.09)	(1.16)	(1.12)	(0.83)	(0.63)	(0.94)	(0.93)	(0.13)	(0.73)	(0.44)	(0.47)
$MBEAT\_YEAR_{i,t}$	0.002	-0.009	0.011	0.012	-0.030	-0.029	0.008	-0.002	0.028	0.008	0.010	0.021
	(0.07)	(0.29)	(0.40)	(0.41)	(0.65)	(0.65)	(0.18)	(0.04)	(0.66)	(0.19)	(0.26)	(0.54)
$AGE_{i,t}$	-0.048*	-0.048*	-0.048*	-0.048*	-0.052	-0.053	-0.053	-0.053	-0.051	-0.049	-0.050	-0.050
	(1.78)	(1.77)	(1.79)	(1.77)	(1.42)	(1.45)	(1.46)	(1.46)	(1.58)	(1.54)	(1.55)	(1.54)
$AUDIT\_BIG4_{i,t}$	0.056	0.056	0.056	0.056	-0.023	-0.022	-0.021	-0.021	0.131**	0.133**	0.132**	0.133**
	(0.95)	(0.96)	(0.96)	(0.96)	(0.26)	(0.26)	(0.25)	(0.24)	(2.07)	(2.10)	(2.10)	(2.10)
$AUDIT\_TENURE_{i,t}$	-0.029	-0.030	-0.029	-0.029	-0.044	-0.044	-0.044	-0.044	-0.016	-0.020	-0.017	-0.017
	(1.03)	(1.06)	(1.04)	(1.04)	(1.03)	(1.03)	(1.04)	(1.04)	(0.50)	(0.61)	(0.54)	(0.54)
$CAP1_{i,t}$	0.048*	0.049*	0.048*	0.048*	0.079*	0.079*	0.081*	0.080*	0.014	0.016	0.014	0.014
	(1.66)	(1.68)	(1.67)	(1.67)	(1.91)	(1.92)	(1.93)	(1.93)	(0.42)	(0.47)	(0.42)	(0.43)
$\Delta UNEMP_{i,t}$	0.012	0.010	0.012	0.011	-0.057	-0.058	-0.059	-0.059	0.041	0.039	0.038	0.038
	(0.26)	(0.23)	(0.26)	(0.24)	(0.51)	(0.52)	(0.54)	(0.54)	(0.98)	(0.93)	(0.92)	(0.92)
$DEPOSITS_{i,t-1}$	-0.054*	-0.053*	-0.054*	-0.054*	-0.065	-0.067	-0.066	-0.066	-0.047	-0.045	-0.046	-0.046
	(1.89)	(1.88)	(1.89)	(1.88)	(1.59)	(1.63)	(1.61)	(1.61)	(1.50)	(1.40)	(1.43)	(1.43)
$DIV\_YIELD_{i,t}$	-0.014	-0.015	-0.015	-0.015	0.011	0.011	0.011	0.011	-0.051	-0.052	-0.052	-0.052
	(0.48)	(0.52)	(0.52)	(0.51)	(0.26)	(0.24)	(0.24)	(0.24)	(1.30)	(1.33)	(1.31)	(1.31)
$\Delta CAP1_{i,t}$	0.044	0.043	0.043	0.043	0.093**	0.091**	0.090**	0.090**	-0.008	-0.007	-0.008	-0.008
	(1.56)	(1.54)	(1.52)	(1.53)	(2.18)	(2.13)	(2.10)	(2.11)	(0.25)	(0.24)	(0.25)	(0.25)
$MODIFIED_{i,t}$	0.135	0.135	0.136	0.136	0.072	0.073	0.080	0.078	0.208	0.205	0.209	0.209
	(0.97)	(0.97)	(0.98)	(0.98)	(0.29)	(0.30)	(0.33)	(0.32)	(1.53)	(1.51)	(1.54)	(1.54)
$NOA_{i,t}$	-0.041*	-0.040	-0.041*	-0.041	-0.046	-0.046	-0.047	-0.047	-0.040	-0.037	-0.038	-0.038
	(1.66)	(1.62)	(1.65)	(1.65)	(1.35)	(1.37)	(1.39)	(1.38)	(1.30)	(1.19)	(1.23)	(1.23)
$REV\_GROWTH_{i,t}$	0.073**	0.072**	0.072**	0.072**	0.075	0.074	0.073	0.073	0.066*	0.066*	0.066*	0.066*
	(2.16)	(2.15)	(2.14)	(2.14)	(1.44)	(1.42)	(1.40)	(1.41)	(1.80)	(1.80)	(1.80)	(1.80)
$SIZE_{i,t-1}$	0.145***	0.147***	0.145***	0.145***	0.209***	0.206***	0.204***	0.205***	0.096**	0.101***	0.098**	0.098**
	(4.00)	(4.09)	(4.04)	(4.05)	(3.73)	(3.73)	(3.69)	(3.72)	(2.44)	(2.60)	(2.53)	(2.52)
$COLLAB_{i,t}$	-0.032	-0.033	-0.032	-0.032	0.009	0.009	0.009	0.010	-0.070**	-0.073**	-0.071**	-0.071**
	(1.38)	(1.41)	(1.38)	(1.38)	(0.18)	(0.18)	(0.18)	(0.19)	(2.09)	(2.17)	(2.14)	(2.13)
$CREATE_{i,t}$	-0.049**	-0.050**	-0.049**	-0.050**	-0.037	-0.036	-0.036	-0.035	-0.067**	-0.069**	-0.068**	-0.068**
	(2.26)	(2.30)	(2.28)	(2.29)	(0.96)	(0.94)	(0.93)	(0.93)	(2.26)	(2.36)	(2.34)	(2.33)
$CONTROL_{i,t}$	-0.027	-0.028	-0.027	-0.028	0.008	0.009	0.009	0.009	-0.075*	-0.078*	-0.076*	-0.076*
	(1.18)	(1.20)	(1.19)	(1.19)	(0.16)	(0.19)	(0.19)	(0.20)	(1.78)	(1.84)	(1.82)	(1.82)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.37	0.37	0.37	0.37	0.36	0.36	0.36	0.36	0.39	0.39	0.39	0.39
N	2,799	2,799	2,799	2,799	1,375	1,375	1,375	1,375	1,424	1,424	1,424	1,424

(* p<0.1; ** p<0.05; *** p<0.0

Table 4.8: Robustness Tests: Relationship between Bank Competition Culture and Alternative Discretionary Loan Loss Provisioning

This table presents ordinary least squared (OLS) regression estimates for the relationship between bank competition culture and the discretionary loan loss provisioning for the data period 1994 – 2021. The key independent variables of interest, $COMP_{i,t}$, $\Delta COMP_{i,t}$, $COMP_{i,t\text{-}1}$, $\Delta COMP_{i,t\text{-}1}$, and $COMP_{i,t\text{-}2}$, represent contemporaneous and lagged levels and differences in my relative measure of bank competition culture. Besides, $|DLLP^{A}_{i,t}|$, denotes the absolute value of the residual from the equation (4.2b), which includes the loan loss allowance; $Pos\_DLLP^{A}_{i,t}$, is defined as the positive components of $DLLP^{A}_{i,t}$; while $Neg\_DLLP^{A}_{i,t}$, represents the absolute value of the negative components of $DLLP^{A}_{i,t}$. All other variables are defined in Table 4.9. The estimates include the year fixed effect. All models include a constant (not shown) and the standard errors are clustered at the firm level. The t-statistics are given in parentheses.

	$\lvert DLLP^{A}_{i,t}\rvert$	$\lvert DLLP^{A}_{i,t}\rvert$	$\lvert DLLP^{A}_{i,t}\rvert$	$Pos\_DLLP^{A}_{i,t}$	$Pos\_DLLP^{A}_{i,t}$	$Pos\_DLLP^{A}_{i,t}$	$Neg\_DLLP^{A}_{i,t}$	$Neg\_DLLP^{A}_{i,t}$	$Neg\_DLLP^{A}_{i,tt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$COMP_{i,t}$	-0.230*			-0.260**			-0.356*		
	(1.88)			(2.48)			(1.81)		
$\Delta COMP_{i,t}$		-0.109*	-0.106**		-0.214***	-0.187***		-0.099	-0.120
		(1.65)	(2.19)		(3.10)	(3.31)		(0.88)	(1.43)
$COMP_{i,t-1}$		-0.129			-0.269***			-0.103	
		(1.50)			(2.99)			(0.71)	
$\Delta COMP_{i,t-1}$			-0.100**			-0.181***			-0.112
			(2.02)			(3.12)			(1.29)
$COMP_{i,t-2}$			-0.127**			-0.249***			-0.125
			(1.97)			(3.32)			(1.12)
$AGE_{i,t}$	-0.003	-0.003	-0.003	-0.040***	-0.040***	-0.041***	0.030	0.030	0.030
	(0.22)	(0.24)	(0.25)	(2.80)	(2.85)	(2.88)	(1.37)	(1.35)	(1.36)
$AUDIT\_BIG4_{i,t}$	0.020	0.020	0.020	-0.025	-0.023	-0.022	0.040	0.040	0.039
	(0.56)	(0.56)	(0.56)	(0.59)	(0.55)	(0.53)	(0.77)	(0.77)	(0.75)
$AUDIT\_TENURE_{t}$	-0.021	-0.021	-0.021	0.005	0.005	0.005	-0.043	-0.044	-0.044
	(1.30)	(1.30)	(1.29)	(0.29)	(0.30)	(0.33)	(1.51)	(1.52)	(1.53)
$CAP1_{i,t}$	0.018	0.018	0.018	-0.056***	-0.056***	-0.057***	0.064***	0.063***	0.063***
	(1.22)	(1.20)	(1.19)	(4.09)	(4.07)	(4.12)	(2.69)	(2.64)	(2.64)
$\Delta UNEMP_{i,t}$	0.005	0.006	0.006	-0.004	-0.004	-0.005	0.022	0.025	0.026
	(0.22)	(0.25)	(0.25)	(0.09)	(0.10)	(0.14)	(0.54)	(0.60)	(0.62)
$DEPOSITS_{i,t\text{-}1}$	-0.058***	-0.058***	-0.058***	-0.149***	-0.150***	-0.150***	-0.005	-0.005	-0.005
	(3.17)	(3.17)	(3.17)	(4.50)	(4.54)	(4.55)	(0.19)	(0.19)	(0.19)
$DIV\_YIELD_{i,t}$	-0.020	-0.021	-0.021	0.038**	0.039**	0.039**	-0.086***	-0.087***	-0.087***
	(1.36)	(1.39)	(1.40)	(2.06)	(2.07)	(2.07)	(3.93)	(3.99)	(4.00)
$\Delta CAP1_{i,t}$	0.007	0.007	0.007	-0.066***	-0.067***	-0.068***	0.056***	0.056***	0.056***
	(0.48)	(0.47)	(0.47)	(4.91)	(4.95)	(4.96)	(2.80)	(2.81)	(2.82)
$MODIFIED_{i,t}$	0.116*	0.117*	0.117*	0.023	0.024	0.021	0.169	0.168	0.169
	(1.83)	(1.85)	(1.84)	(0.37)	(0.38)	(0.35)	(1.63)	(1.63)	(1.63)
$NOA_{i,t}$	-0.085***	-0.085***	-0.085***	-0.112***	-0.112***	-0.111***	-0.067***	-0.066***	-0.066***
	(5.92)	(5.90)	(5.90)	(6.75)	(6.78)	(6.76)	(3.49)	(3.46)	(3.46)
$REV\_GROWTH_{i,t}$	-0.011	-0.011	-0.011	-0.004	-0.005	-0.006	-0.017	-0.018	-0.018
	(0.70)	(0.72)	(0.74)	(0.21)	(0.25)	(0.31)	(0.66)	(0.69)	(0.71)
$SIZE_{i,t\text{-}1}$	0.017	0.017	0.017	0.037**	0.037**	0.037**	0.002	0.003	0.004
	(1.01)	(1.04)	(1.04)	(2.41)	(2.42)	(2.38)	(0.07)	(0.12)	(0.13)
$COLLAB_{i,t}$	-0.205*	-0.116	-0.112**	-0.230**	-0.234***	-0.207***	-0.317*	-0.100	-0.119
	(1.92)	(1.60)	(2.15)	(2.37)	(2.95)	(3.21)	(1.87)	(0.82)	(1.31)
$CREATE_{i,t}$	-0.121*	-0.068	-0.065*	-0.127**	-0.129***	-0.114***	-0.190*	-0.057	-0.069
	(1.87)	(1.51)	(1.94)	(2.21)	(2.69)	(2.81)	(1.83)	(0.76)	(1.21)
$CONTROL_{i,t}$	-0.196	-0.089	-0.084	-0.143	-0.147	-0.116	-0.382*	-0.119	-0.141
	(1.54)	(1.03)	(1.34)	(1.32)	(1.65)	(1.58)	(1.87)	(0.81)	(1.30)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.21	0.21	0.21	0.23	0.23	0.23	0.25	0.25	0.25
N	6,865	6,865	6,865	2,474	2,474	2,474	4,505	4,505	4,505

(* p<0.1; ** p<0.05; *** p<0.01)

Table 4.9: Definition of Variables for Chapter 4

Symbol		Definitions
Competition culture		
COMP	=	Bank's relative competition culture estimated for each fiscal year using the text-analysis approach and computed as [compete words/ (compete words + create words + collaborate words + control words)];
Meeting and beating earnings forecasts		
*MBEAT*_2	=	An indicator that equals to 1 if earnings meet or just beat by a maximum of 2 cent of analysts' forecasts and otherwise, equals to 0;
*MBEAT*_3	=	An indicator that equals to 1 if earnings meet or just beat by a maximum of 3 cents of analysts' forecasts and otherwise, equals to 0;
*MBEAT*_4	=	An indicator that equals to 1 if earnings meet or just beat by a maximum of 4 cents of analysts' forecasts and otherwise, equals to 0;
*MBEAT*_5	=	An indicator that equals to 1 if earnings meet or just beat by a maximum of 5 cents of analysts' forecasts and otherwise, equals to 0;
Discretionary loan loss provisioning		
DLLP	=	The absolute value of the residual from the following equation multiplied by 100: $LLP_{i,t} = \alpha_1 + \alpha_2 \Delta NPA_{i,t+1} + \alpha_3 \Delta NPA_{i,t} + \alpha_4 \Delta NPA_{i,t-1} + \alpha_5 \Delta NPA_{i,t-2} + \alpha_6 SIZE_{i,t-1} + \alpha_7 \Delta LOAN_{i,t} + \alpha_8 \Delta GDP_{i,t} + \alpha_9 CSRET_{i,t} + \alpha_{10} \Delta UNEMP_{i,t} + \varepsilon_{i,t}$; where *LLP* is loan loss provision [Compustat item: pll] divided by lagged total loans [Compustat item: lntal], Δ*NPA* is the change in non-performing assets [Compustat item: npat], *SIZE* is the natural logarithm of bank's total assets [Compustat item: at], Δ*LOAN* is the change in total loans [Compustat item: lntal], Δ*GDP* is the change in GDP over the fiscal year, CSRET is the return on the Case-Shiller Real Estate Index over the fiscal year, and Δ*UNEMP* represents the change in the unemployment rate over the fiscal year;
Other variables		
AGE	=	The number of years since the bank first appears in CRSP/COMPUSTAT;
*AUDIT_BIG*4	=	An indicator that is equal to 1 if the bank is audited by one of the Big 4 accounting firms (i.e., KPMG, PWC, Deloitte, and E&Y) [Compustat item: au = 3, 4, 5, 6, or 7] and is 0 otherwise;
AUDIT_TENURE	=	The number of years the bank is audited by the same accounting firm;
*CAP*1	=	The bank's tier 1 risk-adjusted capital ratio [Compustat item: capr1] at the beginning of the fiscal year, divided by 100;
Δ*UNEMP*	=	The change in the US employment rate over the fiscal year;
DEPOSITS	=	The lagged total deposits [Compustat item: dptc] divided by total assets [Compustat item: at];
DIV_YIELD	=	The annual dividend yield computed as [Compustat item: dvpsp_f] divided by [Compustat item: prcc_f];
Δ*CAP*1	=	change in *CAP1* over the fiscal year;
MODIFIED	=	An indicator that equals to 1 if the bank's auditor issues a modified auditor opinion [Compustat item: auop = 2, 4 or 5], and equals to 0 otherwise;
NOA	=	The net operating asset (i.e., shareholders' equity [Compustat item: seq] minus cash [Compustat item: che] and marketable securities [Compustat item: msa], plus total debt [Compustat item: dt]) at the end of the prior fiscal year, scaled by revenue [Compustat item: revt] for the prior fiscal year.
NUMEST	=	The number of analysts whose forecast are included in the consensus forecast over the fiscal year;
NUMUP	=	The number of analysts whose forecast are revised upwards;
NUMDOWN	=	The number of analysts whose forecast are revised downwards;

Table 4.9 cont'd.

Symbol		Definitions
Other variables		
REV_GROWTH	=	The change in revenue [Compustat item: revt] for the fiscal year divided by revenue for the prior fiscal year;
SIZE	=	The natural logarithm of bank's total assets [Compustat item: at];
COLLAB	=	Bank's relative collaborate culture estimated for each fiscal year using the text-analysis approach and computed as [collaborate words / (compete words + create words + collaborate words + control words)];
CREATE	=	Bank's relative create culture estimated for each fiscal year using the text-analysis approach and computed as [create words / (compete words + create words + collaborate words + control words)];
CONTROL	=	Bank's relative control culture estimated for each fiscal year using the text-analysis approach and computed as [control words/ (compete words + create words + collaborate words + control words)]; and
Robustness tests		
$DLLP^A$	=	The absolute value of the residual from the following equation multiplied by 100: $LLP_{i,t} = \alpha_1 + \alpha_2 \Delta NPA_{i,t+1} + \alpha_3 \Delta NPA_{i,t} + \alpha_4 \Delta NPA_{i,t-1} + \alpha_5 \Delta NPA_{i,t-2} + \alpha_6 SIZE_{i,t-1} + \alpha_7 \Delta LOAN_{i,t} + \alpha_8 \Delta GDP_{i,t} + \alpha_9 CSRET_{i,t} + \alpha_{10} \Delta UNEMP_{i,t} + \alpha_{11} \boldsymbol{ALW}_{i,t-1} + \varepsilon_{i,t}$; where *LLP* is loan loss provision [Compustat item: pll] divided by lagged total loans [Compustat item: lntal], Δ*NPA* is the change in non-performing assets [Compustat item: npat], *SIZE* is the natural logarithm of bank's total assets [Compustat item: at], Δ*LOAN* is the change in total loans [Compustat item: lntal], Δ*GDP* is the change in GDP over the fiscal year, CSRET is the return on the Case-Shiller Real Estate Index over the fiscal year, and Δ*UNEMP* represents the change in the unemployment rate over the fiscal year, and ***ALW*** is the loan loss allowance [Compustat item: rcl] divided by total loans [Compustat item: lntal].

5 The Influence of Organizational Culture on Cyber Risks and Data Breaches

5.1 Introduction

In an era where digital transactions and communications predominate, the specter of cyber risk looms over organizations worldwide. As organizations rely heavily on digital technologies, their exposure to cyber threats increases, making cybersecurity a business imperative (Böhme & Schwartz, 2010). The last decade has witnessed an escalation in cyber incidents, with significant financial implications for affected firms. Research consistently highlights the increasing sophistication of cyber-attacks and the expanding scale of potential disruptions (Gordon et al., 2011; Anderson et al., 2013). Cyber risks now extend beyond mere operational disruptions to pose substantial threats to the integrity and confidentiality of critical digital assets, with consequences that can severely undermine a corporation's market value and stakeholder trust (Kamiya et al., 2021).

Moreover. cyber risks have escalated to systemic risks, leading to intensified regulatory scrutiny and heightened investor awareness (Kopp et al., 2017). Recent incidents highlight a disturbing trend: cyber risks are escalating in frequency and magnitude, posing a critical threat to informational assets and organizational integrity. According to Jamilov et al. (2021), significant institutions like the World Economic Forum have identified systemic cyber risks as a major threat to global business stability (WEF, 2016). Similarly, the European Systemic Risk Board has recognized cyber risks as a systemic threat to the European financial ecosystem (ESRB, 2020). Additionally, surveys of financial market participants rank cybersecurity as the second most significant risk faced by firms, only surpassed by political risk (BoE, 2020). This growing recognition underscores the profound impact of cyber threats on the international economic environment.

Extensive literature centers around technological solutions and regulatory frameworks acknowledging their critical roles in addressing cyber risks (see, e.g., Boasiako and Keefe 2021; Ashraf, 2022; Wang et al.,2024). As global business landscapes evolve, the integration of cyber risk management with robust internal control systems has become increasingly crucial.[26]The literature consistently points out that effective internal control systems are vital in mitigating cyber risks. These internal control systems, known for their stringent checks and balances, are instrumental in pinpointing vulnerabilities, enforcing security policies, and upholding regulatory compliance, thereby significantly mitigating potential cyber threats (Gordon et al., 2010).

In the architecture of internal control systems, organizational culture is an indispensable component as different organizational cultures guide organizations in shaping their internal control systems with varying dimensions and levels of tolerance. The Competing Values Framework (CVF), introduced by Quinn and Rohrbaugh (1983), is a highly regarded model in organizational culture area and has been validated across different aspects over 30 years.[27] Also, based on Competing Values Framework (CVF), Cameron and Quinn (2011) did extensive research and developed the Organizational Culture Assessment Instrument (OCAI), in which the organizational culture can be categorized into two main dimensions--internal focus versus external focus and stability versus flexibility--thereby providing a clear articulation of the four cultural types: collaborate, create, compete, and control. Among these, collaborate and control cultures are characterized by their internal

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[26] A non-exhaustive list of studies includes Knowles et al. (2015), Bozkus and Caliyurt (2018), Jarison et al. (2018), Calderon and Gao (2021), Lois et al. (2021), Blakely et al. (2022), Rosati et al. (2022), Kurniawan and Mulyawan (2023).

[27] A non-exhaustive list of studies includes Cameron and Quinn, 1983; Quinn and Rohrbaugh, 1983; Berrio, 2003; Cameron and Quinn, 2011; Hartnell et al., 2011; Schneider et al., 2013; Fiordelisi and Ricci, 2014; Fiordelisi et al., 2019; Cameron et al., 2022.

focus, which foster a structured and cohesive environment that prioritizes well-defined processes and stringent control mechanisms. These cultures emphasize well-defined processes and rigorous control mechanisms, which are essential for alignment, consistency, and compliance (key elements of an effective internal control system and robust risk management strategy). Given the critical role of internal control in mitigating cyber risks, this chapter explores the interface between organizational culture and cyber risk, particularly focusing on how internal-focused cultures mediate cyber risks. Therefore, I am motivated to consider the following research question: "*What is the relationship between cyber risk and internal focused culture?*". I expect to find empirical evidence to demonstrate the mechanism that organizations with a strong internal focus may exhibit enhanced capabilities in decreasing cyber risks. According to CVF, both collaborate and control culture are internal-focused. Then I am motivated to investigate either collaborate or control culture, or both collaborate and control cultures would exhibit a negative correlation with cyber risk. Therefore, I am motivated to consider the second research question: "*As both collaborate and control cultures are internal oriented, either collaborate or control culture, or both collaborate and control cultures would exhibit a negative correlation with cyber risk?*"

The empirical results present a negative and significant relationship between internal focused culture and cyber risk, indicating that the enhancement of internal culture can effectively mitigate the threats of cyber risk. In specific culture, the control culture consistently bolsters cyber risk management across various organizational sizes due to their structured approach to compliance and risk mitigation. Conversely, the influence of collaborate cultures on cybersecurity is more nuanced and heavily dependent on organizational size. For organizations with between 100 and 10,000 employees, collaborate culture is effective in mitigating cyber risks, benefiting from enhanced communication and more agile consensus-building in these relatively smaller settings, which is key for prompt and proactive cybersecurity management. However, in mega size organizations, those with over 10,000 employees, the dynamics of collaborate cultures change. In such expansive settings, the typical characteristics of collaborate culture, including a strong focus on consensus and extensive employee involvement, may inadvertently slow down decision-making processes and introduce security vulnerabilities. This can make mega-companies particularly prone to significant data breaches, illustrating a complex relationship between organizational culture, company sizes, and effectiveness of cyber risk management.

Cyber risk represents a spectrum of potential vulnerabilities and exposures organizations face due to cyber-attacks or data breaches. A data breach, defined as unauthorized access to sensitive information, is a critical outcome of cyber risks, often inflicting severe financial and reputational damage upon organizations. Recognizing that internal-oriented cultures, specifically collaborate and control culture, may significantly bolster cybersecurity defences, it becomes crucial to explore further how these cultures influence the occurrence and management of data breaches. Based on the premise that internal-focused organizational cultures inherently prioritize security and cyber risk management within their operational and strategic frameworks, which should, in theory, result in a lower probability of data breach incidences. Therefore, I am motivated to consider the following hypothesis: *"Internal focused cultures, particularly collaborate or control culture, significantly reduce the likelihood of data breach incidents."*. I expect to find empirical evidence to demonstrate a negative relationship between internal oriented collaborate or control culture and the likelihood of data breach incidents. The empirical results I observed support my expectations.

For the empirical investigation, I use a large sample of US public listed firm-level information during the period 2007 – 2018. My methodology combines the Competing Value Framework (CVF) and Organizational Culture Assessment Instrument (OCAI), following the footsteps of Andreou et al. (2020b). I employ a relative measurement of organizational culture by conducting a textual analysis of firms' 10-K filings[28] obtained from the SEC's Edgar database. Similarly, I leverage the robust database provided by Florackis et al. (2023a and 2023b) to quantify cybersecurity risk derived from 10–K filings, specifically the "Item 1A. Risk Factors" section. Furthermore, I screen data breach information from a dataset of all reported data breaches in the U.S. collected by Privacy Rights Clearinghouse (PRC).[29] Thus, this chapter includes the following dataset: the 10–K filings for listed companies from SEC's Edgar database; the data breach dataset the PRC and the firm-level financial data from the CRSP /Compustat Merged. [30]

This study situates itself within the rapidly growing field of cyber risk management, which has garnered substantial attention due to the increasing sophistication and frequency of cyber threats. Existing research has explored technological solutions and regulatory frameworks for managing cyber risks (e.g., Gordon et al., 2010; Anderson et al., 2013; Kopp et al., 2017), as well as the role of internal controls (e.g., Knowles et al., 2015; Calderon and Gao, 2021). However, there remains a gap in systematically examining how organizational culture impacts cyber risk. While some studies have tangentially touched upon the topic (e.g.,

[28] 10-K filings have been identified as a channel for managers to convey useful and important information about distinctive, yet latent, firm traits (Loughran and McDonald, 2009, 2011). 10-K filings are different from annual reports, which include glossary and marketing materials. 10-K filings provide management's disclosure of the company's businesses and operations, including its main products and services, the market environment and conditions, the risk factors and prospects the company faces and so on, thus providing a natural setting for eliciting important information about culture.

[29] The Privacy Rights Clearinghouse (PRC) was founded in 1992 as a program of the University of San Diego School of Law's Center for Public Interest Law. The PRC is a nonprofit entity dedicated to enhancing public understanding and awareness of privacy issues. Over the years, the PRC has emerged as a key resource for data on privacy breaches, making significant contributions to academic and policy-making discussions on privacy issues. I have leveraged their comprehensive dataset of all reported data breaches in the U.S., collected by the PRC, for my research.

[30] The timeframe of this study, 2007–2018, was determined based on the availability and consistency of the data sources used. Specifically, the cyber risk data employed in this research is sourced from Florackis et al. (2023a, 2023b), whose database spans the period from 2007 to 2018. Utilizing this dataset ensures consistency with the established literature and provides a reliable basis for measuring cyber risks. Additionally, the PRC data incorporated in the analysis covers the period from 2005 to 2019. To maintain coherence and completeness, the study focuses on the overlapping period from 2007 to 2018.

Kamiya et al., 2021), they have not focused explicitly on the nuanced mechanisms through which specific cultural attributes shape a firm's cybersecurity posture.

This chapter aims to fill this gap. By empirically validating the impact of specific cultural attributes on cyber risk mitigation, this research offers novel insights into the strategic alignment between corporate culture and cyber risk management. It contributes to the literature by highlighting how nuanced aspects of organizational culture can significantly impact a firm's cybersecurity posture. Furthermore, it provides practical recommendations for corporate leaders to tailor their cultural strategies to enhance their firm's resilience against cyber threats.

In pursuing this investigation, this chapter leverages a comprehensive methodological approach, combining quantitative analyses of cyber risk and cultural indicators derived from textual analysis of 10-K filings. This approach enhances the robustness of the findings and ensures that the insights are grounded in real-world data, providing actionable intelligence for both academics and practitioners. As cybersecurity threats evolve in complexity and intensity, understanding the cultural dimensions that contribute to effective cyber risk management becomes increasingly crucial. This chapter aims to gain a deeper understanding of these dynamics and lay the groundwork for future research exploring the additional variables and contexts in which organizational culture influences cybersecurity effectiveness.

This chapter is structured as follows. Section 5.2 provides a detailed overview of the theoretical underpinnings that link organizational culture to cybersecurity and the development of hypotheses; Section 5.3 describes the methodology and data sources used in this research; Section 5.4 presents the empirical results and robustness check. Finally, Section 5.5 concludes this chapter by summarizing the key findings, discussing the current limitations of this chapter, and outlining directions for future research.

5.2 Literature Review and Hypotheses Development

5.2.1 Literature Review

5.2.1.1 Internal Focused Culture Types: Collaborate and Control

Organizational culture is a critical and complex issue that plays a significant role in shaping a company's identity by establishing its beliefs and operational philosophy (Schein, 1990). The Competing Values Framework (CVF), introduced by Quinn and Rohrbaugh (1983), is a highly regarded model for categorizing organizational cultures. CVF classifies organizational culture into two main dimensions--internal focus versus external focus and stability versus flexibility--thereby dividing culture into four types (see Figure 2.1): Clan (collaborate), Adhocracy (create), Market (compete), and Hierarchy (control), creating a robust taxonomy for studying organizational practices and outcomes (Cameron and Quinn, 2011).

The framework has been widely recognized for its robustness and utility in categorizing organizational cultures and has been validated across different aspects over 30 years (Cameron and Quinn, 1983; Quinn and Rohrbaugh, 1983; Berrio, 2003; Cameron and Quinn, 2011; Hartnell et al., 2011; Schneider et al., 2013; Fiordelisi and Ricci, 2014; Fiordelisi et al., 2019; Cameron et al., 2022). This chapter focuses on internal-focused cultures, namely the collaborate and control cultures, which emphasize an inward focus on integration, coordination, and unity.

Organizations with a dominant collaborate culture often exhibit a strong commitment to employee development and welfare, believing that a harmonious workplace leads to higher satisfaction and productivity. This culture fosters a supportive and nurturing environment where loyalty and tradition are cherished, and employee involvement is encouraged to achieve collective goals (Cameron and Quinn, 1983; Schein, 1990; Cameron et al., 2022). In a control culture, leadership focuses on coordination, organization, and tightly controlled business processes. Efficiency and reliability are paramount, and the emphasis is on delivering consistent and predictable results. Organizations with a control culture operate under strict guidelines, where rules and procedures are designed to manage every aspect of operations, minimizing uncertainty and variability in performance.

Both collaborate and control cultures are internal focused and they emphasize stability and cohesive internal processes to optimize organizational efficiency. They manage employee behavior distinctly but rigorously--collaborate cultures through shared values and consensus, while control cultures use strict rules and formal procedures. This internal orientation enhances risk management, with collaborate culture promoting swift, collective responses to risks, and control culture benefiting from systematic risk assessment and mitigation practices. These shared attributes highlight their commitment to maintaining a structured and unified internal environment.

For a detailed literature review on organizational culture, please refer to Chapter 2 of this thesis.

5.2.1.2 Cyber Risk

Since the beginning of the twenty-first century, the number of cyber-security incidents has continued to escalate annually, leaving major institutions losing more than $500 billion from operational risk events over the decade of 2011-2020, predominantly due to cyberattacks (Gordon et al., 2011; Anderson et al., 2013; Rosati et al., 2019; Jamilov et al., 2021; Kamiya et al., 2021). According to Kopp et al. (2017), cyber risks threaten the confidentiality, integrity, and availability of digital assets. The impact of cyber risks can be profound, ranging from loss of sensitive or proprietary information and operational disruptions to severe financial losses and reputational damage, making it a critical issue for today's organizations (Kamiya et al., 2021; Florackis et al.,2023a).

Cyber risk is increasingly becoming a central concern due to the rise in digitalization and the growing sophistication of cyber-attacks. As organizations rely heavily on digital technologies, their exposure to cyber threats increases, making cybersecurity a business imperative (Böhme & Schwartz, 2010). Cyber risks have escalated to the level of systemic risks, leading to intensified regulatory scrutiny and heightened investor awareness (Kopp et al., 2017). Jamilov et al., (2021) summarize that the World Economic Forum highlights systemic cyber risk as a prominent and influential threat to business (WEF, 2016); The European Systemic Risk Board (ESRB) categorizes cybersecurity as a systemic risk to the European financial system (ESRB, 2020); and systemic risk surveys of financial market participants suggests that cybersecurity is the second most challenging risk for firms to manage, right behind political risk (BoE, 2020).

The increasing prevalence of cyber risks stems from multiple factors. For examples, technological complexity, as organizations adopt diverse technologies, like the increasing use of the internet, cloud computing, mobile devices and so on, amplifying system complexity and vulnerabilities (Allodi and Massacci, 2017); human factors, as employees or contractors may inadvertently expose firms to risks, like phishing attacks, weak passwords, or poor cyber hygiene (Hadlington, 2017; Corradini and Nardell ,2019); third-party risks, as outsourcing and extensive supply chains increase the potential entry points for attackers when these partners have inadequate security measures(Cavusoglu et al., 2004); advanced threat actors, as hackers and organized cybercriminals have developed sophisticated tactics, including social engineering and ransomware, posing a continuous threat (Ablon et al., 2018); and sometimes, the regulatory and compliance issues due to the inconsistent regulations across jurisdictions complicate efforts to establish standardized cybersecurity protocols.

Anderson et al. (2013) emphasizes the value of continuous network monitoring for detecting threats early; Kshetri (2013) emphasizes the need to comply with cybersecurity regulations, especially across multiple jurisdictions; Gordon et al. (2014) explored the underinvestment issue in cybersecurity and recommended insurance to cover potential residual risks. Engels et al. (2022) provide compelling evidence of the economic impact of cyber risk on banks, showing a significant decline in total deposits following breaches of personally identifiable information. Several studies focus on the impact of cyberattacks on firm valuation (e.g., Johnson et al., 2017; Amir et al., 2018; Iyer et al.,2020). Other studies focus on how firms adjust their financial, investment, governance, and risk management policies following costly cyberattacks (e.g., Boasiako and Keefe, 2021; Ashraf, 2022; Wang et al.,2024). Ongoing research delves into the economics of cybersecurity, emphasizing the importance of understanding cybersecurity not just as a technical issue but also as a critical management challenge (Gordon et al., 2014).

In the evolving landscape of global business, the intertwining of cybersecurity with internal controls has become increasingly significant. As organizations navigate through complex networks of data and technology, the role of internal control in managing cyber risks has expanded. A rich stream of literature explores the effects of improving internal control on mediating cybersecurity risk (Knowles et al. (2015), Bozkus and Caliyurt (2018), Jarison et al. (2018), Calderon and Gao (2021), Lois et al. (2021), Blakely et al. (2022), Rosati et al. (2022), Kurniawan and Mulyawan (2023)). The literature consistently indicates that effective internal control systems are vital in mitigating cyber risks. By providing rigorous checks and balances, these systems play a crucial role in identifying vulnerabilities, enforcing security policies, and ensuring compliance with regulatory requirements, thereby reducing potential cyber threats (Gordon et al., 2010).

Cyber risks are potential threats that could lead to harmful consequences, such as data breaches, system damage, or unauthorized access. Attackers can exploit weaknesses in software, systems, or processes to gain unauthorized access to data systems. Actors such as hackers, malicious insiders, or even negligent employees constantly threaten data security. These threats can manifest as phishing attacks, malware, ransomware, or direct unauthorized access, potentially leading to data breaches.

5.2.1.3 Firm-level Effects from Data Breaches

Data breaches involve unauthorized access to or disclosure of personal, financial, or other sensitive data. They vary in type and scope, from accidental exposures due to human error to deliberate attacks aimed at stealing data for financial gain or espionage. As Kwon and Johnson (2013) highlight, the complexity of data breaches often reflects the interplay between internal vulnerabilities and external threats. Also, data breaches are a critical component of the broader category of cyber risks. They are specifically concerned with the unauthorized access and exfiltration of data, which can result from cyber-attacks such as hacking or phishing. As such, they are both a cause and a result of security failures, playing a central role in cyber risk management discussions (Ablon et al., 2014; Rosati et al., 2022).

Data breaches have profound impacts, including immediate financial losses and long-term reputational damage. The economic impact of data breaches extends beyond immediate remediation costs (Johnson et al. (2017); Kamiya et al. (2021); Engels et al. (2022)). The damage to both company valuation and investor confidence can last for an extended period, highlighted by a sharp fall in share price following the announcement of a material breach. These studies underline the importance of robust cyber defence mechanisms to safeguard shareholder value.

Many scholars use the data breaches database provided by the Privacy Rights Clearinghouse (PRC). The Privacy Rights Clearinghouse (PRC) is a nonprofit organization established in 1992 that serves as a valuable resource in the data privacy landscape, focusing on consumer information and issues related to data breaches. The organization tracks and compiles data on breaches, providing insights into the frequency, causes, and impacts of these incidents across various sectors. They educate the public about privacy rights and advocate for those rights in the face of evolving privacy challenges, benefiting individuals and the broader community (Holtfreter and Harrington (2015), Sen and Borle (2015), Karyda and Mitrou (2016), Cheng et al. (2017), Barati and Yankson (2022)). The PRC database provides valuable insights into the threats faced by different sectors, including public institutions and publicly traded companies.

5.2.2 Hypotheses Development

The escalation of cyber risks is a pressing concern for modern organizations, driven by the growing sophistication of cyber-attacks and the increasing reliance on digital technologies. These risks, threatening the confidentiality, integrity, and availability of digital assets, lead to significant operational and reputational damages. Factors contributing to these risks include technological complexities, human errors, third-party vulnerabilities, sophisticated cybercriminal activities, and regulatory challenges (Allodi and Massacci, 2017; Cavusoglu et al., 2004). Studies have shown that effective internal controls are essential for mitigating cyber risks, suggesting that these systems help identify vulnerabilities and enforce security policies, thereby reducing potential cyber threats (Gordon et al., 2014; Johnson et al., 2017).

Organizational culture significantly shapes a company's identity and operational philosophy. The Competing Values Framework (CVF), introduced by Quinn and Rohrbaugh (1983), effectively categorizes organizational cultures into four types: collaborate, create, compete and control. This model distinguishes cultures based on their focus (internal vs. external) and their approach to processes (stability vs. flexibility). Research over the past decades has validated the utility of CVF across various sectors, confirming its robustness in aligning organizational practices with cultural attributes (Cameron et al., 2022; Hartnell et al., 2011).

The internal-focused culture, which emphasizes stability and control, includes the collaborate and control culture. Such internal-oriented cultures prioritize internal management and process consistency. Characteristics of internal-focused cultures often include rigorous adherence to internal controls, streamlined operations, and a strong emphasis on traditional managerial practices (Hartnell et al., 2011). These cultural attributes align closely with internal auditing practices, crucial for risk management and compliance. According to Arena and Azzone (2009), practical internal control functions can significantly enhance a company's ability to manage and mitigate risks, including cyber security threats. Given the alignment between internal control and internal-focused culture, it is reasonable to hypothesize that organizations with a robust internal focus may exhibit enhanced capabilities in managing cyber risks. Therefore, I am motivated to consider the following hypothesis:

Hypothesis 1*: Internal-focused cultures, which prioritize structured and cohesive internal processes, are negatively associated with cyber risk.*

According to Cameron and Quinn (2011), both collaborate and control cultures are internal-focused. These cultures promote stability and consistency, which are crucial for effective risk management strategies. A dominant collaborate culture values teamwork and employee involvement, fostering a proactive approach to risk identification and response. Conversely, a control culture emphasizes stringent internal controls and formal procedures, enhancing systematic risk assessment and mitigation. This orientation potentially enhances the organization's capability to manage and mitigate cyber risks effectively (Cameron and Quinn, 1983; Schein, 1990). Thus, if a significantly negative correlation exists between cyber risk and internal focused culture, I can explore the relationship between cyber risk and the specific culture. Then, I will investigate whether either collaborate or control culture or both collaborate and control cultures would negatively correlate with cyber risk. Therefore, I am motivated to consider the following hypothesis:

Hypothesis 2: *Both collaborate and control cultures, as internal focused culture types, are negatively correlated with cyber risk.*

Data breaches are significant manifestations of cyber risks, often resulting in substantial financial and reputational damages to organizations. Given the comprehensive review of how internal-oriented cultures, specifically collaborate and control cultures, potentially strengthen cybersecurity and manage cyber risks, it is essential to extend this investigation into how these cultures influence the likelihood of data breach incidents. The relationship between internal oriented cultures, specifically collaborate and control cultures, and the likelihood of data breaches can be grounded in their fundamental characteristics. Collaborate cultures, emphasizing employee involvement and collective responsibility, potentially foster an environment where cybersecurity awareness is heightened, and employees proactively identify and mitigate risks. On the other hand, control cultures, with their strict protocols and emphasis on compliance and oversight, might significantly reduce the occurrence of breaches due to stringent security measures and formal risk assessments. Therefore, I am motivated to consider the following hypothesis:

Hypothesis 3: *Internal focused cultures, particularly collaborate or control culture, significantly reduce the likelihood of data breach incidents.*

This hypothesis is formulated based on the premise that internal-focused organizational cultures inherently prioritize security and cyber risk management within their operational and strategic frameworks, which should, in theory, result in a lower incidence of data breaches. Using PRC data will enable a detailed examination of this relationship, providing empirical evidence to either support or challenge the protective role of internal-oriented cultures in cybersecurity.

5.2.3 Research Motivation

Corporate culture is an indispensable component in the architecture of internal control systems. Different corporate cultures guide organizations in shaping their internal control systems with varying dimensions and levels of tolerance. Within the Competing Values Framework (CVF), internal-oriented cultures such as collaborate, and control inherently foster a structured and cohesive environment that prioritizes well-defined processes and stringent control mechanisms. These cultures underscore the importance of alignment, consistency, and compliance, which are pivotal for an effective internal control system and risk management strategy. Given the critical role of internal controls in mitigating cyber risks, this chapter explores whether the internal focused corporate cultures that profoundly influence these controls also significantly reduce cyber risks.

This study contributes to the literature by empirically investigating the relationship between internal-focused cultures and cybersecurity outcomes. While prior research has explored the role of internal controls in mitigating cyber risks, this study integrates organizational culture into the analysis, providing a novel perspective. By examining the impact of collaborate and control cultures on cyber risks and data breaches, this research fills a critical gap in understanding how cultural attributes influence organizational resilience against cybersecurity threats. Furthermore, the use of PRC data for robustness testing strengthens the empirical validity of these findings, offering practical insights for managers and policymakers seeking to enhance organizational security frameworks.

5.3 Data, Variables and Summary Statistics

5.3.1 Data

In this chapter, my sample period is fiscal years 2007 – 2018. Four main data sets serve to construct the sample with the required data: the firm-level cyber risk database (following Florackis et al., 2023a and 2023b) derived from 10–K filings in the SEC's Edgar database; the firm-level culture metrics (followed Andreou et al., 2020b) derived from 10-K filings as well; the firm-level financial data from the CRSP /Compustat Merged; and a dataset of all reported data breaches in the U.S. collected by Privacy Rights Clearinghouse (PRC).

This study commences in 2007, aligning with the coverage of the cyber risk database (following Florackis et al., 2023a and 2023b) which spans from 2007 to 2018, albeit with a relatively smaller amount of data for the two years 2007 and 2018.[31] To ensure the robustness of my findings, I take measures to mitigate the effects of outliers by winsorizing all continuous variables at the upper and lower one percentile of their distributions. Furthermore, I include firms that became inactive or were acquired during the study period in my sample, a step taken to attenuate distortions caused by survivorship bias. Definitions of the variables used in this chapter are presented in Table 5.12.

[Insert Table 5.12 Here]

5.3.2 Measuring Internal Focused Culture

A rich stream of literature explores the effects of improving internal control on mediating cyber risk (Knowles et al. (2015), Bozkus and Caliyurt (2018), Jarison et al. (2018), Calderon and Gao (2021), Lois et al. (2021), Blakely et al. (2022), Rosati et al. (2022), Kurniawan and Mulyawan (2023)). The literature consistently points to the critical role of internal control in enhancing cybersecurity risk management through the integration of established frameworks, leveraging technology, and adapting to regulatory changes. As cyber threats continue to evolve, the need for internal control to enhance their methodologies and

[31] Selecting this period also aligns with the increasing relevance of cyber risks in the organizational context. Earlier timeframes, such as those before 2005, are less practical for this study as the prevalence and awareness of cyber risks were significantly lower during those years due to the limited adoption of digital technologies. While cyber risks undoubtedly existed earlier, they did not garner the same level of organizational attention or systematic reporting until more recent decades. Consequently, the 2007–2018 period captures a meaningful and actionable timeframe for analyzing cyber risk trends in a methodologically consistent manner.

practices in cybersecurity risk management remains imperative. In the context, I aim to explore whether the internal focused cultures are also related to cyber risk from the organizational culture perspective. Also, based on the Competing Values Framework (CVF), Cameron and Quinn (2011) did extensive research and developed the Organizational Culture Assessment Instrument (OCAI) to identify cultural strength, cultural congruence and cultural types and divide corporate cultures into four dominant quadrants (collaborate, create, compete and control), Figure 2.1 shows that both collaborate and control cultures are internal-focused.

I reviewed the extensive literature in this area to quantify the organizational culture. Traditionally, as constrained by limited access to large amounts of promptly public archivable data, scholars rely on a small sample of interviews or point-in-time surveys (Sheridan (1992); Ke and Wei (2008); Kotter (2008); Cameron et al. (2011) and Graham et al. (2022)). However, surveys or interviews, accompanied by high time and economic costs, are often internal documents and must maintain a narrow focus to be effective (Graham et al., 2022). In addition to employing survey-based methodologies, with the advancement of technology and the continuous increase in regulatory and disclosure requirements, there has been a growing trend in utilizing textual analysis techniques to assess different dimensions of corporate culture quantitatively. This approach has gained popularity in recent years, as evidenced by the works of Fiordelisi and Ricci (2014), Loughran and McDonald (2011,2016), Fiordelisi et al. (2019), Grennan (2019), Andreou et al. (2020a), Andreou et al. (2020b) and Andreou et al. (2022). The rationale in employing textual analysis is taking advantages of the big data tools with more diverse and informative ways under higher levels of public disclosure requirement to interpret cultural information hidden in public archival data and conveys information. Furthermore, the increased number of tools developed in computer science (for example, machine learning and natural language processing (NPL)) helps to actively embrace the premise that words chosen by management in producing firms' disclosures are representative of firms' culture. Thus, there has been a growing application of diverse textual analysis methodology in the finance and accounting literature pertaining to corporate culture to boost insights into the relationship between organizational culture and various economic phenomena.

Based on the combination of the Competing Value Framework (CVF) and Organizational Culture Assessment Instrument (OCAI), I implement the methodology proposed in the first study to quantify organizational culture by conducting a textual analysis of firms' 10-K filings obtained from the SEC's Edgar database. In keeping with recent work, I assume that firms' documents (e.g., the 10-K filings) can reveal information concerning firms underlying culture (see, e.g., Fiordelisi and Ricci, 2014; Andreou et al., 2020a; Andreou et al., 2020b; Andreou et al., 2022).

To compute my measure, firstly, I take words from the OCAI questionnaire and check their corresponding synonyms from the Princeton University WorldNet lexical database and Harvard IV-4 psychosocial dictionary. Then, I consider whether all the variants (of selected words and related synonyms) have specific cultural meanings, as I only retain variants with a specific semantic meaning. Therefore, I check the contextual words captured before and after the variants in the 10-K filings to understand whether the usage of these variants is meaningful in the financial area. Finally, I only take these variants as keywords, which consistently appear to capture only the semantic cultural meaning in 10-K filings and form a bag of words (89 word-roots and retain 261 keywords).[32] Following the necessary pre-processing steps, I then produce my measure of different organizational culture: the collaborate culture variable, *COLLAB* by counting the frequencies of lexical tokens describing the collaborate culture together and then divided by the total number of lexical

[32] Please see Table 3.4 for further details on the bag of words used to capture the cultures of the competing values framework.

tokens for all types of CVF cultures appear in a firm's 10-K filings; similarly, the control culture variable, *CONTROL* by counting the frequencies of lexical tokens describing the control culture together and then divided by the total number of lexical tokens for all types of CVF cultures; and the internal focused culture variable, *INTERNAL_FOCUS*, which is the combination of collaborate and controls in CVF theory, by counting the frequencies of lexical tokens describing the collaborate or control culture together and then divided by the total number of lexical tokens for all types of CVF cultures. Simply put, I apply the simple word count algorithm to estimate organizational culture as follows:[33]

$$COLLAB = \frac{Number\ of\ lexical\ tokens\ describing\ the\ Collaborate\ Culture}{Total\ number\ of\ lexical\ tokens\ for\ all\ types\ of\ CVF\ cultures};$$

$$CONTROL = \frac{Number\ of\ lexical\ tokens\ describing\ the\ Control\ Culture}{Total\ number\ of\ lexical\ tokens\ for\ all\ types\ of\ CVF\ cultures};$$

$$INTERNAL\_FOCUS\ =\ COLLAB + CONTROL$$

$$= \frac{Number\ of\ lexical\ tokens\ describing\ the\ Collaborate\ or\ ControlCulture}{Total\ number\ of\ lexical\ tokens\ for\ all\ types\ of\ CVF\ cultures}.$$

For a detailed quantification process of the methodology and measurement of the organizational culture score, please refer to Chapter 3 of this thesis.

5.3.3 Measuring Cyber Risk

In the realm of finance, assessing cybersecurity risk at the firm level has become increasingly pertinent, driven by the escalation of cyber threats impacting corporate governance and financial stability.[34] In response to this pressing issue, Florackis et al. (2023a,

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[33] While conducting the count, I exclude negation of the lexical tokens by ignoring occasions when the word is preceded by "no", "non", "not", "less", "few" or "limited" by three or fewer words before or after keywords.
[34] The importance of cybersecurity risk is not limited to the finance and economics fields. According to "The Global Risks Report 2019" (14th Edition) by the World Economic Forum, and a 2017 survey from DTCC, it is currently one of the top global concerns for firm executives and market participants in advanced economies. This is not surprising given the increase in significant cyberattacks in recent years. A recent report from the

2023b) develop a robust database quantifying cybersecurity risk for publicly listed firms in the U.S. Their pioneering work provides a systematic measure, derived from a comprehensive analysis of regulatory filings, precisely the "Item 1A. Risk Factors" section of 10-K reports filed with the Securities and Exchange Commission (SEC).

Florackis et al. (2023a, 2023b) developed their cybersecurity risk measure using a rigorous two-step process. First, they established a training sample of firms that had experienced cyberattacks, assuming that these firms disclosed heightened cybersecurity risks in their 10-K filings prior to the attacks. Second, they calculated the similarity between the cybersecurity disclosures of firms in the training sample and those of other firms using cosine similarity—a widely accepted metric in text analysis. This approach builds on the premise that firms with similar cybersecurity risk levels disclose similar language and themes in their risk factors. The final cybersecurity risk score is derived as the average cosine similarity between a firm's disclosures and the training sample disclosures.

In detail, according to Florackis et al. (2023a, 2023b), they refine the text by removing specific word types such as pronouns, conjunctions, common words, compound words, geographic terms, names, and any word appearing less than 10 times first. Then they identify word roots using a web-crawling algorithm (https://www.merriam-webster.com/), reporting a dataset of 3,210 unique word roots. They implement these roots to create word vectors for each firm's cybersecurity-risk disclosures in their 10-K filings. By comparing these vectors, they assess the similarity between any two 10-K filings based on their cybersecurity-risk language. This similarity in disclosures is quantified using cosine similarity, a metric commonly used in text analysis to measure the angle between two vectors in a multi-dimensional space, where each dimension represents a term or phrase from the disclosures. Formally, the cybersecurity risk score for a firm i in the year t is defined as:

Center for Strategic and International Studies and McAfee revealed that the amount lost to cybercrime every year is experiencing a rapidly increasing trend, valued at nearly 1% of global GDP for 2018. This global context underscores the importance and potential impact of Florackis et al.'s research in quantifying cybersecurity risk.

$$CYBER\_RISK_{i,t} = \sum_{n=1}^{N} \frac{CS_{i,n,t}}{N_{t-1}}.$$

Where $CS_{i,n,t}$ is the cosine similarity between the cybersecurity disclosure of firm *i* and each firm *n* in the training sample; N_{t-1} is the number of firms in the training sample that have reported cyberattacks in the year prior to *t*; $CYBER\_RISK_{i,t}$ is the cybersecurity risk for each firm *i* and year *t* as the average cosine similarity across all N_{t-1} similarities.

The methodology employed by Florackis et al. (2023a, 2023b) reflects broader practices in natural language processing (NLP) and machine learning, as established by prior research (e.g., Hoberg and Phillips, 2016; Loughran and McDonald, 2011; Brown and Tucker, 2011). Their textual analysis extracts relevant cybersecurity-related language, which is refined by removing irrelevant words and identifying key word roots. This generates a comprehensive dataset of cybersecurity-related terminology, enabling a systematic and replicable analysis of firms' risk disclosures.

In this study, I adopt the cybersecurity risk measure provided by Florackis et al. (2023a, 2023b) to ensure consistency with established methodologies and to leverage the rigor of their approach. The data and detailed methodology are publicly available on their official website, ensuring transparency and accessibility. By using this measure, I aim to investigate the relationship between internal-focused organizational cultures and cybersecurity outcomes, contributing to the growing literature on the intersection of organizational behavior and cyber risk management.

5.3.4 Screening Data Breach Incidents

This study aims to shed light on whether the internal focused culture is also related to cyber risk from the organizational culture perspective. Cyber risk is the potential for exposure or loss from a cyber-attack or data breach. It encompasses the likelihood of a security incident occurring and its impact if it did occur. A data breach occurs when sensitive, protected, or confidential data is accessed, used, or disclosed unauthorizedly. This includes instances where data is viewed, stolen, or used by an individual unauthorized to do so. The relationship between a data breach and cyber risk is that a data breach is a realized cyber risk. Therefore, by merging the data breach database, I can further demonstrate the effect of strengthening internal control on mitigating cyber risks.

The data on data breaches was sourced from the Privacy Rights Clearinghouse (PRC) database, which contains detailed information on breach incidents, including the date of breach announcement, company name, city and state of the company, type of breach (e.g., hacking, insider leak), type of organization (e.g., business enterprises (hotels), medical (hospitals and clinics), educational institutions (universities)) and the number of records breached. These data were primarily collected through government agencies, media reports, and other public channels, providing rich information for studying data breaches. Therefore, only those data breach incidents that have been publicly acknowledged are included in Privacy Rights Clearinghouse's dataset. Many other data breach incidents might not be reported and are, therefore, unknown to the public.

The PRC database provides valuable insights into the threats faced by different sectors, including public institutions and publicly traded companies. This information is crucial for enhancing security measures and ensuring compliance with data protection standards. Organizations can use this data to analyse previous breaches to better understand the risks associated with data security within their sector. By identifying common patterns and vectors in past breaches, companies and institutions can develop more effective strategies to prevent future occurrences. This information helps organizations comply with data protection laws and regulations by demonstrating areas of vulnerability that need to be addressed.

The PRC database employed in this chapter contains detailed records of 9,015 data breach incidents, spanning from 2005 to 2019. Among the data, the most frequent source of information is the U.S. Department of Health and Human Services, with close to 2500 incidents (Barati and Yankson, 2022). To merge this data with firm-level data from the Compustat/CRSP dataset, I employed a fuzzy matching approach due to variations in how company names are recorded across these sources. For example, inconsistencies may arise from abbreviations, punctuation, or variations in naming conventions (e.g., "Inc." vs. "Incorporated").

Fuzzy matching was performed using the Jaro-Winkler distance metric, a widely accepted method for string similarity analysis, particularly effective in handling minor typographical differences. This approach assigns a similarity score to each potential match, with higher scores indicating greater similarity. A threshold score was set (e.g., 0.9) to identify plausible matches while minimizing false positives. Additionally, for firms with ambiguous matches, auxiliary information such as headquarters location and industry classification was cross-referenced to confirm identity. To validate the matching results, I manually reviewed all incidents and screened out about 1043 incidents with corresponding fundamental information.This dual-layered approach enhanced the robustness of the data merging process.

The use of fuzzy matching was necessary due to the absence of unique identifiers, such as *CIKs* or *CUSIPs* or *GVKEYs*, in the PRC database. This method is widely adopted in empirical research to integrate datasets with inconsistent naming conventions (e.g., Bertrand et al., 2004; Hoberg and Phillips, 2010; Florackis et al., 2023a). By employing this approach, I ensured a comprehensive and reliable integration of breach data with firm-level information, enabling a nuanced analysis of the relationship between organizational culture and cybersecurity risk.

After matching with the CRSP /Compustat Merged database, , I use *CIK* and the fiscal year provided in the CRSP /Compustat Merged database to merge with the culture score and cyber risk database. From 2007 to 2018, I identified 337 companies[35] with data breach records and corresponding culture and cyber risk information (it does not mean only 337 incidents matched, as data breach incidents may occur more than once within the same year). The sample size I obtained after merging was essentially the same as Rosati et al. (2022), supporting the integrity of my data screening process. Following necessary pre-processing steps, I then produce my data breach incident identifier variable $BREACH\ DUMMY_t$, an indicator equal to 1 if a data breach incident occurred in the company during this fiscal year or 0 otherwise.

5.3.5 Control Variables

In the main regression models specified in Equation 5.1 and in all subsequent analyses, several control variables are included to account for firm-specific characteristics that may influence cybersecurity risk. These variables are selected based on their theoretical relevance and empirical findings, ensuring robustness and reliability across models.

Firm size (*SIZE*), measured as the natural logarithm of the firm's total assets, captures the scale effects on cybersecurity risk. Larger firms generally possess more resources to invest in cybersecurity infrastructure, which could lead to a negative relationship with cybersecurity risk (Kamiya et al., 2021). However, larger firms may also be more attractive targets for cyberattacks due to their visibility and scale, potentially complicating this relationship.

Leverage (*LEVERAGE*), defined as the debt in current liabilities scaled by total assets, reflects the financial constraints of a firm. Higher leverage ratios may reduce a firm's

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[35] In regression analysis, some of the control variables I selected may be missing, thus when I do regression analysis using balanced data, the actual sample size with $BREACH\ DUMMY_t$ =1 may be less than 337.

financial flexibility, limiting its ability to implement robust cybersecurity measures, and are therefore expected to positively correlate with cybersecurity risk (Gordon et al., 2011). However, highly leveraged firms may adopt more disciplined financial and risk management practices to mitigate potential cyber risks as well. Profitability (*ROA*), calculated as net income scaled by total assets, reflects a firm's financial performance and resource availability. Firms with higher profitability are likely to have greater capacity to invest in cybersecurity measures, potentially mitigating their exposure to risk (Florackis et al., 2023a).

The binary variable *AUDIT_BIG4* indicates whether a firm is audited by one of the Big 4 accounting firms (KPMG, PWC, Deloitte, or E &Y). Firms audited by Big 4 firms are often subject to stricter compliance and risk management standards, which could enhance transparency and mitigate cybersecurity risks (Hogan and Wilkins, 2008). However, firms with Big 4 auditors are not necessarily less prone to cyber risks but may disclose such risks more comprehensively, reflecting greater transparency and regulatory scrutiny. Lastly, liquidity (*CASH*), measured as cash and short-term investments scaled by total current liabilities, captures a firm's financial flexibility. Higher liquidity may facilitate investments in preventive cybersecurity measures, and thus a negative relationship with cybersecurity risk is anticipated (Gordon et al., 2010).

These control variables are systematically incorporated into all subsequent equations to isolate the influence of the primary explanatory variables on cybersecurity risk. The observed relationships provide valuable insights into how firm-specific characteristics interact with cybersecurity vulnerabilities and management practices, offering a nuanced perspective that complements the existing literature.

5.3.6 Descriptive Statistics and Correlations

All tables for Chapter 5 are included at the end of this chapter. Table 5.1 provides summary statistics of the variables used in my empirical analysis.[36] The table presents the mean, median, standard deviation, and range (minimum and maximum values) for each variable, alongside the quartiles (25th and 75th percentiles). All variables are measured at the firm/fiscal-year level. For variable definitions and details of their construction, see Table 5.12.

In particular, the mean value of my main dependent variable, *CYBER_RISK*, is 0.242. And the mean values of the culture variables, *INTERNAL_FOCUS*, *COLLAB*, and *CONTROL* are 0.353, 0.122, and 0.230, respectively. Moreover, for the dummy variable *INTERNAL_DUMMY*, the mean value of the variable *INTERNAL_FOCUS* is 0.353, and the sum of the internal focused culture score and external focus culture score is 1. Therefore, when the internal focused culture score is greater than the average value, it does not mean that the company is dominated by internal focused culture. I use 0.5 as the critical value to judge whether the company is dominated by internal culture or not. The mean value of *INTERNAL_DUMMY* is 0.124, which means that companies dominated by an internal focused culture (collaborate and control) are far less than those dominated by an externally focused culture (create and compete), which is consistent with the conclusion of my previous study (Andreou et al.,2020). Notably, the variable *EMP*, denoting the number of employees in thousands, exhibits a mean of 10.355 and a median of 1.220. The substantial disparity between the mean and median suggests that the average is significantly influenced by a few firms with huge employee counts, skewing the mean upwards relative to the median. This wide range indicates the diverse nature of firms in terms of employee numbers within my sample, providing a context for analyzing the impact of firm employment scale on cybersecurity risk management.

[36] To mitigate the effects of outliers, all continuous variables are winsorized at the 1% and 99% levels.

Additionally, for the dummy variable *BREACH_DUMMY*, I find that the mean value is only 0.009. This makes sense as when I merged the breach event data, only 337 observations matched, which means that only 337 observations in my full dataset have observed data breaches.

[Insert Table 5.1 Here]

Further, in this chapter, Pearson correlation coefficients were calculated for the variables used in the empirical analysis, as reported in Table 5.2. The decision to use Pearson correlation, rather than Spearman, was based on the specific requirements of the analysis. Pearson correlation is well-suited for evaluating linear relationships, which align with the linear regression models employed in this chapter. Furthermore, the dataset in this study satisfies the assumptions of Pearson correlation, including continuity of data and approximate normality, making it an appropriate choice. In contrast, Spearman correlation, designed to measure monotonic relationships, was not necessary, as no significant non-linear associations were identified in the preliminary analysis.

In Table 5.2, while the results do not reveal the expected significantly negative relationships between *CYBER_RISK* and *INTERNAL_FOCUS*, or between *CYBER_RISK* and *COLLAB* or *CONTROL*, this does not necessarily conflict with the findings of the regression analyses presented later in this chapter. The primary purpose of employing a Pearson correlation matrix was twofold: to identify potential linear relationships between variables and to diagnose multicollinearity, a crucial step in ensuring the robustness of the regression results. For example, while the correlation matrix indicates a positive correlation between *CYBER_RISK* and *INTERNAL_FOCUS*, as well as between *CYBER_RISK* and *COLLAB* or *CONTROL*, these relationships may shift in direction or magnitude when additional variables and fixed effects are included in the regression framework. This underscores the utility of

Pearson correlation as a preliminary diagnostic tool, complementing the more comprehensive insights derived from multivariate analysis.

[Insert Table 5.2 Here]

5.4 Empirical Results

5.4.1 Internal Focused Culture and Cyber Risk

A burgeoning literature extensively examines the impact of bolstering internal control on mediating cyber risks.[37] In this chapter, I focus on the corporate culture perspective to explore whether an internal focused culture negatively correlates with cyber risk for the time period 2007-2018. The first research question is: *"What is the relationship between cyber risk and internal focused culture?*" (Hypothesis 1). I expect to observe a negative relationship between internal focused culture and cyber risk, as I consider this relation to be plausible since firms with a strong internal focused culture should be more proactive in implementing robust security measures, relative to the firms, and should also be more likely to decrease the likelihood of security breaches. Hence, I test whether internal focused culture is negatively related to the cyber risk. To do this, I estimate the following regression model:

$$
\begin{aligned}
CYBER\_RISK_{i,\,t} \;=\; & \alpha_1 + \boldsymbol{\alpha_2 INTERNAL\_FOCUS_{i,\,t}} \\
& + \alpha_3 SIZE_{i,t} + \alpha_4 LEVERAGE_{i,t} + \alpha_5 ROA_{i,t} + \alpha_6 AUDIT\_BIG4_{i,t} + \alpha_7 CASH_{i,t} \\
& + \nu_t + \gamma_s + \varepsilon_{i,\,t} \qquad (5.1)
\end{aligned}
$$

All other variables are as previously defined. In addition, I include year fixeds effect(ν_t) to control for unobserved time-varying factors that are constant across firms within the same year in this and all subsequent models. Industry fixed effects(γ_s) are included to account for time-invariant characteristics specific to industries. The results of ordinary least

[37] A burgeoning literature includes Knowles et al. (2015), Bozkus and Caliyurt (2018), Jarison et al. (2018), Calderon and Gao (2021), Lois et al. (2021), Blakely et al. (2022), Rosati et al. (2022), Kurniawan and Mulyawan (2023)).

squared (OLS) regression estimates are provided in Table 5.3 where the coefficient term -0.074 on the *INTETRNAL_FOCUS*$_{i,t}$ variable in columns (1) captures the relationship between internal focused culture and cyber risk. Consistent with the expectation outlined in Hypothesis 1, the relationship is negative and significant, which underscores the importance of cultivating an internal-focused culture as a strategic approach to cyber risk management.

[Insert Table 5.3 Here]

5.4.2 Internal Focused Culture Types (Collaborate and Control) and Cyber Risk

As there exists a significantly negative correlation between cyber risk and internal focused culture, according to CVF (Cameron and Quinn, 2011), both collaborate and control culture are internal-focused, it is plausible for us to infer that either collaborate or control culture, or both these two internal-oriented cultures would exhibit a negative correlation with cyber risk over the time period 2007-2018.. Thus, I estimate the following regression model to investigate the second research question: "*Either collaborate or control culture, or both collaborate and control cultures would exhibit a negative correlation with cyber risk?*" (Hypothesis 2):

$$\begin{aligned} CYBER\_RISK_{i,t} &= \alpha_1 + \boldsymbol{\alpha_2 CULTURE_{i,t}} \\ &+ \alpha_3 SIZE_{i,t} + \alpha_4 LEVERAGE_{i,t} + \alpha_5 ROA_{i,t} + \alpha_6 AUDIT\_BIG4_{i,t} + \alpha_7 CASH_{i,t} \\ &+ \nu_t + \gamma_s + \varepsilon_{i,t} \qquad (5.2a) \end{aligned}$$

where, the variable *CULTURE*$_{i,t}$ is measured by one of *COLLAB*$_{i,t}$ or *CONTROL*$_{i,t}$. All other variables are as previously defined.

The ordinary least squares (OLS) regression estimates for the above specifications are reported in column (1) and column (4) of Table 5.4. For Eq. (5.2a), the coefficient of the variable *COLLAB*$_{i,t}$ in column (1) is -0.019, significant at the 5 percent level, and the coefficient of $CONTROL_{i,t}$ in column (4) is -0.081, significant at the 1 percent level. These findings align with Hypothesis 2, which posits that internal-focused cultures, including collaborate and control cultures, are negatively associated with cybersecurity risk. The stronger negative relationship observed for $CONTROL_{i,t}$ compared to $COLLAB_{i,t}$ highlights the heightened effectiveness of control-oriented cultures in mitigating cyber risks. This result suggests that the systematic processes and stringent compliance practices characteristic of control cultures play a more substantial role in reducing cybersecurity risk than the proactive and team-oriented approach of collaborate cultures.

[Insert Table 5.4 Here]

Additionally, I estimate dynamic models to examine the relationship between lagged values and differences in internal oriented collaborate or control culture and firm-level cyber risk. The rationale for including these variables is grounded in the literature on organizational culture dynamics, which suggests that cultural shifts typically occur gradually and may exhibit persistent effects over time (Hartnell et al., 2011; Fiordelisi et al., 2019). The inclusion of lagged differences further allows for testing whether changes in cultural attributes over time have an immediate impact on cybersecurity risks. This distinction between levels and differences provides a more nuanced understanding of the interplay between static cultural traits and dynamic adjustments in response to external factors, such as evolving cyber threats. Notably, I estimate the following empirical models:

$$CYBER\_RISK_{i,t} = \alpha_1 + \boldsymbol{\alpha_2 \Delta CULTURE_{i,t}} + \boldsymbol{\alpha_3 CULTURE_{i,t-1}} + \alpha_4 SIZE_{i,t} + \alpha_5 LEVERAGE_{i,t} + \alpha_6 ROA_{i,t} + \alpha_7 AUDIT\_BIG4_{i,t} + \alpha_8 CASH_{i,t} + \nu_t + \gamma_s + \varepsilon_{i,t} \tag{5.2b}$$

$$CYBER\_RISK_{i,t} = \alpha_1 + \boldsymbol{\alpha_2 \Delta CULTURE_{i,t}} + \boldsymbol{\alpha_3 \Delta CULTURE_{i,t-1}} + \boldsymbol{\alpha_4 CULTURE_{i,t-2}} + \alpha_5 SIZE_{i,t} + \alpha_6 LEVERAGE_{i,t} + \alpha_7 ROA_{i,t} + \alpha_8 AUDIT\_BIG4_{i,t} + \alpha_9 CASH_{i,t} + \nu_t + \gamma_s + \varepsilon_{i,t} \tag{5.2c}$$

where, the key independent variables of interest, $\Delta COLLAB_{i,t}$, $COLLAB_{i,t-1}$, $\Delta COLLAB_{i,t-1}$, and $COLLAB_{t-2}$, represent lagged levels and differences in the relative measure of firm's collaborate culture; Besides, $\Delta CONTROL_{i,t}$, $CONTROL_{i,t-1}$, $\Delta CONTROL_{i,t-1}$, and $CONTROL_{i,t-1}$, represent lagged levels and differences in my relative measure of firm's control culture. All other variables are as previously defined.

The ordinary least squares (OLS) regression estimates for the above specifications are presented in Table 5.4. For collaborate culture, the results from Equation (5.2b) indicate a significant negative relationship between both the change and lagged level of collaborate culture and cyber risk. Specifically, the coefficients for $\Delta COLLAB_{i,t}$ and $COLLAB_{i,t-1}$, are -0.015 and -0.025, respectively, with t-values of -3.07 and -2.67, significant at the 1 percent level in column (2). Furthermore, in Equation (5.2c), the coefficients for $\Delta COLLAB_{i,t}$, $\Delta COLLAB_{i,t-1}$ and $COLLAB_{i,t-2}$, are -0.015, -0.023, and -0.028, respectively, all significant at the 1 percent level in column (3). These results highlight the immediate and persistent protective effects of collaborate culture against cyber risks.

For control culture, Equation (5.2b) shows that $\Delta CONTROL_{i,t}$ and $CONTROL_{i,t-1}$ have coefficients of -0.009 and -0.089, respectively, both significant and negative in column (5). Similarly, in Equation (5.2c), the coefficients for $\Delta CONTROL_{i,t}$, $\Delta CONTROL_{i,t-1}$ and $CONTROL_{i,t-2}$, are -0.008, -0.017, and -0.094, respectively, and remain significant and negative in column (6). These findings underscore the enduring influence of control culture's structured and systematic risk management practices in mitigating cybersecurity risks.

Overall, the results in Table 5.4 consistently demonstrate significant negative relationships between both the changes and lagged levels of internal-oriented cultures (collaborate and control) and cyber risks. This supports the hypothesis that internal-focused cultures play a critical role in enhancing organizational resilience to cyber threats.

The cyber risk stems from various factors and necessitates interdepartmental coordination and cooperation. According to Corradini and Nardell (2019), employees play a critical role in cybersecurity prevention strategies, given that people are often considered the weakest link in the security chain. In fact, international reports analyzing cyber-attacks confirm that the main problem is represented by human's actions, e.g. opening phishing mail and unchecked attached files, giving sensitive information away through social engineering attacks (Brockett et al.,2012; Corradini and Nardell, 2019). Therefore, maintaining effective relationships with other groups and departments within the organization and providing adequate employee training sessions regarding cyber risk are always critical procedures for internal control. Companies of different employee sizes may adopt different business strategies or place different emphasis on internal structure, employee education, and other issues. Here, I employ different subsamples for heterogeneity analysis to explore employee sizes' role in the mechanism of different corporate cultures in cyber risk for the period 2007-2018..

In Table 5.1, the variable $EMP_{i,t}$, denoting the number of employees in thousands, exhibits a mean of 10.355 and a median of 1.220. The substantial disparity between the mean and median suggests that the average is significantly influenced by a few firms with huge employee counts, skewing the mean upwards relative to the median. The two numbers are rounded up to 10 and 1, respectively. As the employee number is displayed in thousands [CRSP /Compustat Merged], I take 1,000 and 10,000 as thresholds to categorize subsamples. In addition, I adopt 100 as another threshold, as companies with fewer than 100 employees are typically classified as small and medium-sized companies. So far, I have divided the data into four subsamples based on the number of employees: (1) companies with 100 employees or fewer; (2) companies with more than 100 employees but fewer than or equal to 1000; (3) companies with more than 1000 employees but fewer than or equal to 10,000; (4) companies with more than 10,000 employees. Then I estimate Hypothesis 2: "*Both collaborate and control cultures, as internal focused culture types, are negatively correlated with cyber risk.*" based on subsamples.

The ordinary least squared (OLS) regression estimates for the above specifications are reported in Table 5.5. The coefficient terms -0.051, -0.085, -0.079 and -0.088 on the $CONTROL_{i,t}$ variable in columns (2), (4), (6) and (8) are negative and significant, indicating a negative correlation between control culture and cyber risk in firms of all sizes. This demonstrates a universally positive impact of control culture on cyber risk mitigation across enterprises of varying sizes. In contrast, for collaborate culture, no significant results are provided in columns (1) and (7), which means in companies with 100 employees or fewer; or in companies with more than 10,000 employees, there is no significant relationship between an enhanced collaborate culture and reduced cyber risk. While in columns (3) and (5), the coefficient terms -0.036 and -0.024 on the $COLLAB_{i,t}$ variable are significant and negative at the 5 percent level. Empirical evidence suggests that in large scale companies (more than 100 employees), fostering a culture of collaboration among employees can significantly reduce cyber risk, though this effect diminishes in mega-companies (more than 10,000 employees). Experts emphasize the vital role of employees in cybersecurity strategies, noting that they are often seen as the weakest link in security protocols. Reports on cyber-attacks globally reaffirm that human actions, such as falling for phishing scams or sharing sensitive data through social engineering, pose significant risks (Corradini and Nardell, 2019). This may partly explain that in mega-companies (>10,000 employees), the collaborate culture may be counterproductive in reducing cyber risk and in contrast, the control culture is more effective for mega-companies; procedures in place help the company to run more efficiently and smoothly, and safely.

[Insert Table 5.5 Here]

5.4.3 Internal Focused Culture Types (Collaborate and Control) and Data Breach Incidents

Cyber risk encompasses the potential exposure or loss due to cyber-attacks or data breaches. A data breach occurs when unauthorized access is gained to sensitive information. Cyber risks are potential threats that could lead to harmful consequences, such as data breaches, system damage, or unauthorized access. The impact of a cyber risk turning into a data breach can be severe, including financial losses, reputational damage, operational disruption, and legal liabilities. The scope of the impact often depends on the sensitivity of the data exposed and the scale of the breach. I collect data breach incidents data from Privacy Rights Clearinghouse (PRC) for the time period 2007-2018., merge with the cyber risk database (followed by Florackis et al., 2023a and 2023b), corporate culture score data (followed Andreou et al., 2020b) and firm-level fundamental information database (CRSP /Compustat Merged) to investigate the third research question: *"What is the relationship between the likelihood of data breach incident and internal focused culture (collaborate or control culture)?*" (Hypothesis 3). I expect to observe a negative relationship between internal oriented collaborate or control culture and the likelihood of data breach incidents. To do this, I estimate the following regression model:

$$
\begin{aligned}
BREACH\_DUMMY_{i,t} = {} & \alpha_1 + \boldsymbol{\alpha_2 CULTURE_{i,t}} \\
& + \alpha_3 SIZE_{i,t} + \alpha_4 LEVERAGE_{i,t} + \alpha_5 ROA_{i,t} + \alpha_6 AUDIT\_BIG4_{i,t} + \alpha_7 CASH_{i,t} \\
& + \nu_t + \gamma_s + \varepsilon_{i,t} \qquad (5.3)
\end{aligned}
$$

where the variable *BREACH DUMMY*$_{i,t}$ is a dummy variable that equal to 1 if a data breach incident occurred in the company during this fiscal year or 0 otherwise; the variable *CULTURE*$_{i,t}$ is measured by one of *COLLAB*$_{i,t}$ or *CONTROL*$_{i,t}$; all other variables are as previously defined.

The results of Linear Probit Model (LPM) regression estimates are provided in Table 5.6, where the coefficient term 0.002 on the $COLLAB_{i,t}$ variable in columns (1) capture the relationship between collaborate culture and the likelihood of data breach incident at the 5 percent level. This is contrary to my expectations and further research is needed to explore the reasons for this discrepancy. For control culture, the coefficient term -0.003 on the $CONTROL_{i,t}$ variable in columns (2) is significant and negative at the 1 percent level. The relationship between control culture and the likelihood of data breach incident is consistent with my expectations, lending support to Hypothesis 3.

[Insert Table 5.6 Here]

Since I observe a positive and significant relationship between collaborate culture and the likelihood of data breach incidents, this is contrary to my expectation as I expect a negative and significant relationship between the two, just like the relationship between control culture and cyber risk. Further investigation is needed to explore the reasons for this contradiction. Hence, I conduct heterogeneity analysis in different subsamples (the same subsample classification mentioned above[38]) to explore the effect of differences in employee size on the moderating effect of corporate culture on the likelihood of data breach incidents.

The Linear Probit Model (LPM) estimates for the above specifications are reported in Table 5.7. In my merged data, I have only one observation with a data breach incident ($BREACH\_DUMMY_{i,t}$ =1) in the first subsample (100 employees or fewer) and the other 4,310 observations without a publicly acknowledged data breach incident ($BREACH\_DUMMY_{i,t}$ =0), which explains the lack of corresponding results reported in the table. The coefficient terms -0.001, -0.003 and -0.011 on the $CONTROL_{i,t}$ variable in columns (2), (4) and (6) are significant and negative, demonstrating a universally positive

[38] This study divides the data into four subsamples: (1) companies with 100 employees or fewer; (2) companies with more than 100 employees but fewer than or equal to 1000; (3) companies with more than 1000 employees but fewer than or equal to 10,000; (4) companies with more than 10,000 employees.

impact of control culture on the decreased likelihood of data breach incidents across enterprises of varying sizes (except for firms with fewer than 100 employees). In contrast, for collaborate culture, no significant results are provided in columns (1) and (3), which means in companies with fewer than 10,000 employees, there is no significant relationship between an enhanced collaborate culture and likelihood of data breach incidents.

While in column (5), the coefficient term 0.006 on the $COLLAB_{i,t}$ variable is significant and positive at the 5 percent level, indicating that an increase in collaborative culture in mega-companies (with more than 10,000 employees) may exacerbate the likelihood of data breach incidents. This finding does not conflict with my broader expectations, as seen in Table 5.5, where collaborate culture is negatively associated with cyber risk for firms with employee ranges of 100 to 1,000 and 1,001 to 10,000. The difference observed for mega-companies may arise from the unique structural and operational challenges of such organizations, where sheer scale and complexity necessitate stricter formal controls rather than an over-reliance on collaborative approaches. Thus, the results are consistent with my prior analyses and highlight the nuanced interplay between firm size and the effectiveness of internal-oriented cultural attributes in mitigating cyber risks.

[Insert Table 5.7 Here]

Furthermore, in Table 5.1, for the variable *BREACH DUMMY*, only 337 observations from PRC are matched, which means that only 337 observations in my full dataset have observed data breaches. Privacy Rights Clearinghouse (PRC) states that when data breach incidents have been publicly acknowledged, these records will be included in the PRC dataset. I have defaulted all the other over 40,000 observations observing no data breach event. According to Lawrence et al. (2018) and Rosati et al. (2022), to minimize potential changes in the likelihood of breach incident due to firm’s characteristics, I employ propensity score matching (PSM). First, I estimate the probability of a firm becoming a breach target

(Equation 5.4).[39] To preserve the size of the sample, I chose a Nearest-Neighbour approach. I then match each breached firm (treatment) with four closet non-breached firms (control sample), controlling for year and industry fixed effects. After propensity score matching, the treatment(breached) sample size cut down to 273[40]and control (non-breached) sample is 1027[41]. The probability model follows the model outlined:

$$
\begin{aligned}
PROBIT\left[BREACH\_DUMMY_{i,t} = 1\right] = f\,(&\beta_1 + \beta_2 SIZE_{i,t-1} + \beta_3 LEVERAGE_{i,t-1} \\
&+ \beta_4 ROA_{i,t-1} + \beta_5 AUDIT\_BIG4_{i,t-1} + \beta_6 CASH_{i,t-1} \\
&+ \nu_t + \gamma_s + \varepsilon_{i,t}) \qquad (5.4)
\end{aligned}
$$

Table 5.8 Panel A presents descriptive statistics for treated firms that experience a data breach incident involving financial information over the period 2007 to 2018 and control firms that do not experience data breach incidents over the same period. The propensity score is calculated using the Linear Probit Model (LPM) of $BREACH\_DUMMY_{i,t}$ on firm size, leverage, return on asset, auditors, and cash. In descriptive statistics table (Table 5.8 Panel A). Panel B presents that after implementing propensity score matching, biases in variables like $SIZE_{i,t-1}$, $LEVERAGE_{i,t-1}$, $ROA_{i,t-1}$, $AUDIT\_BIG4_{i,t-1}$, and $CASH_{i,t-1}$ are significantly reduced. For each variable, the p-values post-matching are greater than 0.1, indicating that the differences between the matched treated and control groups are not statistically significant.

[39] To avoid post-treatment bias, the right-hand side variables of the same equation should be lagged once (Imbens and Rubin, 2015)

[40] I employed nearest-neighbor matching without replacement, pairing each treated firm with the four most similar control firms (n=4) based on propensity scores. These propensity scores were estimated using a probit model that included predictors such as firm size, leverage, return on assets, and industry classification. While caliper width was not applied to restrict the matching process, this decision was made to ensure sufficient matches for treated observations and maintain the robustness of subsequent analyses. Iterative testing revealed that imposing a caliper significantly reduced the number of matched observations, potentially affecting the generalizability of the results. As a result of the matching procedure, the final sample comprises 273 treated firms, reflecting a minimal loss of observations from the original dataset. In propensity score matching, it is common to exclude treated units that cannot find adequate matches under the specified criteria (e.g., closest four neighbors). This ensures that the quality and balance of the matching process are maintained, even if certain treated units are excluded from the analysis.

[41] It is expected to have 1092(=273*4) control observations, but I only have 1027, which is still within reasonable bounds and can be considered normal in some cases of Propensity Score Matching (PSM). For example, there might simply not be enough control units that are close enough in propensity score to all treated units.

Consequently, I fail to reject the null hypothesis[42] for these variables, suggesting that the matching process has effectively neutralized differences in these variables between the treated and control firms. Panel C visualizes the standardized percentage bias across various covariates both before and after matching. It shows a substantial reduction in bias for all measured covariates, illustrating the efficacy of the matching process. The graph provides a clear, visual confirmation of the textual data provided in Panel B, reinforcing the findings that the propensity score matching has achieved a high degree of balance between the groups. The results of Linear Probit Model (LPM) estimates based on propensity score matched sample are provided in Table 5.8 Panel D, where the coefficient term 0.024 on the $COLLAB_t$ variable in columns (1) captures the relationship between collaborate culture and the likelihood of data breach incident at the 5 percent level. For control culture, the coefficient term -0.059 on the $CONTROL_{i,t}$ variable in columns (2) is significant and negative at the 1 percent level. This positive coefficient on the $COLLAB_t$ variable is consistent with the findings reported in Table 5.6 prior to propensity score matching, indicating that the propensity score matching procedure does not fundamentally alter the observed relationship, which lending support to Hypothesis 3,

[Insert Table 5.8 Here]

Furthermore, I conduct heterogeneity analysis in different subsamples (the same subsample classification mentioned above[43]) similar to Table 5.7, for robustness to explore the effect of differences in employee size on the effect of corporate culture (collaborate or control) on the likelihood of data breach incidents for the same period 2007-2018.. The Linear Probit Model (LPM) estimates for the above specifications are reported in Table 5.9.

[42] Null Hypothesis (H_0): There is no difference in the respective variable distributions between the treated and control groups after matching.

[43] This study divides the data into four subsamples: (1) companies with 100 employees or fewer; (2) companies with more than 100 employees but fewer than or equal to 1,000; (3) companies with more than 1,000 employees but fewer than or equal to 10,000; (4) companies with more than 10,000 employees.

For the same reason as table 5.7, the first subsample (100 employees or fewer) also does not report results.

The coefficient terms -0.211 and -0.087 on the $CONTROL_{i,t}$ variable in columns (2) and (6) are significant and negative, demonstrating a universally positive impact of control culture on the decreased likelihood of data breach incidents across enterprises of varying sizes. In contrast, for collaborate culture, no significant results are provided in columns (1) and (3), which means in companies with fewer than 10,000 employees, there is no significant relationship between an enhanced collaborate culture and likelihood of data breach incidents. While in columns (5), the coefficient term 0.037 on the $COLLAB_{i,t}$ variable is significant and positive, which means that the increase of collaborate culture in mega-companies (more than 10,000 employees) may exacerbate the likelihood of data breach incidents. This finding does not conflict with my broader expectations, as the results align with previous analyses demonstrating that collaborate culture is negatively associated with cyber risk for firms with fewer employees but may exhibit a different effect in mega-companies due to their operational scale and structural complexity. Since all previous results are in line with my expectations, I tentatively assume that the non-significance of column (4) is the result of a statistical problem that does not affect the conclusions. Thus, in the detailed heterogeneity analysis based on propensity score matched sample, the results do not conflict with the expectations and are consistent with the empirical analysis of my previous tables.

[Insert Table 5.9 Here]

5.4.4 Robustness Tests

To ensure the robustness of my findings on the relationship between internal focused organizational cultures and cyber risks, I employed several rigorous testing methods. The primary analysis using the variable $INTERNAL\_FOCUS_{i,t}$, a continuous internal focus score variable ranging from 0 to 1 with a mean of 0.395, indicated a potentially stronger cyber risk mitigation effect in firms with relatively higher internal focus scores. However, to address potential concerns about model specification and the influence of unobserved heterogeneity, I conducted additional robustness tests.

5.4.4.1: Robustness Tests 1: Relationship between Culture and Cyber Risk Based on Propensity Score Matched Sample

For the time period 2007-2018, to control for observed covariates that could influence both the internal focus of a firm and its cybersecurity risk profile, I implemented Propensity Score Matching (PSM). This method helps match firms with high internal focus scores to those with lower scores on relevant characteristics, ensuring comparability across matched samples. Using PSM before conducting regression can enhance the analysis by ensuring that the treatment and control groups are comparable on observed covariates, reducing the confounding effects of those covariates. This method is beneficial for decreasing a significant selection bias based on observed variables like $SIZE_{i,t-1}$, $LEVERAGE_{i,t-1}$, $ROA_{i,t-1}$, $AUDIT\_BIG4_{i,t-1}$, and $CASH_{i,t-1}$. For the robustness test involving PSM, I introduced the dummy variable $INTERNAL\_DUMMY_{i,t}$ (equal to 1 when variable $INTERNAL\_FOCUS_{i,t}$ is more than 0.5 and 0 otherwise) and estimate the probability of a firm with $INTERNAL\_DUMMY_{i,t}$ equal to 1 (Equation 5.5).[44] This binary variable is used in regression analyses post-PSM to examine the impact of having a predominately internal focus on cyber risks more distinctly. To preserve the size of the sample, I choose a Nearest-Neighbour approach, I match each treated firm with four closet non-breached control samples controlling for year and industry fixed effects.[45] The probability model follows the model

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[44] To avoid post-treatment bias, the right-hand side variables of the same equation should be lagged once (Imbens and Rubin, 2015)

[45] I employed nearest-neighbor matching without replacement, pairing each treated firm with the four most similar control firms (n=4) based on propensity scores. These propensity scores were estimated using a probit model that included predictors such as firm size, leverage, return on assets, and industry classification. While caliper width was not applied to restrict the matching process, this decision was made to ensure sufficient

outlined:

$$PROBIT\left[INTERNAL\_DUMMY_{i,t} = 1\right] = f\,(\beta_1 + \beta_2 SIZE_{i,t-1} + \beta_3 LEVERAGE_{i,t-1} + \beta_4 ROA_{i,t-1} + \beta_5 AUDIT\_BIG4_{i,t-1} + \beta_6 CASH_{i,t-1} + \nu_t + \gamma_s + \varepsilon_{i,t}) \quad (5.5)$$

Table 5.10 Panel A presents that after implementing propensity score matching, biases in variables like $SIZE_{i,t-1}$, $LEVERAGE_{i,t-1}$, $ROA_{i,t-1}$, $AUDIT\_BIG4_{i,t-1}$, and $CASH_{i,t-1}$ are significantly reduced. For each variable, the p-values post-matching are greater than 0.1, indicating that the differences between the matched treated and control groups are not statistically significant. Consequently, I fail to reject the null hypothesis[46] for these variables, suggesting that effective neutralization of differences across these key variables, validating the comparability of the treated and control firms. Panel B visualizes the standardized percentage bias across various covariates both before and after matching. The graph vividly demonstrates that all biases are substantially reduced to well below 10%, a threshold generally considered acceptable in bias reduction. Together, Panels A and B confirm the efficacy of the propensity score matching process, highlighting the achieved balance and comparability between treated and control groups and affirming the robustness and precision of the matching methodology employed.

[Insert Table 5.10 Here]

Based on the propensity score matched table, I expect to observe a negative relationship between $INTERNAL\_DUMMY_{i,t}$ and cyber risk. The dummy variable can further help isolate the impact of having a strong internal focus score from having a moderate or no internal focus. This binary approach making it more straightforward to see the direct impact of a high internal focus on cyber risk. To do this, I estimate the following regression model:

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matches for treated observations and maintain the robustness of subsequent analyses. Iterative testing revealed that imposing a caliper significantly reduced the number of matched observations, potentially affecting the generalizability of the results.

[46] Null Hypothesis (H_0): There is no difference in the respective variable distributions between the treated and control groups after matching.

$$CYBER\_RISK_{i,t} = \alpha_1 + \boldsymbol{\alpha_2 INTERNAL\_DUMMY_{i,t}} + \alpha_3 SIZE_{i,t} + \alpha_4 LEVERAGE_{i,t} + \alpha_5 ROA_{i,t} + \alpha_6 AUDIT\_BIG4_{i,t} + \alpha_7 CASH_{i,t} + \nu_t + \gamma_s + \varepsilon_{i,t} \quad (5.6)$$

The results of ordinary least squared (OLS) regression estimates based on propensity score matched sample are provided in Table 5.10 Panel C, where the coefficient term -0.096 on the *INTERNAL_DUMMY*$_{i,t}$ variable in columns (1) captures the relationship between internal focused culture and cyber risks at the 1 percent level.

5.4.4.2: Robustness Tests 2: Relationship between Champions in Collaborate/ Control Culture and Cyber Risk

To strengthen the robustness of my findings, I further investigate the relationship between internal-oriented culture and cyber risk by focusing on firms with exceptionally strong internal-oriented cultures, referred to as "champions." This approach is motivated by the expectation that firms excelling in either collaborate or control culture—those ranked in the top deciles—would exhibit a particularly strong negative association with cyber risk. The premise is that such firms, with highly developed internal processes and risk management practices, should be even better equipped to mitigate cyber risks compared to their peers with less pronounced internal-oriented cultural attributes. To do this, I estimate the following regression model:

$$CYBER\_RISK_{i,t} = \alpha_1 + \boldsymbol{\alpha_2 CHAMPION\_CULTURE_{i,t}} + \alpha_3 SIZE_{i,t} + \alpha_4 LEVERAGE_{i,t} + \alpha_5 ROA_{i,t} + \alpha_6 AUDIT\_BIG4_{i,t} + \alpha_7 CASH_{i,t} + \nu_t + \gamma_s + \varepsilon_{i,t} \quad (5.7)$$

where, the variable *CHAMPION_CULTURE*$_t$ represents firms that are champions in internal-oriented culture, measured by indicators such as *COLLAB_CHAMPION9*$_{i,t}$, *CONTROL_CHAMPION9*$_{i,t}$, *COLLAB_CHAMPION8*$_{i,t}$ and *CONTROL_CHAMPION8*$_{i,t}$. For example, $COLLAB\_CHAMPION9_{i,t}$ equals 1 if a firm's collaborate culture ranks in decile 9 or above and 0 otherwise. All other variables are as previously defined.

The ordinary least squared (OLS) regression estimates for these specifications are reported in Table 5.11. For collaborate culture, the coefficients on $COLLAB\_CHAMPION9_{i,t}$ and $COLLAB\_CHAMPION8_{i,t}$ are -0.039 and -0.047, indicating a significant negative relationship between champion firms in collaborate culture and cyber risk at the 1 percent level in columns (1) and (3). Similarly, the coefficients of the $CONTROL\_CHAMPION9_{i,t}$ and $CNTROL\_CHAMPION8_{i,t}$, are negative and significant with coefficient terms of -0.085 and -0.103 in column (2) and (4), respectively. These results corroborate the findings from earlier analyses, emphasizing that firms with exceptionally strong internal-oriented cultures—whether collaborate or control—are particularly effective in mitigating cyber risks. The consistency across both culture types and robustness tests underscores the importance of fostering strong internal-oriented cultures as a strategic approach to managing cyber risk. The findings also reinforce the theoretical argument that highly structured and cohesive internal environments enhance a firm's ability to anticipate, identify, and respond to cybersecurity threats effectively.

[Insert Table 5.11 Here]

The robustness tests conducted in this chapter serve as a critical component of my analysis, ensuring that the relationships identified between internal-focused organizational cultures and cybersecurity outcomes are not artifacts of specific sample characteristics or modelling choices. These tests validate the stability and reliability of my results across various scenarios, reinforcing the generalizability and credibility of my findings.

5.5 Conclusion

This chapter rigorously investigates the relationship between internal-focused organizational cultures—specifically, collaborate and control cultures—and their impact on cybersecurity, with an emphasis on cyber risks and data breach incidents. Using comprehensive data sources, including the Privacy Rights Clearinghouse, SEC's Edgar database, and the CRSP/Compustat Merged database, this study provides robust evidence demonstrating the significant role organizational culture plays in shaping cybersecurity outcomes.

The findings underscore that control culture consistently enhances cybersecurity outcomes across organizations of varying sizes due to its structured approach to compliance and risk mitigation. In contrast, the influence of collaborate culture is more nuanced and size-dependent. For organizations with 100 to 10,000 employees, collaborate culture effectively reduces cyber risks by fostering enhanced communication and rapid consensus-building, essential for proactive cybersecurity management. However, in mega-organizations with over 10,000 employees, the inherent characteristics of collaborate culture—such as widespread employee involvement and consensus-driven processes—may inadvertently hinder decision-making speed and increase vulnerabilities, leading to a heightened likelihood of significant data breaches.

These findings have several policy and managerial implications. First, the integration of the Competing Values Framework (CVF) into the domain of cybersecurity provides a novel perspective, highlighting the strategic importance of aligning organizational culture with cybersecurity objectives. Policymakers can use these insights to design differentiated guidelines that reflect organizational size and cultural characteristics, ensuring a more tailored approach to cybersecurity.

For managers, the research offers actionable insights for crafting effective, size-appropriate cybersecurity strategies. Organizations with a dominant collaborate culture should recognize its potential limitations in large-scale settings and consider supplementing it with structural controls to enhance agility and security. Conversely, control cultures should leverage their strengths in risk mitigation while remaining vigilant about fostering adaptability to respond to emerging cyber threats.

Future research could expand on these findings by exploring the relationship between organizational culture and cyber risks across different industries and regulatory environments. Investigating how cultural dynamics evolve over time and their impact on cybersecurity effectiveness would further enrich the understanding of this interplay. Additionally, global studies examining cultural differences and cybersecurity practices could offer valuable insights into how regional and cultural contexts shape organizational responses to cyber risks, contributing to a more comprehensive framework for global cybersecurity strategies.

Tables and Figure

Table 5.1: Summary Statistics

This table presents the mean, median, 25th percentile, 75th percentile, minimum value, maximum value, standard deviation and the number of observations for all variables for the time span from 2007 to 2018 used in this chapter. All variables are measured at the firm/fiscal-year level. For variable definitions and details of their construction, see Table 5.12.

Variable	Obs	Mean	S.D.	Min	0.25	Mdn	0.75	Max
CYBER_RISK	32091	0.235	0.219	0.000	0.000	0.266	0.440	0.652
INTERNAL_FOCUS	32091	0.353	0.120	0.116	0.264	0.344	0.431	0.738
COLLAB	32091	0.122	0.075	0.016	0.068	0.106	0.158	0.428
CONTROL	32091	0.230	0.085	0.076	0.168	0.220	0.279	0.618
INTERNAL_DUMMY	32091	0.124	0.330	0.000	0.000	0.000	0.000	1.000
BREACH_DUMMY	32091	0.009	0.092	0.000	0.000	0.000	0.000	1.000
SIZE	32091	6.344	2.076	1.993	4.849	6.303	7.783	11.774
LEVERAGE	32091	0.032	0.072	0.000	0.000	0.004	0.030	0.515
ROA	32091	-0.059	0.284	-1.456	-0.063	0.027	0.071	0.327
AUDIT_BIG4	32091	0.720	0.449	0.000	0.000	1.000	1.000	1.000
CASH	32091	1.703	3.031	0.003	0.211	0.636	1.733	19.537
EMP	32091	10.355	50.661	0.000	0.238	1.220	6.500	2300
COLLAB_CHAMPION9	32091	0.195	0.397	0.000	0.000	0.000	0.000	1.000
COLLAB_CHAMPION8	32091	0.290	0.454	0.000	0.000	0.000	1.000	1.000
CONTROL_CHAMPION9	32091	0.069	0.253	0.000	0.000	0.000	0.000	1.000
CONTROL_CHAMPION8	32091	0.159	0.366	0.000	0.000	0.000	0.000	1.000

Table 5.2: Pearson Correlation Matrix

This table presents the Pearson correlation coefficients for the main variables used in the empirical analyses. T-statistics have been conducted and *, ** and *** indicate 10%, 5%, and 1% levels of significance, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CYBER_RISK	(1)	1											
INTERNAL_FOCUS	(2)	0.013***	1										
COLLAB	(3)	-0.004	0.553***	1									
CONTROL	(4)	0.017***	0.843***	0.024***	1								
INTERNAL_DUMMY	(5)	0.024***	0.783***	0.381***	0.692***	1							
BREACH_DUMMY	(6)	0.048***	0.015***	0.034***	-0.005	0.008	1						
SIZE	(7)	0.257***	0.404***	0.248***	0.330***	0.273***	0.109***	1					
LEVERAGE	(8)	-0.044***	0.095***	0.056***	0.080***	0.074***	-0.000	0.010**	1				
ROA	(9)	0.081***	0.282***	0.159***	0.238***	0.135***	0.031***	0.413***	-0.109***	1			
AUDIT_BIG4	(10)	0.141***	-0.027***	0.140***	-0.122***	-0.075***	0.050***	0.454***	-0.089***	0.137***	1		
CASH	(11)	-0.068***	-0.305***	-0.206***	-0.249***	-0.106***	-0.024***	-0.282***	-0.169***	-0.179***	-0.077***	1	
EMP	(12)	0.074***	0.042***	0.097***	-0.011**	0.001	0.186***	0.272***	-0.006	0.077***	0.122***	-0.085***	1
COLLAB_CHAMPION9	(13)	0.020***	0.397***	0.787***	-0.024***	0.295***	0.033***	0.181***	0.041***	0.107***	0.121***	-0.135***	0.078***
COLLAB_CHAMPION8	(14)	0.020***	0.430***	0.792***	0.015***	0.276***	0.035***	0.206***	0.038***	0.126***	0.119***	-0.164***	0.078***
CONTROL_CHAMPION9	(15)	0.049***	0.649***	-0.045***	0.809***	0.691***	-0.014***	0.221***	0.065***	0.115***	-0.164***	-0.063***	-0.040***
CONTROL_CHAMPION8	(16)	0.025***	0.686***	-0.002	0.827***	0.636***	-0.012**	0.252***	0.084***	0.153***	-0.126***	-0.109***	-0.026***

		(14)	(15)	(16)	(17)
COLLAB_CHAMPION9	(13)	1			
COLLAB_CHAMPION8	(14)	0.00200	1		
CONTROL_CHAMPION9	(15)	-0.101***	-0.025*	1	
CONTROL_CHAMPION8	(16)	0.032**	-0.0150	-0.034*	1

Table 5.3: Relationship between Internal Focused Culture and Cyber Risk

This table presents ordinary least squared (OLS) regression to investigate the relationship between internal focused culture and the cyber risk for the time priod 2007-2018. The estimates include year and industry fixed effects. All variables are defined in Table 5.12, the model includes a constant (not shown in the table), and the standard error is clustered at the firm level. The t-statistics are given in parentheses.

	$CYBER\_RISK_{i,t}$
	(1)
$INTERNAL\_FOCUS_{i,t}$	-0.074***
	(-6.78)
$SIZE_{i,t}$	0.175***
	(15.94)
$LEVERAGE_{i,t}$	-0.027***
	(-3.56)
$ROA_{i,t}$	0.005
	(0.61)
$AUDIT\_BIG4_{i,t}$	0.168***
	(7.76)
$CASH_{i,t}$	-0.025***
	(-3.21)
YEAR FE	Yes
INDUSTRY FE	Yes
Adj. R^2	0.49
N	32091

(* p<0.1; ** p<0.05; *** p<0.01)

Table 5.4: Relationship between Collaborate/Control Culture and Cyber Risk

This table presents ordinary least squared (OLS) regression estimates for the relationship between collaborate/control culture and cyber risk for the time priod 2007-2018. The key independent variables of interest $\Delta COLLAB_t$, $COLLAB_{t\text{-}1}$, $\Delta COLLAB_{t\text{-}1}$, and $COLLAB_{t\text{-}2}$, represent lagged levels and differences in the relative measure of the firm's collaborate culture. Besides, $\Delta CONTROL_t$, $CONTROL_{t\text{-}1}$, $\Delta CONTROL_{t\text{-}1}$, and $CONTROL_{t\text{-}2}$, represent lagged levels and differences in the relative measure of firm's control culture. All other variables are defined in Table 5.12. The estimates include the year and industry fixed effects. All models include a constant (not shown in the table) and the standard errors are clustered at the firm level. The t-statistics are given in parentheses.

	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$COLLAB_{i,t}$	-0.019**					
	(-2.54)					
$\Delta COLLAB_{i,t}$		-0.015***	-0.015***			
		(-3.07)	(-3.03)			
$COLLAB_{i,t-1}$		-0.025***				
		(-2.67)				
$\Delta COLLAB_{i,t-1}$			-0.023***			
			(-3.14)			
$COLLAB_{i,t-2}$			-0.028***			
			(-2.60)			
$CONTROL_{i,t}$				-0.081***		
				(-6.61)		
$\Delta CONTROL_{i,t}$					-0.009**	-0.008*
					(-2.15)	(-1.72)
$CONTROL_{i,t-1}$					-0.089***	
					(-6.53)	
$\Delta CONTROL_{i,t-1}$						-0.017***
						(-3.01)
$CONTROL_{i,t-2}$						-0.094***
						(-6.48)
$SIZE_{i,t}$	0.170***	0.170***	0.814***	0.816***	0.034*	0.038**
	(15.19)	(15.47)	(93.58)	(93.52)	(1.88)	(2.09)
$LEVERAGE_{i,t}$	-0.029***	-0.027***	-0.008	-0.007	-0.028***	-0.026***
	(-3.91)	(-3.56)	(-1.45)	(-1.27)	(-3.84)	(-3.50)
$ROA_{i,t}$	-0.001	0.005	-0.082***	-0.079***	0.012	0.018**
	(-0.18)	(0.72)	(-17.40)	(-17.17)	(1.61)	(2.40)
$AUDIT\_BIG4_{i,t}$	0.173***	0.163***	0.386***	0.384***	0.109***	0.101***
	(7.92)	(7.55)	(25.21)	(24.90)	(4.81)	(4.50)
$CASH_{i,t}$	-0.020**	-0.024***	-0.069***	-0.071***	-0.008	-0.013
	(-2.52)	(-3.04)	(-13.09)	(-13.53)	(-1.07)	(-1.58)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.49	0.49	0.49	0.49	0.5	0.5
N	32091	30925	29530	32091	30925	29530

(* p<0.1; ** p<0.05; *** p<0.01)

Table 5.5: Heterogeneity Analysis: Relationship between Collaborate/Control Culture and Cyber Risk

This table presents ordinary least squared (OLS) regression to investigate the relationship between collaborate/control culture and cyber risk for the time priod 2007-2018. This study employs four subsamples based on the number of employees: (1) companies with 100 employees or fewer; (2) companies with more than 100 employees but fewer than or equal to 1000; (3) companies with more than 1000 employees but fewer than or equal to 10,000; (4) companies with more than 10,000 employees. The estimates include year and industry fixed effects. All variables are defined in Table 5.12, the model includes a constant (not shown in the table) and the standard error is clustered at the firm level. The t-statistics are given in parentheses.

	Employee <=100		100 <Employee <=1000		1000 <Employee<=10000		Employee>10000	
	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$COLLAB_{i,t}$	-0.018		-0.036**		-0.024**		-0.000	
	(-0.77)		(-2.41)		(-2.52)		(-0.00)	
$CONTROL_{i,t}$		-0.051*		-0.085***		-0.079***		-0.088***
		(-1.67)		(-3.61)		(-5.24)		(-3.49)
$SIZE_{i,t}$	0.259***	0.251***	0.179***	0.177***	0.170***	0.169***	0.132***	0.129***
	(6.50)	(6.22)	(5.23)	(5.17)	(13.38)	(13.60)	(5.24)	(5.28)
$LEVERAGE_{i,t}$	0.016	0.017	-0.048***	-0.045***	-0.019**	-0.016*	0.008	0.012
	(1.25)	(1.30)	(-3.77)	(-3.52)	(-2.12)	(-1.86)	(0.40)	(0.57)
$ROA_{i,t}$	-0.033***	-0.030**	-0.007	-0.002	-0.005	0.001	0.002	0.006
	(-2.88)	(-2.54)	(-0.60)	(-0.17)	(-0.66)	(0.09)	(0.07)	(0.21)
$AUDIT\_BIG4_{i,t}$	0.079*	0.075*	0.165***	0.151***	0.179***	0.170***	0.212**	0.204**
	(1.77)	(1.67)	(4.78)	(4.40)	(6.90)	(6.59)	(2.24)	(2.23)
$CASH_{i,t}$	-0.005	-0.007	-0.022	-0.022	-0.022***	-0.025***	0.037	0.030
	(-0.55)	(-0.67)	(-1.49)	(-1.49)	(-2.70)	(-3.09)	(1.19)	(0.97)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.35	0.35	0.44	0.44	0.47	0.47	0.55	0.56
N	4311	4311	9309	9309	20334	20334	6135	6135

(* $p<0.1$; ** $p<0.05$; *** $p<0.01$)

Table 5.6: Relationship between Collaborate/Control Culture and Data Breach Incident

This table presents Linear Probit Model (LPM) estimates for the relationship between collaborate/control culture and the likelihood of data breach incidents for the time priod 2007-2018. The estimates include year and industry fixed effects. All variables are defined in Table 5.12, the model includes a constant (not shown in the table) and the standard error is clustered at the firm level. The *t*-statistics are given in parentheses.

	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$
	(1)	(2)
$COLLAB_{i,t}$	0.002**	
	(2.08)	
$CONTROL_{i,t}$		-0.003***
		(-2.95)
$SIZE_{i,t}$	0.013***	0.013***
	(8.00)	(8.00)
$LEVERAGE_{i,t}$	0.000	0.000
	(0.34)	(0.69)
$ROA_{i,t}$	-0.002***	-0.002***
	(-4.88)	(-4.42)
$AUDIT\_BIG4_{i,t}$	-0.006***	-0.006***
	(-3.96)	(-4.04)
$CASH_{i,t}$	0.001***	0.001**
	(3.34)	(2.56)
YEAR FE	Yes	Yes
INDUSTRY FE	Yes	Yes
Adj. R^2	0.04	0.04
N	32091	32091

(* p<0.1; ** p<0.05; *** p<0.01)

Table 5.7: Heterogeneity Analysis: Relationship between Collaborate/Control Culture and Data Breach Incident

This table presents Linear Probit Model (LPM) to investigate the relationship between collaborate/control culture and the likelihood of data breach incidents for the time priod 2007-2018. I employ four subsamples based on the number of employees: (1) companies with 100 employees or fewer (no results reported in the table); (2) companies with more than 100 employees but fewer than or equal to 1000; (3) companies with more than 1000 employees but fewer than or equal to 10,000; (4) companies with more than 10,000 employees. The estimates include year and industry fixed effects. All variables are defined in Table 5.12, the model includes a constant (not shown in the table) and the standard error is clustered at the firm level. The *t*-statistics are given in parentheses.

	100 <Employee <=1000		1000 <Employee<=10000		Employee>10000	
	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$COLLAB_{i,t}$	0.000		-0.001		0.006**	
	(0.60)		(-1.65)		(2.46)	
$CONTROL_{i,t}$		-0.001***		-0.003*		-0.011**
		(-2.76)		(-1.88)		(-2.23)
$SIZE_{i,t}$	0.003***	0.003***	0.008***	0.008***	0.033***	0.034***
	(2.83)	(2.79)	(3.42)	(3.29)	(5.31)	(5.38)
$LEVERAGE_{i,t}$	0.000	0.000	0.001	0.001	0.001	0.001
	(0.89)	(1.31)	(1.02)	(1.12)	(0.20)	(0.33)
$ROA_{i,t}$	-0.000	0.000	0.001	0.001	-0.008	-0.008
	(-0.03)	(0.29)	(0.71)	(0.82)	(-1.64)	(-1.59)
$AUDIT\_BIG4_{i,t}$	0.001	0.000	-0.003	-0.004	-0.013	-0.013
	(0.68)	(0.47)	(-1.25)	(-1.42)	(-1.40)	(-1.48)
$CASH_{i,t}$	0.001	0.001	0.007	0.007	0.004	0.003
	(1.44)	(1.29)	(1.57)	(1.55)	(0.98)	(0.58)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	-0.00	-0.00	0.02	0.02	0.06	0.06
N	9309	9309	11757	11757	6135	6135

(* p<0.1; ** p<0.05; *** p<0.01)

Table 5.8: Validation Analysis: Relationship between Collaborate/Control Culture and Data Breach Incident Based on Propensity Score Matched Sample

This table presents the descriptive statistics for treated firms that experience a data breach incident involving financial information over the period 2007 to 2018 and control firms that do not experience data breach incident over the same period, including the mean, median, 25th percentile, 75th percentile, minimum value, maximum value, and the number of observations (Panel A). Panel B presents the bias reduction and matching quality between treated and control samples after implementing propensity score matching, using metrics such as mean, bias percentage, bias reduction, and t-tests. Panel C visually represents the standardized percentage biases across various covariates, both before and after matching. Panel D presents Linear Probit Model (LPM) estimates for the relationship between collaborate/control culture and the likelihood of data breach incidents based on propensity score matched sample. The estimates include year and industry fixed effects. All variables are defined in Table 5.12, the model includes a constant (not shown in the table) and the standard error is clustered at the firm level. The *t*-statistics are given in parentheses.

Panel A: Descriptive statistics for treated firms that experience a data breach incident and control firms.

Variable	Obs	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Treatment firms with a data breach event (N=273):								
SIZE	273	8.818	1.845	2.007	7.493	8.904	10.294	11.774
LEVERAGE	273	0.026	0.046	0.000	0.000	0.009	0.030	0.387
ROA	273	0.047	0.094	-0.531	0.017	0.053	0.090	0.327
AUDIT_BIG4	273	0.949	0.221	0.000	1.000	1.000	1.000	1.000
CASH	273	0.908	1.475	0.003	0.162	0.424	1.053	10.408
Control firms without a data breach event (N=1027):								
SIZE	1027	8.734	1.829	2.790	7.436	8.797	10.181	11.774
LEVERAGE	1027	0.027	0.047	0.000	0.001	0.010	0.035	0.515
ROA	1027	0.044	0.088	-0.617	0.015	0.048	0.082	0.327
AUDIT_BIG4	1027	0.938	0.242	0.000	1.000	1.000	1.000	1.000
CASH	1027	0.999	2.078	0.003	0.166	0.422	0.978	19.537

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Table 5.8 cont'd.

Panel B: Demonstrating the effectiveness of the propensity score matching.

Variable	Unmatched	Mean		Bias	Reduct Bias	t-test	
	Matched	Treated	Control	(%)	(%)	t	P > |t|
SIZE	U	1.0306	-0.1723	127.9		20.03	0.000
	M	1.0254	1.0301	-0.5	99.6	-0.06	0.951
LEVERAGE	U	-0.1531	-0.0813	-9.6		-1.33	0.185
	M	-0.1519	-0.1403	-1.5	83.8	-0.24	0.813
ROA	U	0.3629	-0.0639	51.1		6.29	0.000
	M	0.3602	0.3515	1.0	98.0	0.29	0.775
AUDIT_BIG4	U	0.9489	0.7175	65.3		8.50	0.000
	M	0.9487	0.9405	2.3	96.4	0.42	0.674
CASH	U	-0.2626	0.0009	-33.6		-4.36	0.000
	M	-0.2624	-0.2403	-2.8	91.6	-0.45	0.656

Panel C: Visual representation of the standardized percentage biases across various covariates, both before and after matching.

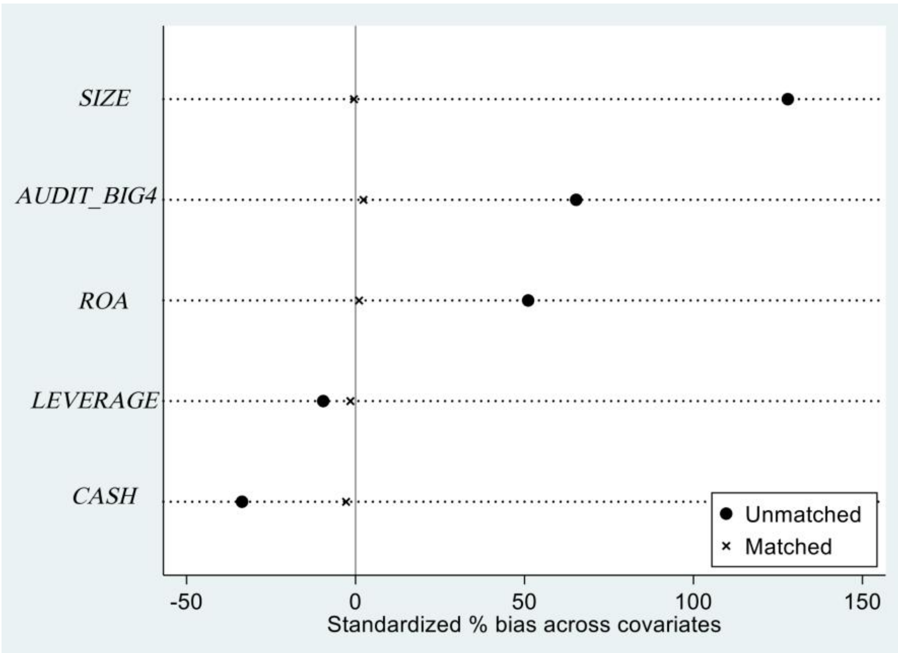

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Table 5.8 cont'd.

Panel D: LPM estimates based on propensity score matched sample.

	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$
	(1)	(2)
$COLLAB_{i,t}$	0.024**	
	(2.16)	
$CONTROL_t$		-0.059***
		(-2.84)
$SIZE_{i,t}$	0.009	0.014
	(0.57)	(0.82)
$LEVERAGE_{i,t}$	-0.003	-0.001
	(-0.16)	(-0.07)
$ROA_{i,t}$	-0.020	-0.012
	(-0.58)	(-0.33)
$AUDIT\_BIG4_{i,t}$	0.007	0.018
	(0.15)	(0.36)
$CASH_{i,t}$	0.002	-0.003
	(0.12)	(-0.20)
YEAR FE	Yes	Yes
INDUSTRY FE	Yes	Yes
Adj. R^2	0.17	0.18
N	1299	1299

(* p<0.1; ** p<0.05; *** p<0.01)

Table 5.9: Heterogeneity Analysis: Relationship between Collaborate/Control Culture and Data Breach Incident Based on Propensity Score Matched Sample

This table presents Linear Probit Model (LPM) based on propensity score matched sample to further validate the relationship between collaborate/control culture and the likelihood of data breach incidents for the time priod 2007-2018. I employ four subsamples based on the number of employees: (1) companies with 100 employees or fewer (no results reported in the table); (2) companies with more than 100 employees but fewer than or equal to 1000; (3) companies with more than 1000 employees but fewer than or equal to 10,000; (4) companies with more than 10,000 employees. The estimates include year and industry fixed effects. All variables are defined in Table 5.12, the model includes a constant (not shown in the table) and the standard error is clustered at the firm level. The t-statistics are given in parentheses.

	100 <Employee <=1000		1000 <Employee<=10000		Employee>10000	
	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$	$BREACH\_DUMMY_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$COLLAB_{i,t}$	0.036		-0.017		0.037***	
	(0.69)		(-0.80)		(2.75)	
$CONTROL_{i,t}$		-0.211***		-0.031		-0.087**
		(-2.81)		(-1.51)		(-2.47)
$SIZE_{i,t}$	0.060	0.120	-0.038	-0.044	-0.001	0.002
	(0.54)	(1.08)	(-0.86)	(-0.98)	(-0.04)	(0.07)
$LEVERAGE_{i,t}$	0.086	0.127*	0.007	0.007	0.003	0.004
	(1.09)	(1.88)	(0.30)	(0.28)	(0.10)	(0.12)
$ROA_{i,t}$	0.033	0.056	-0.001	-0.004	-0.023	-0.030
	(0.35)	(0.63)	(-0.02)	(-0.06)	(-0.29)	(-0.39)
$AUDIT\_BIG4_{i,t}$	0.079	0.087	-0.055	-0.055	0.211	0.219
	(0.65)	(0.73)	(-0.77)	(-0.78)	(1.34)	(1.38)
$CASH_{i,t}$	0.036	0.047	0.089	0.088	-0.120**	-0.134**
	(0.46)	(0.65)	(1.49)	(1.48)	(-2.26)	(-2.41)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	-0.03	0.04	0.19	0.19	0.19	0.19
N	99	99	437	437	692	692

(* p<0.1; ** p<0.05; *** p<0.01)

Table 5.10: Robustness Tests: Relationship between Culture and Cyber Risk Based on Propensity Score Matched Sample

This table presents the bias reduction and matching quality between treated (*INTERNAL_DUMMY* equal to 1, which means the variable *INTERNAL_FOCUS* is more than 0.5) and control samples (*INTERNAL_DUMMY* equal to 0) after implementing propensity score matching, using metrics such as mean, bias percentage, bias reduction, and t-tests in key financial metrics (Panel A). Panel B visually represents the standardized percentage biases across various covariates, both before and after matching. Panel C presents ordinary least squared (OLS) regression estimates for the relationship between collaborate/control culture and the likelihood of data breach incidents based on propensity score matched sample for the time priod 2007-2018. The estimates include year and industry fixed effects. All variables are defined in Table 5.12, the model includes a constant (not shown in the table) and the standard error is clustered at the firm level. The *t*-statistics are given in parentheses.

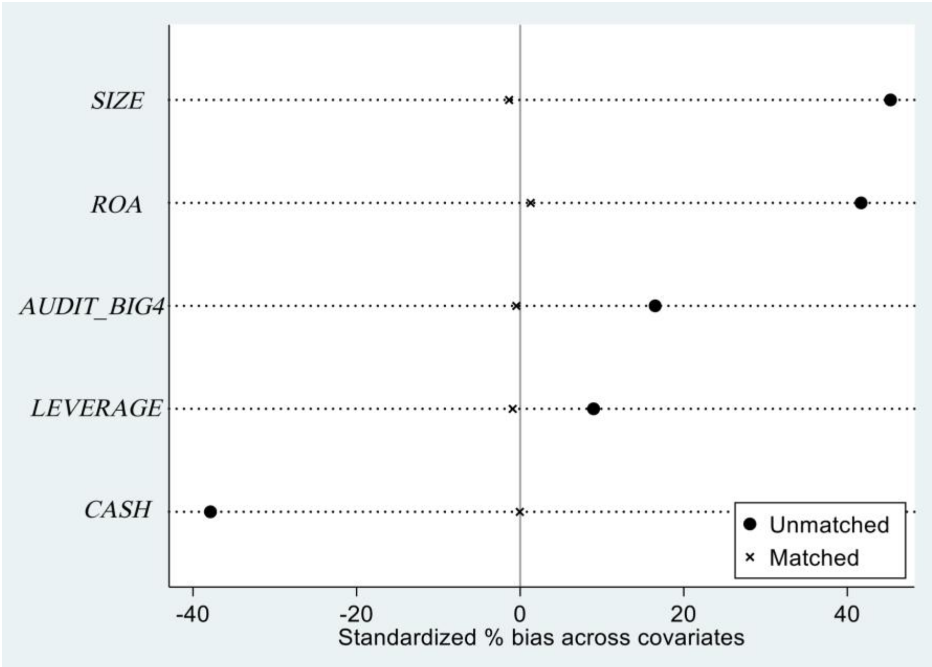
Panel A: Demonstrating the effectiveness of the propensity score matching.

Variable	Unmatched	Mean		Bias	Reduct Bias	t-test	
	Matched	Treated	Control	(%)	(%)	t	P > |t|
SIZE	U	0.2345	-0.2182	45.3		27.17	0.000
	M	0.2346	0.2482	-1.4	97.0	-0.62	0.537
LEVERAGE	U	-0.0097	-0.0913	9.0		5.4	0.000
	M	-0.0111	-0.0027	-0.9	89.7	-0.4	0.692
ROA	U	0.2773	-0.1090	41.7		20.56	0.000
	M	0.2774	0.2657	1.3	97.0	0.86	0.391
AUDIT_BIG4	U	0.7821	0.7105	16.5		9.43	0.000
	M	0.7820	0.7841	-0.5	97.1	-0.22	0.823
CASH	U	-0.2812	0.0383	-37.9		-19.06	0.000
	M	-0.2812	-0.2807	-0.1	99.9	-0.04	0.971

continued on the next page

Table 5.10 cont'd.

Panel B: Visual representation of the standardized percentage biases across various covariates, both before and after matching.



Panel C: OLS regression estimates based on propensity score matched sample.

	$CYBER\_RISK_{i,t}$
	(1)
$INTERNAL\_DUMMY_{i,t}$	-0.096***
	(-4.65)
$SIZE_{i,t}$	0.162***
	(12.77)
$LEVERAGE_{i,t}$	-0.036***
	(-4.04)
$ROA_{i,t}$	0.001
	(0.06)
$AUDIT\_BIG4_{i,t}$	0.147***
	(5.50)
$CASH_{i,t}$	0.007
	(0.43)
YEAR FE	Yes
INDUSTRY FE	Yes
Adj. R^2	0.52
N	14921

(* p<0.1; ** p<0.05; *** p<0.01)

Table 5.11: Robustness Tests: Relationship between Champions in Collaborate/ Control Culture and Cyber Risk

This table presents ordinary least squared (OLS) regression to investigate the relationship between champions in collaborate or control culture and the cyber risks for the time priod 2007-2018. $COLLAB\_CHAMPION9_{i,t}$, $CONTROL\_CHAMPION9_{i,t}$, $COLLAB\_CHAMPION8_{i,t}$ and $CONTROL\_CHAMPION8_{i,t}$ represent champions in relative culture. The estimates include year and industry fixed effects. All variables are defined in Table 5.12, the model includes a constant (not shown in the table) and the standard error is clustered at the firm level. The *t*-statistics are given in parentheses.

	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$	$CYBER\_RISK_{i,t}$
	(1)	(2)	(3)	(4)
$COLLAB\_CHAMPION9_{i,t}$	-0.039**			
	(-2.49)			
$CONTROL\_CHAMPION9_{i,t}$		-0.085***		
		(-3.27)		
$COLLAB\_CHAMPION8_{i,t}$			-0.047***	
			(-3.27)	
$CONTROL\_CHAMPION8_{i,t}$				-0.103***
				(-5.26)
$SIZE_{i,t}$	0.168***	0.166***	0.169***	0.167***
	(15.15)	(14.97)	(15.20)	(15.10)
$LEVERAGE_{i,t}$	-0.029***	-0.029***	-0.029***	-0.028***
	(-3.92)	(-3.83)	(-3.93)	(-3.75)
$ROA_{i,t}$	-0.002	0	-0.001	0.001
	(-0.21)	(-0.04)	(-0.19)	-0.14
$AUDIT\_BIG4_{i,t}$	0.173***	0.170***	0.173***	0.168***
	(7.91)	(7.81)	(7.93)	(7.74)
$CASH_{i,t}$	-0.019**	-0.019**	-0.020**	-0.020**
	(-2.42)	(-2.40)	(-2.49)	(-2.53)
YEAR FE	Yes	Yes	Yes	Yes
INDUSTRY FE	Yes	Yes	Yes	Yes
Adj. R^2	0.49	0.49	0.49	0.49
N	32091	32091	32091	32091

(* p<0.1; ** p<0.05; *** p<0.01)

Table 5.12: Definition of Variables for Chapter 5

Symbol		Definitions
Cyber risk variable		
CYBER_RISK	=	The cosine similarity between a firm's cyber risk disclosure and the cyber risk disclosures of firms that have been subject to a cyberattack during the 1-year period prior to the firm's current filings (Florackis et al., 2023);
Culture variables		
INTERNAL_FOCUS	=	Firm's relative internal focused culture estimated for each fiscal year using the text-analysis approach and computed as [(collaborate words + control words) / (collaborate words + create words + compete words + control words)];
COLLAB	=	Firm's relative collaborate culture estimated for each fiscal year using the text-analysis approach and computed as [collaborate words / (collaborate words + create words + compete words + control words)];
CONTROL	=	Firm's relative control culture estimated for each fiscal year using the text-analysis approach and computed as [control words/ (collaborate words + create words + compete words + control words)];
INTERNAL_DUMMY	=	An indicator that equals to 1 if the *INTERNAL_FOCUS* score [(collaborate words + control words) / (collaborate words + create words + compete words + control words)] is more than 0.5 and equals to 0 otherwise;
Breach variable		
BREACH_DUMMY	=	An indicator that is equal to 1 if a data breach event occurred in the company during this fiscal year and is 0 otherwise;
Control variables		
SIZE	=	The natural logarithm of firm's total assets [Compustat item: at];
LEVERAGE	=	The debt in current liabilities [Compustat item: dlc] scaled by total assets [Compustat item: at];
ROA	=	The return on assets is calculated as net income [Compustat item: ni] scaled by total assets [Compustat item: at];
*AUDIT_BIG*4	=	An indicator that equals to 1 if the company is audited by one of the Big 4 accounting firms (i.e., KPMG, PWC, Deloitte, and E&Y) [Compustat item: au = 3, 4, 5, 6, or 7] and equals to 0 otherwise;
CASH	=	Cash and short-term investments [Compustat item: che] scaled by toal current liabilities [Compustat item: lct];
Other variables		
EMP	=	The number of employees which is measured in thousands [Compustat item: emp];
Robustness tests		
COLLAB_CHAMPION9	=	An indicator that equals to 1 if score high (decile sorting ranked 9 or above) in collaborate culture and equals to 0 otherwise;
COLLAB_CHAMPION8	=	An indicator that equals to 1 if score high (decile sorting ranked 8 or above) in collaborate culture and equals to 0 otherwise;
CONTROL_CHAMPION9	=	An indicator that equals to 1 if score high (decile sorting ranked 9 or above) in control culture and equals to 0 otherwise;
CONTROL_CHAMPION8	=	An indicator that equals to 1 if score high (decile sorting ranked 8 or above) in control culture and equals to 0 otherwise;

6 Conclusion

This thesis makes substantial contributions to the field of organizational culture by developing and applying a novel text-based methodology for measuring organizational culture and investigating its implications across three critical domains: organizational adaptation during crises, financial performance in the banking sector, and cybersecurity risk management. These interconnected studies advance the understanding of organizational culture measurement and its role in shaping strategic outcomes, offering actionable insights for researchers, managers, and policymakers.

The first study develops a text-based methodology for measuring organizational culture using 10-K filings. Traditional approaches such as surveys and interviews are resource-intensive, often lack longitudinal scope, and are inaccessible to external stakeholders. This research addresses these limitations by employing a bag-of-words approach grounded in the Competing Values Framework (CVF) and the Organizational Culture Assessment Instrument (OCAI). The methodology allows for dynamic, longitudinal analysis of organizational culture, providing a powerful tool for internal and external stakeholders. A key contribution of this study lies in bridging the gap between theory and practice, offering a replicable and scalable approach that makes culture measurable in a dynamic and objective way. The empirical validation of this methodology, including its application during the COVID-19 pandemic, highlights its ability to uncover the interplay between cultural evolution and organizational adaptability during crises. A key policy implication is the potential for regulators and market participants to leverage text-based metrics as standardized indicators of corporate culture, improving transparency and accountability. Policymakers could also promote initiatives that encourage cultural adaptability to help organizations better withstand external shocks.

Building on this methodological foundation, the second study explores the relationship between competition culture and financial performance within the banking sector. The findings reveal that banks with strong competition culture are more likely to meet or beat analysts' forecasts and are less inclined to engage in earnings manipulation through discretionary loan loss provisions. This research significantly extends the application of the culture measurement methodology to the financial sector, demonstrating how culture shapes decision-making behaviors in a regulated industry. An important contribution of this chapter is its empirical evidence on how competition culture aligns managerial behavior with long-term financial performance while reducing opportunistic practices, offering a balanced view of the competitive environment. These results have critical policy implications. For regulators, fostering an environment that encourages balanced competition culture can enhance financial transparency and ethical reporting practices. For banking institutions, the findings highlight the importance of integrating cultural assessments into risk management frameworks to align managerial incentives with long-term organizational goals. Policymakers could also consider guidelines that link cultural attributes with regulatory compliance to enhance financial integrity.

The third study examines the influence of collaborate and control cultures on cybersecurity outcomes, focusing on cyber risks and data breach incidents. The results indicate that a control culture significantly enhances cyber risk management through structured compliance and systematic risk mitigation approaches. Meanwhile, collaborate culture demonstrates varied effectiveness, mitigating risks in smaller organizations but potentially exacerbating vulnerabilities in larger firms. A key contribution of this study is its novel application of organizational culture to the domain of cybersecurity, demonstrating that cultural attributes influence not only internal operations but also external risk profiles. By empirically linking culture types to cybersecurity outcomes, this research bridges the fields of organizational studies and information security. The policy implications are twofold. First, organizations should align their cultural strategies with their size and operational complexities, as a one-size-fits-all approach to cybersecurity may be counterproductive. Second, regulators and firms should prioritize strengthening internal control systems as part of broader cybersecurity strategies, ensuring cultural alignment enhances resilience against cyber threats.

Across all three studies, the thesis emphasizes the transformative potential of organizational culture as a strategic tool. The text-based methodology provides a replicable and scalable framework that transcends industry boundaries, offering robust insights into how culture influences critical outcomes. For policymakers, these findings highlight the need to incorporate cultural metrics into regulatory frameworks and corporate governance standards, ensuring that organizational culture aligns with broader societal and economic goals. For practitioners, the research underscores the importance of adopting culture-informed strategies to enhance organizational resilience, financial transparency, and risk management capabilities.

While this thesis provides valuable insights, its scope and methodology also present overarching limitations. The reliance on 10-K filings, while offering objectivity and scalability, may exclude cultural dimensions not explicitly articulated in corporate disclosures. Furthermore, the focus on U.S.-based firms may restrict the generalizability of findings to other contexts. Methodological challenges, such as potential biases in text processing and the selection of keywords, underscore the need for further validation and refinement of the text-based approach. Addressing these limitations in future research could enhance the robustness and applicability of the findings.

Future research should build on the strengths of this work by expanding its methodological and contextual boundaries. Exploring the interaction between organizational culture and emerging technologies such as artificial intelligence and blockchain could provide new insights into culture-driven innovation. Cross-industry and cross-regional studies would enhance the generalizability of the methodology, while experimental designs could establish causal relationships between culture and organizational outcomes. Additionally, integrating qualitative methods, such as interviews or ethnographic studies, could complement the text-based approach, offering a richer understanding of cultural nuances.

In conclusion, this thesis makes significant contributions to the understanding and measurement of organizational culture, offering a robust, scalable methodology and demonstrating its application across diverse domains. By addressing key gaps in traditional culture measurement methods and linking cultural attributes to critical organizational outcomes, this research provides actionable insights for theory, practice, and policy. While acknowledging its limitations, the thesis lays the groundwork for future investigations into the dynamic and multifaceted role of organizational culture, emphasizing its strategic importance in navigating an increasingly complex and interconnected global landscape.

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