DOES BANK CULTURE MATTER FOR BANK PERFORMANCE: EVIDENCE FROM MACHINE LEARNING APPROACH

Abstract

This paper further expands the recent study by Li et al. (2021b). In particular, we investigate the impact of bank culture on the performance of selected U.S. bank holding companies. By using an innovative machine learning approach, we argue that the strong bank culture may lead to higher banks' performance. We also find the positive impact of strong bank culture still holds in volatile environments, such as during unexpected crises. The paper highlights the value of an optimal bank culture in order to improve the performance of the banking system.

1. Introduction

What makes some banks perform worse in a crisis and what makes some other banks more sensitive to crises? A great deal of time and resources has been devoted to design policy measures and governance interventions that should in theory effectively prevent disturbances caused by economic crises and safeguard the stability of markets. Yet, the lesson from the 2008-09 global financial crisis is that such measures had seemingly failed to work.

Despite this rather questionable effort of implemented macroprudential policy imposed by policy makers, we have recently been observing a new wave of research studies that apply a different approach to tackle the causes of bank failures. This strand of research focuses on social factors that are less tangible and may complement formal institutions. There has been a number of influential studies that have shed light on the importance of corporate culture in shaping banks' behaviors and in maintaining systemic and financial stability (i.e., Fahlenbrach et al., 2012; Dudley, 2014; Financial Stability Board, 2014; Group of Thirty, 2015; Chaly et al., 2017). This direction of research has been strongly supported by anecdotal evidence from the Wells Fargo scandal or the collapse of the Lehman Brothers have suggested that the competitive culture has induced their employees to take excessive risk. Another example is the risk culture of Goldman Sachs, which allowed the bank to perform better than its competitors during the crisis. More recently, the difficulties of former high executives of Goldman Sachs such as John Corzine in their post-Goldman Sachs life have been viewed as further evidence that these executives were successful at Goldman Sachs not simply because of their skills but also because of the culture they belonged to.

Building on the study of Li et al. (2021b), we further expand their work in an innovate manner by quantifying bank culture with seven different cultural dimensions. In our study we shed light on answering the question of whether

and how bank culture matters in shaping bank performance during a crisis. That would provide important policy implications for regulators in supervising financial institutions as well as in the attempt of preventing a potential crisis. The expansion of this research has been limited due to the nebulous nature of culture which caused measurement issues as has been pointed out by Guiso et al., 2006 and Fiordelisi et al., 2014 among others. Furthermore, there is a complete lack of empirical research that would explore how bank culture affects banks performance during an unexpected shock, e.g., a financial crisis.

Thus, we formulate the following research questions: Does bank culture matter for bank performance during a financial crisis? If yes, does the strong culture developed by banks will help them perform better during other different crises, such as a health crisis (i.e., the Covid-19 pandemic) or any other natural disasters in the future? Ultimately, what are the channels through which the strong bank culture has helped a bank better deal with a crisis?

In contrast to the previous studies that investigate the role of culture in explaining firm performance during the financial crisis 2008 only, we focus on the COVID-19 pandemic as an additional economic shock event. The COVID-19 crisis, which began in late 2019 and continues to this day, is one of humanity's most severe natural disaster. While this health crisis and the global financial crisis (GFC) of 2007–2008 are similar in terms of their economic shocks of the unprecedented scale and both have detrimental effect on the global economy, there are a few variations between the two.

This paper differs from the previous research by providing the first empirical evidence of how bank culture may affect the performance of banks in the current pandemic, this study contributes to the literature in several ways. First, the paper is the first one that proposes the most recent machine learning approaches to quantify bank culture—the word embedding model (Mikolov et al. 2013). Although, a growing strand of literature has started applying machine

learning in measuring culture in firms (i.e., Aswani and Fiordelisi, 2020; Wyrobek, 2020; and Bonsall et al., 2021), so far, to our best knowledge, there is no paper that deploys the word embedding model as a novel method to quantifying culture in the banking sector. As such, by applying the word embedding model, we make a significant methodological contribution to the contemporary research on corporate culture in the particular case of banking industry.

Second, we add to the growing body of research examining the relevance of corporate culture to firm value and performance. For instance, Guiso et al. (2015) document survey-based evidence that a culture of integrity enhances firm value. Graham et al. (2017) present interview- and survey-based evidence that culture, when effectively enforced by cultural norms and formal institutions, adds to firm value. Lins et al. (2017) find that firms with more social capital fared better during the 2008-09 financial crisis, consistent with a greater support from stakeholders due to a more trustful relationship. Li et al. (2021a) applies machine-learning techniques, analyze text on earnings call transcripts, and document that firms with a strong culture have high firm value during normal and bad times. However, no study so far investigates the role of corporate culture in the banking sector. As such, our study offers a deeper awareness of how intangible factors in general, and how bank cultural factors, are associated with bank performance during the pandemic.

Third, given the fact that the COVID-19 pandemic is exogenous to a bank's fundamentals, this unique setting allows us to establish a causal effect of crisis on the bank culture-performance link in the banking industry. This is critical because the finance literature (i.e., Gallagher, 2014; Bernile et al., 2017; Dessaint and Matray, 2017) is increasingly interested in understanding how natural disasters influence organisations' risk perceptions and performance, especially those have experiences of surviving from a crisis in the past. Unfortunately, no study so far examines this link in the context of banking. As such, our study will

contribute to the literature by showing empirical evidence to shed light on the impact of bank culture on bank performance in many aspects during the pandemic.

The paper is organized as follows: After the introduction, we provide a literature review of the related research and by identifying a gap in the literature we propose research hypotheses in section 2. In Section 3, we provide an overview of the word embedding model and how we use it to measure bank culture as well as some validation tests. Section 4 presents data and methodology while Section 5 concludes.

2. Related literature and hypothesis development

2.1 Literature about bank culture

It has been recognized and broadly accepted that corporate culture plays a significant role in driving firm and market outcomes (see, for example, Zingales., 2011; Fahlenbrach et al., 2012; Guiso et al., 2015; Graham et al., 2016; Karolyi, 2016; and Egan et al., 2019 among others). Zingales (2011) provides the definition of corporate culture as the common assumptions, attitudes, and ideas that assist employees determine which behaviours are more suitable. The findings from a survey of over 1,300 chief executives and financial officers of North American public and private firms have revealed that culture is one of the top three elements that determine corporate value (Graham et al., 2016; Graham et al., 2017).

In theory, corporate culture may be thought of as an unfinished contract between the company and its employees (Gorton and Zentefis, 2020). Although employment contracts can explicitly punish employees with written agreements, they cannot define all feasible situations because of contractual expenses. Corporate culture aids in the resolution of this issue by providing a common guideline for employees in terms of appropriate behaviours. Since this shared

notion is not documented in any official reports or documents, outsiders may not easily observe, assess and measure the corporate culture of an organization.

Given the important role of corporate culture in explaining firm's behaviors and business outcomes, the last decade has witnessed a revolution of cultural studies in economics and finance research (i.e., Zingales, 2011; Guiso et al., 2015; Karolyi, 2016 and Barth and Mansouri, 2021). Accordingly, there have been a variety of concepts and methodologies used to measure corporate culture. For example, according to O'Reilly and Chatman (1996), the definition of corporate culture is "a collection of rules and values that are broadly shared and strongly held within the firm". Schein (1991) illustrates that corporate culture may be manifested into three different levels: basic assumptions; common beliefs and values and the artefacts. In banking literature, a growing number of studies attempt to address some aspects of corporate culture. For example, Guiso et al. (2015) develop nine corporate culture categories based on the company's core values listed on its website. In addition, the theoretical study of Song and Thakor (2019) develops a culture model, which highlights that culture plays an important role in matching the bank itself with its manager who shares common beliefs.

The extant literature has limited empirical evidence about the effect of corporate culture, partly because of the nebulous nature of corporate culture and its numerous measurement issues (Zingales, 2011). Recent scholars have started to address this issue by applying a particularly common approach namely counting word occurrences from word lists (dictionaries) with similar meanings. For instance, some studies have utilized the Competing Values Framework (CVF) to quantify corporate culture and examine its impact on numerous economic phenomena (i.e., Cameron et al., 2006; Hartnell et al., 2011; Fiordelisi and Ricci, 2014; Nguyen et al., 2019 and Andreou et al., 2021). As a result, the CVF has increasingly become one of the most widely used frameworks for

measuring corporate culture since it can capture the well-perceived dilemmas of organizational life.

More recently, machine learning (ML) methods have increasingly become an advanced technology for research in finance in the 2020s. Literature about the application of machine learning in corporate finance and baking can briefly be classified into different seven following groups: bankruptcy prediction, stock price prediction, portfolio management, oil price prediction, anti-money laundering, behavioral finance, asset pricing, big data analytics and block chain.

The *first* research stream emphasizes on using ML to anticipate business bankruptcy, credit risk, credit scoring, and credit ratings. For example, neural networks and support vector machines (SVMs) have been applied in the study of Jones et al. (2017) to predict the creditworthiness and perform better than the traditional classification models such as linear discriminant analysis, binary logistic, probit and logit models. Similarly, other scholars (i.e., Chen et al., 2011; Kwak et al., 2012; Lahmiri and Bekiros, 2019) have used ML approaches, such as decision trees, neural networks, a generalized multiple kernel machines and SVMs to predict the bankruptcy of firms and banks and have shown that their prediction results are more accurate. In terms of credit risk, Khandani et al. (2010) applied ML techniques to evaluate customer credit risk; Trustorff et al. (2011) utilized SVMs to predict default classification and default probability and Acheampong and Elshandidy (2021) applied ML algorithm to estimate customers' default risk and all these authors found better prediction results. Finally, neural networks and ML techniques have also extensively used by many authors (i.e., Huang et al., 2004; Abdou et al., 2014; De Moor et al., 2018 and Plakandaras et al., 2020) to forecast bond ratings, credit scoring, credit ratings and demonstrated that their approaches significantly improve the old methods.

The *second* stream of ML research (i.e., Gorenc Novak and Veluscek, 2016; Ghosh et al., 2021 and Liu et al., 2021) focuses on predicting stock prices by using SVMs, random forests and long short-term memory (LSTM). This line of research has become increasingly popular in the last decades thanks to its higher accuracy in prediction compared to traditional methods. Besides that, ML techniques have also used in managing portfolio, estimating stock volatility, and calculating stock liquidity (i.e., Manela and Moreira, 2017 and Braun et al., 2020). In addition, to predict and examine factor pricing models, Giglio and Xiu (2017) and Gu et al. (2019) use dimension reduction approaches. Tree-based methods are also used by Moritz and Zimmermann (2016) to rank portfolios. Shrinkage and selection approaches are used by other scholars (i.e., Kozak et al., 2020 and Freyberger et al., 2020) to approximate a stochastic discount factor and a nonlinear function for expected returns.

Third, ML techniques, such as ANNs, LSTM, time delay neural network (TDNN), and deep belief networks have also been often used to predict changes in prices of oil, gold and agricultural commodities since they can produce higher prediction accuracy. *Fourth*, ML methods have been widely applied to detect money laundering activities in different contexts such as banks or charity organizations (i.e., Kannan and Somasundaram, 2017; Garcia-Bedova et al., 2020; Jullum et al., 2020; and Singh and Lin, 2020); to detect fraudulent financial reporting (i.e., Goel and Uzuner, 2016) and to manage risks (Omar et al., 2017 and Falco et al., 2021). *Fifth*, many scholars have seen ML techniques as a popular tool for behavioral studies. For instance, by applying random forest or deep neural networks, Felix et al. (2020) can build volatility sentiment, while Ghosh et al. (2018) can identify possible explosive moments in the stock index in India. Moreover, Konigstorfer and Thalmann (2020) used ML methods to improve security in processing payments and customer retention.

Many other scholars have utilized ML methods in the asset pricing studies. For example, Rapach et al. (2013) used lasso to forecast global equity

market returns based on all countries' lagged performance. In a number of papers, neural networks are employed to predict derivatives prices (i.e., Yao et al., 2000); to estimate mortgage prepayment, delinquency and foreclosure (Sirignano et al., 2016) or to select a portfolio (Heaton et al., 2016). In addition, regression trees are also used by Khandani et al. (2010) to forecast consumer credit and delinquencies and defaults. *Finally,* AI, block chain and big data analytics are well known as the top ten emerging technologies in financial industries recently. ML techniques, such as random forest, decision trees and XGBoost can be used to enhance customer service (Hanafy and Ming, 2021) or to obtain competitive advantage in AI and big data to outperform competitors (Antoncic, 2020).

In sum, the adoption of ML has become widely known in different areas of finance research since it allows us to construct construct superior and novel measures. When using machine learning methods, we are able to extract information from unconventional data such as text or images. This source of data can then be used as an original and superior measurement of economic factors since it can mitigate measurement error and thus permit for more exact estimation of economic relationships than traditional methods. In addition, this approach enables us to undertake many studies with unmeasurable variables which have seen as impossible in the past. The second explanation is that until now in order to extract information from company reports, most banking and finance studies are depending on textual analysis. For example, counting word occurrences from word lists or dictionaries that have similar meanings is a popular strategy that have been widely used by many researchers. Applications such as tone (sentiment) evaluation (Loughran and McDonald, 2011; Henry and Leone, 2016), text categorization, and topic modelling are based on this "bag-of-words" approach. Nevertheless, as pointed out by Loughran and McDonald (2016), the textual analysis tools work exclusively on the document level and consider words as separate tokens, assuming that order and context are irrelevant.

In this regard, the word embedding model has been developed and appears to be more advanced by utilising a neural network to deeply parse the immediate contexts of words. Consequently, instead of individual tokens, sentences and phrases are represented as numeric vectors. At the expression level, such vectorization allows us to quantify the semantics rather than just the syntactic.

In terms of applying machine learning methods in measuring corporate culture, we recognize that Li et al. (2021b) have made the most progress by utilizing NLP models to exploit key aspects of company culture from transcripts of earnings calls, one source of information given by business leaders. Instead of the conventional "bag of words" technique, they adopt a semi-supervised machine-learning approach with word embedding for textual analysis (Loughran and McDonald 2011). The authors offer a strategy for breaking down corporate culture into the five values that the S&P 500 companies most frequently mention: innovation, honesty, quality, respect, and teamwork (see Guiso, Sapienza, and Zingales). Similarly, the study of Li et al. (2021a) has investigated the role of corporate culture during the COVID-19 pandemics in a very creative manner. Using the word embedding model, these authors have not only quantified corporate culture but even more importantly, develop a new measure of firm exposure and response related to the Covid-19 crisis for 2,894 U.S. firms. They find that firms with a strong corporate culture outperform their peers without a strong culture.

Building on these two most influential studies of Li et al. (2021a&2021b), in this research, we also apply the word embedding model-one of the latest machine learning techniques—to quantify culture in the banking sector– a special industry that has not been examined carefully before. In fact, we have further expanded their work in an innovate manner by quantifying bank culture with seven different cultural dimensions found out from the most frequently advertised values that are manually collected from banks' websites.

2.2 Strong bank culture and bank performance and hypothesis development

A number of studies, see, for example, O'Reilly and Chatman, 1996: 166; O'Reilly, 1989; Gordon and DiTomaso, 1992, used and defined the term strong culture. Broadly speaking the term strong culture might be defined as the adoption of the norms and values that are broadly shared and strongly held within a firm. This strong culture has been seen by many scholars (i.e., Gordon and DiTomaso, 1992; Burt et al., 1994) as an important element within the organization that may help improve corporate performance. Accordingly, the view that strong culture can increase the performance of a firm has been supported by the strand of literature that investigates the consequences of a strong corporate culture. Strong culture acts as a social control mechanism that leads to increased behavioral consistency among employees within an organization (O'Reilly; 1989; O'Reilly and Chatman, 1996). It also shapes people's perceptions of organisational events and fundamental beliefs about organisational procedures. The study of Schein (1991) further highlighted that a strong culture can offer group members a method of providing meaning to their everyday lives, defining guidelines and regulations for how to act, how to behave and how to mitigate the anxiety of coping with an unexpected and changing business condition. Similarly, Gordon and DiTomaso (1992) pointed out that the consensus regarding basic assumptions and widely shared values in the company should boost behavioural consistency and, as a result, improve organisational performance, which is a function of the potential return on an organization's business activities and its capacity to implement those operations. Behavioural consistency has a critical influence execution because corporations having good strategies are more likely to experience poor performance if they cannot execute properly, and firms that perform their routines well may be able to compensate for poor plans.

Although it is likely that organisations strong cultures are good (or bad) at selecting appropriate plans, literature about the impact of strong culture often emphasise on its beneficial influence on the execution of day-to-day routines. Accordingly, there are three interconnected theories explaining the superior performance driven by strong cultures have been proposed by theorists (Kotter and Heskett, 1992). *First*, social control inside the corporation is facilitated by the widespread agreement and acceptance of organisational norms and values. Violations of behavioural norms may be recognised and remedied more quickly when there is widespread agreement that certain acts are more suitable than others. Other workers, regardless of their hierarchy status in an organisation, are more inclined to take corrective action. As a result, informal social control appears to be more effective and less expensive than formal one (O'Reilly and Chatman, 1996). *Second*, the strong culture help strengthen the alignment of targeted goals. In the case that organisational goals and processes are set clear, employees confront less doubt regarding the best course of action when encountering unexpected scenarios, and thus they can respond properly. The alignment of targeted goal also makes cooperation easier since there is less opportunity for disagreement or the conflict of interests among different parties (Kreps, 1990 and Cremer, 1993). *Finally*, strong cultures can boost employee motivation, commitment and thus their performance since employees recognize that their choices are their own (O'Reilly, 1989; O'Reilly and Chatman, 1996). This argument is further supported by the findings of other studies (i.e., Peters and Waterman, 1982; Deal and Kennedy, 1982; Kotter and Heskett, 1992) which conclude that having highly motivated individuals devoted to similar goals benefits firms.

Empirical evidence from previous studies have also shown that firms with stronger cultures perform better than those with weaker ones. For instance, the study of Kotter and Heskett (1992) shows that firms possess strong cultures experienced higher return, greater rise in net income, and more changes in share

price across different industries. Similarly, according to Gordon and DiTomaso (1992), the performance of insurance firms improves when there is a strong agreement on cultural values. Using both qualitatively and quantitatively method, Denison and Spreitzer (1991) concluded that organisational values consensus enhances organisational success. Burt et al. (1994) re-examined Kotter and Heskett's data and discovered that the better performance arising from strong cultures was boosted when market competition becomes fiercer. The explanation is that during a more volatile market condition, such as an increase in competition level, differences in firm performance tend to be driven by differences in the effectiveness of organisational routines. Furthermore, Henderson and Van den Steen (2015) found that the strong culture has increased firm profitability because the high consensus on the right course of action in organisations owning a strong culture, has resulted in more effort among employees and cheaper pay.

Based on our thorough review of the current research we identify the established link between strong culture and higher firm performance. However, there is a lack of research that could confirm reject this type of the link for financial institutions in general and banks in particular. We therefore impose the hypothesis that would validate that the strong culture in a bank is also related higher performance. We assume that the strong bank culture can help increase the internal coordination among members within a bank, improve the goal alignment between the managers and employees, and enhance the consistent behavior among employees. This would then lead to higher employee efforts, commitments and performance, and ultimately boost bank performance. As such, we propose the first following hypothesis that link the strong culture of a bank to its performance:

H1: Banks having strong culture are associated with higher performance

While previous studies explore the link between strong culture and firm performance during normal times, the question is whether strong cultures enhance the performance of firm during 'bad' times too. This kind of the analysis is somehow neglected by current recent studies. Thus, we further argue that if the strong culture of a bank holding company helps build trust, consistent behavior and cooperation among employees to achieve better performance, it should pay off more during bad times, such as a financial crisis or an unexpected shock of the different nature including COVID-19 pandemic. By doing so, we attempt to demonstrate that a strong bank culture may improve not just the consistency with which a bank executes its organisational routines in normal times, but also the degree to which such routines are properly adaptable to changing market conditions. The support for testing the hypothesis is based on the notion described below.

From the perspective of stakeholders, Guiso et al. (2008) suggest that when investors decide to invest in a firm's stock, they assess not only the risk-return trade-off but also the extent to which a firm is reliable and trustworthy, and its overall system is fair. This is because during an unexpected crisis when public trust is deteriorated, outsider investors are more concerned about the reliability and creditability of financial information which based on that they make decisions (Lins et al., 2017). As such, they tend to seek more metrics such as the culture a bank belongs to, the social capital a bank is rated which speak more about how a bank is valued and is trusted in a crisis. In this circumstance, the strong and consistent culture developed by banks over times will act as a positive signal to earn trust from investor, which ultimately help bank better withstand from a crisis.

From the perspective of other shareholders, such as employees, customers, and the community in general, much of their communication and interaction with a bank happens via implicit or incomplete contracts that is less likely to be honored by either party in a crisis. In this circumstance, the strong culture

developed by banks over times will help facilitate communication between parties by strengthening trust and cooperation during a crisis. In banks having strong culture, employees tend to support their organization by for example, being more committed (Flammer and Kacperczyk, 2016) or more willing to receive lower compensation to assist banks in coping with negative shocks. Furthermore, banks having strong culture may have higher probability of survival due to their more formal and detailed internal audit and compliance, self-regulation, and risk management systems. Such institutions have more capabilities to solve contingencies, absorb negative shocks, and reduce losses during market crisis, thanks to their better-organized procedures and strategies. Furthermore, because of their organisational stability, such institutions are less likely to undertake significant employment and wage cuts, which helps to sustain staff morale and productivity (Kube et al., 2013). During times of crisis, banks with strong cultures may have more tighter risk controls, higher solvency, lower capital expense, and greater access to external finance (Levine et al., 2018; Lins et al., 2017), which ultimately help banks perform better than their peers with weak culture in crisis times.

Based on the above discussion, we predict that the strong bank culture will result in increased goal alignment, stronger motivation and commitment among employees and better controls without having to pay above-market rates. These impacts become more salient in a volatile business climate (i.e., a financial crisis or the COVID-19 pandemic) since the strong bank culture plays a critical role in encouraging both bank leaders and employees to have consistent behaviors and activities as well as put more effort to help banks effectively withstand the crises. As such, we propose the second following hypotheses:

H2: Banks having strong culture are associated with higher performance during a crisis

3. Measuring bank culture using word embedding model and validation tests

In this section, we provide a brief overview of the word embedding model that we use to measure bank culture. We then present some validation tests to ensure that our newly constructed measurement of bank culture from the word2vec model are strongly validated.

3.1 Overview of word embedding

In this study, we employ the word embedding to measure our main variable of interest that is bank culture. The reason why we choose it because the purpose of the word embedding is to use a numeric vector to describe the semantics, or in other words, the word's definition. By using simple vector arithmetic, this numeric word vector enables us to identify the connection between words. Then, using the cosine similarity between any two-word vectors, we can determine whether or not any pair of words is a synonym. After that, based on the learned similarity connection to seed words expressing a specific cultural dimension, a large group of words and phrases, which reflect that cultural dimension are then identified and used to score the culture of a bank accordingly.

As suggested by Harris (1954), the underlying fundamental assumption behind the word embedding model is that words appearing with the common neighboring words have similar meanings. As a result, the model determines synonyms from these same neighboring words. For that reason, to examine the relationship between any three specific words, we first count how many times any neighboring words co-occurring near these three words in a set of texts files. Then, for each of these three words, we use a vector to record the number of times those neighboring words that appear most often. Consequently, each vector will represent for each word and by doing so, we are able to calculate the relationship between any two words based on the cosine similarity of the underlying vector. A higher value of similarity between any two-word vectors

implies that these two words are semantically closed. The formula calculating the cosine similarity between any two-word vectors (i.e., v1 and v2) is as follows:

$$\text{Cosine Similarity} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}} \quad (1)$$

The above approach is the simple explanation for the sample where a word has little neighboring words. However, one might concern that the number of possible neighboring words is huge, we then cannot apply this simple count-based method. In this regard, Mikolov et al. (2013) has developed the word2vec model in natural language processing (NLP) which uses a neural network to effectively learn dense and low-dimensional vectors representing the meaning of a word. In particular, the word2vec uses a neural network to "learn" the meaning of a given word by "reading" through textual report and learning to anticipate all its neighbors. The neural network's parameters are chosen at random and are modified using backpropagation (a typical training procedure for neural networks), which enhances the network's ability in anticipating the neighboring words of a word. After the learning process and several iterations through the texts finish, a vector representing the word has been produced based on these parameters. As such, a vector can reflect the attributes of a word's original co-occurrence connection with its neighbors and the fixed dimension of a vector generally ranges from 50 to 500.

3.2 Measurement of bank culture using word2vec

Training the word2vec model

Before using the word2vec model to measure bank culture, we first need to train our word2vec model by using the gensim module in Python. We also require the following parameters as followed by previous studies (i.e., Pennington et al., 2014; Mikolov et al., 2013). We set the window size equals 5. This is the maximum distance between the focus word and its neighbors is

determined by this option. As a result, the algorithm is trained to anticipate the five words to its left and right using the focus word in the middle. We also set the dimension of the word vector is 300. This is the size of the vector we use to represent a word. The number of iterations over the corpus is equal to 20, which means that the number of times the algorithm goes through the corpus in order to train the parameters is twenty times. We omit words that appear in the corpus less than five times by setting the minimum word count is five. Finally, we employ the skip-gram with negative-sampling approach to speed up the training for a huge corpus. When the training process is finished, the word2vec model turns each of the word in the corpus into a 300-dimensional vector that represents the meaning of that word.

Seed words

The initial step of measuring bank culture is to analyze the advertised values of banks. We manually look at the bank holding companies' website and find sections where provide information about the bank holding companies' core values, culture and code of conducts. We then collect all these values and keep maintaining the wording used by them. Bank holding companies frequently define a set of fundamental values, which are then further articulated and clarified through the use of additional key words to clarify their meaning. We keep this clustering of cultural values as meaning units, grouping all of the key words used by the organization to define a single cultural value. Because our data was collected in December 2021, the data set represents the content of the Websites during this time.

When we finished collecting data for all bank holding companies, we started an aggregation process to find the dominant cultural values and divide them into different groups. To do so, we began by identifying the most common values across all bank holding companies. Starting from the top recurring value, we checked all the other words that were clustered with it by each bank holding company and their frequency across banks. We then took the one word that was

most associated with the main value and aggregated the two values together in a single category (unit of meaning). Then we went to the second-most-repeated value and did the same process to find the word that was most associated with it and combined the two values to build a new category. After performing this aggregation process for the most recurring values, seven following categories or groups of words emerged from the data:

- **Trust-oriented**– Seed words: Trust, maintain_trust, sustain_trust, public_trust, trust, relationship, deep_relationship, long_relationship, long term_relationship, relation, long_relation, reliable, reliability, mutual_respect, respectful, respect, ethics, ethical, accountable, accountability, honesty, honest, honestly, responsible, responsibility, transparency, transparent, believe, belief, dignity, Integrity, Diversity, diversified, Inclusion, inclusive.
- **Employee-oriented** - Seed words: Safety, Health, Work_balance, Life_balance, balancing, Reward, rewarding, Fun, funny, open_communication, work_environment, working_environment, Flexibility, flexible, Caring, care, careness, Teamwork, Collaboration, collaborate, collaborative, Cooperation, cooperate, cooperative, Fairness, fair, Talent, talented, Empowerment, empower, equality, equal, create_opportunity, generous_benefit, benefit, empathy.
- **Risk-oriented** – Seed words: manage risk, risk management, necessary_risk, accept_risk, acceptable risk, appropriate_risk.
- **Innovation-oriented** - Seed words: Digitalization, digital, Innovation, innovate, innovative, Creativity, create, creative, Entrepreneurship, entrepreneur, passion, passionate, dynamic, digital_capabilities, Leadership, advanced_technology, advanced, advances.
- **Performance-oriented** - Seed words: Growth, grow, Performance, perform, Efficiency, efficient, Results, Hard work, hard-working, Excellence, excellent, Improvement, improve, move_fast, fast_move, fast, speed
- **Customer-oriented -** Seed words: customer, Meet_customer_needs, customer_needs, customer_expectation, meet_customer_expectation +

customers_first, clients_first, customer-centric, exceed expectations, customer_committment, dedicate, dedicated, extraordinary_service, best_service, excellent_service, extraordinary_product best_product, excellent_product, quality, dedication, dedicate, dedicated

- **Community-oriented -** Seed words: caring for the community, commitment with the community, environment, caring, care, and citizenship.

In the spirit of Guiso et al. (2015), we use the seven most frequently mentioned values by banks based on the values advertised on their websites to measure bank culture that are: Trust-oriented, Employee-oriented, Risk-oriented, Innovation-oriented, Performance-oriented Customer-oriented, and Community-oriented to measure bank culture. We also employ the units of meaning (i.e., seed words) for each cultural value provided by these authors. Although the dictionary may be created using simply the value words (e.g., innovation), some of the cultural values listed by Guiso et al. (2015) have connotations that go beyond their cultural values. Thus, in the next step, we use the seed words described in Guiso et al. (2015) to capture the larger meanings of each cultural values.

It is worth to note that the word list obtained from the websites of bank holding companies may not be exactly appropriate to our context of using annual reports (10K-fillings) to calculate bank culture. Thus, after training the word2vec model (in order to obtain the word vector for each cultural value), we thoroughly review each cultural value in Guiso et al. (2015) to ensure that it is clearly defined using a coherent set of seed words and then remove any seed words that do not meet the two following criterias: (i) the term or phrase appears in the text documents and (ii) synonyms of a word or phrase (through word2vec) indicate that this term or phrase is unambiguously associated with bank culture.

We also include new seed words by using various forms of the initial seed words in Guiso et al. (2015). For instance, given that "**cooperation**" is on the list, we add its adjective (cooperative) and its verb (cooperate) in the word list.

We also add phrases that are more frequently used than the one listed in Guiso et al. (2015), such as "**customer commitment**" instead of **commitment**.

Preprocessing data

We first manually download 10-K reports from the Edgar website (www.sec.gov). In the next step, we conduct the preprocessing data and parsing the text. To do this, we use the Stanford CoreNLP package which is a multi-purpose open-source Natural Language Processing (NLP) toolkit (Manning et al. 2014). In this stage, the text documents are segmented into separated sentences and words. These words are then lemmatized into their base forms. However, as suggested by Routledge et al. (2018), phrases or word collocations are also important in expressing information. Therefore, we use the dependency parser available in the CoreNLP package to extract phrases, multiword expression as well as compound words. We also use the *phraser* module available in the *gensim* library to identify any two- or three-word phrases appear in the corpus. We treat all these phrases as a single word by using the underscore symbol "_". Our findings show that these phrases indeed play an important role in reflecting how cultural values are expressed in annual reports. In the final stage, we clean the text by removing any punctuation marks and stop words. We also exclude any single-lettered words presented in multiword expressions and compound words because some of them are part of the latter.

Generating the cultural dictionary

Using the trained word2vec model, we create an expanded, context-specific vocabulary for quantifying cultural values. The cosine similarity in each pair of word vector is calculated to measure the relationship between any two words. By doing this, we can build the cultural dictionary by combining a collection of words obtained from 10-K reports with seed words describing each cultural value. In the literature on information retrieval, a process known as bootstrapping is used to learn new semantic lexicons (Riloff and Jones 1999). Finally, all of the words created in the auto-generated dictionary are carefully

checked and those words that are inappropriate will be removed. We carefully examine the context of a word in 10-K reports when deciding whether it should be omitted.

Measuring bank culture

We calculate each of the seven cultural dimensions at the bank holding company-year level after creating the bank culture dictionary. For each annual report (10-K filing), we use the weighted count of the number of words linked with each cultural value divided by the total number of words in the text. Following Loughran and McDonald (2011) we use the weight tf.idf (term frequency-inverse document frequency). This weighting method gives words that appear more frequently in the texts a lower weight. Therefore, as compared to equal term frequency weighting, more common terms have a reduced impact on the score of cultural value. Particularly, tf (term frequency) reflects the word frequency in the text and idf (inverse document frequency) reflects the inverse frequency of the document with the word in the corpus. As such, this weighting scheme allows us to control for the importance of a word in a text as well as the significance of a word in the corpus.

Finally, as suggested by previous studies (i.e., Sorensen, 2002; Jiang et al., 2019; and Li et al., 2021), the strong culture which is driven by the widely shared and strongly held norms and values throughout the organization and its employees can greatly influence its performance. As such, we attempt to measure the strong culture of a bank holding company at the bank-year level. In particular, the variable "***strong_bank_culture***" takes a value of 1 if the sum of a bank's seven cultural value scores is in the third and fourth quartile across all bank holding companies in a year, and 0 otherwise.

3.3 Validating our measure of bank culture

Given the fact that our methodology of measuring bank culture in this study is new and unique, we need to conduct several validation tests using the well-

known markets for best practices in the corporate and banking literature. All the data come from MSCI database (formerly known as KLD and GMI).

First, to validate the cultural value of community, we use the community strength, community engagement and community impact index. The community strength is calculated as the total number of community strengths minus the total number of community concerns. Both the community engagement and community impact are indicator variables that takes the value of one if a bank is considered to have strengths in community engagement and community impact, respectively and zero otherwise. *Second*, to validate the cultural value of performance, we use the product quality strength, an indicator that equals one if a bank is considered to have strength in product quality. *Third*, to validate the cultural value of customer, we use two indicators namely product quality strength and product safety concerns. The former is an indicator that takes the value of one if a bank is considered to have strengths in product quality strength and zero otherwise. Meanwhile, the latter is an indicator that takes the value of one if a bank is considered to have concerns in product safety and zero otherwise. *Fourth*, to validate the cultural value of innovation, we the innovative giving index, which is a dummy variable that takes the value of one if a bank is considered to have strengths in innovation and zero otherwise. *Fifth*, to validate the cultural value of risk management, we use the financial system instability concern, an indicator that takes the value of one if a bank is considered to have concerns in financial system instability and zero otherwise. We also use leverage ratio, measured as total assets divided by total equity. According to Minton et al. (2019), an increase in leverage ratio makes equity riskier and thus, we would expect a negative relationship between the cultural value of risk management and leverage. *Sixth*, to validate the cultural value of employee, we use several different indicators namely retirement benefits concern, housing support strength, employee involvement, employee relation and diversity. Retirement benefits concern is an indicator variable that takes the value of one if a bank is

considered to have concerns in retirement benefits for employees and zero otherwise. Housing support strength is an indicator variable hat takes the value of one if a bank is considered to have strengths in housing support for employees and zero otherwise. Similarly, employee involvement, employee relation and diversity are three indicators that take the value of one if a bank is considered to have strengths in employee involvement, employee relation and diversity, respectively.

Table 1 of Internet Appendix presents the results for our validation tests for four cultural values namely, community, performance, customer and innovation and risk management. Column (1) of the Table show that the cultural value of *community* is positively and significantly associated with the community strength index. This positive relationship after we include into the OLS regression several bank characteristics variables. Column (2) of the Table show that the cultural value of *community* is positively related to the community engagement although we cannot find a significant link. As shown in column (3) of the table where the community impact concern is the dependent variable, despite the coefficient of the cultural value of *community* is not significant, its sign is negative. In terms of the cultural value of *performance*, our result from Column (4) show that *Performance* has a positive and strongly significant impact on the product quality strength. Column (5) of the table shows that our *customer* culture variable is positively and significantly associated with the strength of product quality. Regarding the product safety concerns indicator, while we cannot find a significant impact of the culture *customer*, its sign is negative. Next, column (7) of the Table provides the result for the cultural value of *innovation* that is a positive, but not significant impact on innovation giving indicator. Turning to our culture of *risk management*, column (8) shows that it has a positive impact on the financial system instability concern indicator. Lastly, column (9) shows that the *risk management* culture has a negative and significant influence on bank leverage. Finally, to validate the cultural value of trust, we use

five following indicators: Business Ethics concern, Privacy & Data Security concern, Union Relations concern, Transparency and Product quality safety concern. Except for transparency only, all four indicators take the value of one if a bank is considered to have concerns in Business Ethics, Privacy & Data Security, Union Relations, and Product quality safety respectively, and zero otherwise. For transparency, it takes the value of one if a bank is considered to have strength in this issue.

Table 2 of Internet Appendix provides the results of validation tests for our culture value of employee. As shown in Column (1) of the Table, the *employee* culture has a negative and significant impact on the retirement benefits concerns of employees and a significantly positive influence on the strength of housing support for employees. We also find that the *employee* culture has a positive influence on the involvement of employee, the employee relation and the diversity of employees within a bank, but they are not significant impacts.

Finally, Table 3 of Internet Appendix present the outcomes of validation checks for our culture of *trust*. Following previous studies (i.e., Ahern et al., 2015 and Mourouzidou-Damtsa et al., 2019) we measure trust by using the World Values Survey, which is the world's biggest non-commercial academic research encompassing the world's major cultural zones. It is undertaken in almost 100 nations and uses a standard questionnaire to reach nearly 90% of the world's population. The WVS survey takes place in waves and is conducted from 1981 to 1984, 1990 to 1994, 1995 to 1998, 1999 to 2004, 2005 to 2009, 2010 to 2014, and 2017 to 2022. Because the last five waves coincide to our sample period, our data spanning from 1995 to 2017. In the WVS survey, trust is quantified based on the answers of respondents for the question of whether or not most individuals can be trusted. It is worth to note that we follow the common practice in prior studies (i.e., Ahern et al., 2015 and Mourouzidou-Damtsa et al., 2019) and track replies to the following survey question "Generally speaking, would you say that most people can be trusted or that you need to be very careful when interacting with individuals?" Higher values suggest a greater level of trust in others. After retrieving trust data from the WVS, we rescale the survey scores to make our trust data range from zero to one.

As can be seen from Column 1 of the Table, the cultural value of *trust* measured from the word embedding model is positively and significantly related to the trust variable collected from the WVS survey. In Column 2 and 3 of the Table, we include several control variables and fixed effects such as year, bank and state fixed effect. Our results show that the positive relationship remain unchanged, suggesting that the cultural value of *trust* is strongly validated. In Column (4) of the Table, the cultural value of *trust* is negatively and significantly associated with the business ethics concern index from MSCI database (formally known as KLD).

4. Data and Methodology

4.1 Data and sample overview

In this study, we build a new and comprehensive dataset that consists of publicly listed U.S. bank holding companies (BHCs). In doing so, we start with all listed U.S. BHCs from Wharton Research Data Services (WRDS). From this initial list consisting of 349 U.S. listed banks over the period 1993-2021.[1] We manually download 10-K reports from the SEC's Edgar website (www.sec.gov) based on their name and stock information (i.e., Ticker Symbol and CIK number). Then, we run the word2vec model to obtain bank cultural data. At this stage of data preparation, we collect 5,786 available reports from 316 BHCs over the 29-year period spanning from 1993 to 2021. After running the word2vec model, we achieve 2,901 cultural data observations. Next, we supplement these cultural data with financial data from CRSP-WRDS database. After the merging process, our final sample includes 1,024 bank-year observations of an unbalanced panel of 208 BHCs during the period 1993-2021.

4.2 Model specification

To investigate the relation between strong bank culture and bank performance we use the following baseline regression:

$$Bank_Perfromance_{it} = \alpha_0 + \alpha_1 Strong_Bank_Culture_{i,t-1} + \\ + \alpha_3 X_{i,t-1} + State\ FEs + \varepsilon_{i,t} \quad (2)$$

Where $Bank_Perfromance_{it}$ is the performance of bank *i* in year *t*. Following previous studies (i.e., Minton et al., 2019) we use a standard accounting-based measures of bank's profitability that is return on equity (*ROE*) to proxy for bank performance and calculate ROE as net income divided by total equity. Our key independent variable is $Strong_Bank_Culture_{i,t-1}$, a dummy variable that takes a value of 1 if the sum of a bank's seven cultural values is in the third and

[1] 1993 is the earliest year for which annual reports of most banks are available and 2021 is the most updated year for which financial information provided by CRSP – WRDS database is available.

fourth quartile across all banks in a year, and 0 otherwise. $X_{i,t-1}$ is a vector of other independent variables controlling for several bank holding companies' characteristics that may affect bank performance as suggested by previous studies. More specifically, we include into the model bank loans to asset ratio (*Loans_Assets*), measured as the ratio of total loans to total assets; bank leverage (*Bank_Leverage*), calculated as the ratio of total equity to total assets; deposits to total assets ratio (*Deposit_Assets*), measured as the share of total deposits divided by total assets; *Loans_Loss_Provision* is the ratio of bank loans loss provision divided by total assets; bank charter value ratio (*Charter_Value*); bank dividend ratio (*Bank_Dividend*). We use bank cost inefficiency (*Cost_Inefficiency*), measured as non-interest expense divided by operating income. We also include bank diversification (*Diversification*) since prior studies (i.e., DeYoung and Roland, 2001; Lepetit, 2008; Kohler, 2015) mention that diversification can enhance banks' profitability. Diversification is measured by one minus HHI (Goddard et al., 2008). HHI is the Herfindahl-Hirschman index and is calculated by subdividing total operating income into its traditional income and non-traditional income components. The full list of all variables used in the model is illustrated in Table 4 of Internet Appendix.

To reduce the potential endogeneity concerns, we follow the common practice in the banking and finance literature and lag all right-hand side variables for one year (Beck et al., 2013; Schaeck et al., 2012; Fiordelisi and Ricci, 2014). We also winsorise all variables at the 1st and 99th percentiles to avoid any concerns that our findings may be driven by outliers. All our regressions include state fixed effects and standard errors are clustered at the year level. Finally, ε_i is the regression residual.

4.3. Summary statistics

In this section we briefly provide the summary statistics of all variables used in our study. As can be seen from Table 1, the mean value of strong bank culture is 0.421, indicating that, on average, the probability that a bank having strong culture is 42.1%. For bank profitability, the mean of return on equity is 0.0928, indicating that net income represents 9.28% of total equity. As for the other bank characteristics variables, the mean value of loans to asset ratio is 0.6426, implying that total loans account for 64.26% of total assets. The mean value of leverage (measured by the ratio of total assets divided by total equity) is 10.81. On average, total deposits of banks in our sample takes up around 76.89% of total assets. The mean value of bank loan loss provision is 0.0044, meaning that the average loan loss provision represents 0.44% of total loans. The mean value of bank charter value is 0.9973, meaning that on average, total equity and liability is nearly the same as total assets. Furthermore, on average bank dividend and non-interest expense takes up 0.35% and 2.8% of total assets since the mean value for dividend and cost inefficiency is 0.0035 and 0.028, respectively. Finally, the mean value of diversification is -10.274, indicating that, on average, total non-interest income accounts for -10.3% of total interest income and total non-interest income.

[Insert Table 1 here]

[Insert Table 2 here]

4.4. Do bank holding companies having strong culture perform better?

We investigate whether the strong culture of a bank can act as a dynamic source to drive the performance of banks by estimating regression model of bank performance as a function of strong bank culture and a number of control variables.

Table 3 presents the regression results that relate our bank profitability variables to bank culture. As can be seen from Column (1) of the Table, the coefficient of ROE is positive and significant at the 1% level, suggesting that banks having strong culture are more profitable. In terms of economic significance, banks with a strong culture are associated with a 1.33 percentage point increase in returns on equity than their peers with a weaker culture. The interpretation of these results is that the performance of bank holding companies are better when they own stronger culture since the presence of a strong bank culture, in which a set of norms and values are widely shared and strongly held throughout an organization (O'Reilly (1989)), will be associated with increased goal alignment and higher levels of motivation among employees, and empowers executives and employees to make consistent decisions and exert greater performance based on long-term perspectives. In terms of the control variables, we find that banks having higher leverage, lower loans loss provision ratio, higher dividend ratio and are more diversified are more profitable.

One might concern that our results may suffer potential endogeneity issues. For example, if the strong culture of a bank holding company is not exogenous and some unobserved factors that are correlated with both the strong bank culture and the performance of bank holding companies, our results may then be biased. To address this concern, we use the two-stage least squares approach with an instrumental variable (IV-2SLS) methodology. We find an instrumental variable to proxy for a bank's culture and is not related to the potential unobserved bank characteristics. As suggested by previous studies (i.e., El Ghoul et al., 2016)

social performance can be varied across different countries in the world and thus, the culture of a bank holding company is likely related to its geographic location. This is because when banks operate in the same area, such as a city, they are more likely to share the same belief, custom and social culture, and thus these banks tend to build their own culture similar with the overall culture of a city. In this regard, it is reasonable to expect that the city-year average of culture variable may act as an effective instrument for the culture variable since while it may greatly affect the culture of a bank, it is less likely to be associated with other unobserved factors which can influence bank performance.

Column 2 of the Table 3 presents our result for the IV-2SLS estimation. As can be seen from the Column, the coefficient of *Strong_Bank_Culture* remains positive and strongly significant at the 1% level, suggesting that our baseline result of the impact of bank culture on bank performance are robust after controlling for endogeneity issue.

[Insert Table 3 here]

4.5 Robustness checks

In this section, we conduct several sensitivity analyses to ensure the robustness of our main findings. It is worth to noting that we use the same sets of control variables and fixed effects as in the baseline specification in all these models. The results of these tests are provided in Table 4.

In the first set of tests provided in Panel A of Table 4, we re-run the baseline model (2) using different alternative measures of strong bank culture. Particularly, in Column 1, we reclassify a bank as having a strong culture when its raw score of seven cultural dimensions falls in the top quartile only. In Column 2, we remain the alternative measure of strong bank culture unchanged as in Column 1 but cluster the standard errors at the bank and year level to account for serial correlation in residuals within a bank and spatial correlation in residuals within a year. In Column 3, we continue to re-categorize the strong bank culture variable by requiring that a bank holding company's score must be in the top decile (top 10%). In Column 4 of Panel A, while we maintain our alternative measure of strong bank culture as in Column 3, we cluster the standard errors at the bank and year level. Next, in Column 5, we reclassify a bank holding company as having a strong culture when its raw score falls in the top quartile for at least half of its sample period. Finally, in Column 6 while we remain the alternative measure of strong bank culture as in Column 5, we include the year fixed effects and cluster the standard errors at the bank and year level to account for serial correlation in residuals within a bank and spatial correlation in residuals within a year. As shown in Columns 1-6 of Panel A, the coefficients of *Strong_Bank_Culture* remain positive and significant, indicating that our results are not sensitive to the specific ways in which our cultural measures are constructed and thus suggesting that our findings are strongly robust and consistent.

In the second set of tests presented in Panel B of Table 4, we use different alternative measures to proxy for bank profitability. Our first alternative measure of bank profitability in Column 1 of Panel B is return on asset (ROA) and is calculated as net income divided by total assets. In Column 2, while we keep ROA as the dependent variable, we add year fixed effect and cluster the standard errors at the bank and year level. Then, in Column 3 and 4 of Panel B, we use both the alternative measure of bank profitability and strong bank culture while keeping the same fixed effects as in the baseline model. Particularly, in Column 3 we use ROA as the dependent variable and use the strong bank culture measured by the top decile as in Column 3 of Panel A. Finally, in Column 4 of Panel B, we further assess the profitability of banks by using another alternative measure, the market-to-book ratio, calculated as the market value of equity divided by the book value of equity. We also use another alternative measure of strong bank culture, which takes value of one if the total scores of seven cultural dimension falls in the top quartile for at least half of its sample period as in Column 5 of Panel A. Our findings from Column 1-4 of Panel B show that the strong bank culture is positively and significantly associated with bank performance, implying that our results are consistent.

In the third set of tests presented in Panel C of the Table 4, we re-estimate the baseline model (2) using different economic specifications. First, in Column 1 of Panel C, we include the year fixed effect into the model to control for any changes across time. In Column 2 of the Panel C, we further add bank fixed effect. This setting not only allows us to control for changes in state-level factors, such as macro-economic attributes and regulatory environment that may affect bank behavior within different locations (Argawal et al., 2014), but it also controls for any variations within banks. Next, in Column 3 of the Panel C, we use different clustering methods. Specifically, while we remain the state fixed effect unchanged, we cluster the standard errors at the state and year level to account for serial correlation in residuals within a state and spatial correlation in

residuals within a year (Cameron and Miller, 2015). In a similar fashion, in Column 4 of the Panel, while we keep the state fixed effect as in the baseline model, we cluster the standard errors at both the bank and year level to control for serial correlation in residuals within a bank and spatial correlation in residuals within a year. Then, in Column 5, we use VCE robust. In Column 6, we retain cluster the standard errors at the year level as in the baseline model and replace state fixed effects with state-year trend fixed effects in order to control for pre-trend in the data. Finally, in Column 7, while we also use the state-year trend fixed effects as in Column 6, we cluster the standard errors at both the bank and year level. As can be seen from Columns 1-7 of Panel C-Table 4, the coefficients of *Strong_Bank_Culture* are positive and strongly significant across different economic models, suggesting that our baseline findings are strongly consistent and robust.

In the final set of tests presented in Panel D of the Table 4, we present several additional robustness checks to mitigate the potential concerns that our results might be affected by noises from some economic crises that happened during our studied period. For this reason, in Column 1 of Panel D, we control for the crisis 2000-2002 by excluding any observations that are in the year from 2000 to 2002. In addition, we check for the crisis 2007-2008 by removing these years from our sample in Column 2 of the Panel D. Our findings in Panel D show that the signs and magnitudes of the interested coefficients are strongly consistent with the baseline result.

One may also be concerned that our findings are mainly driven by some big banks with the "too-big-to-fail" status. As such, in Column 3, the top-five largest banks ranked by assets are excluded from the sample. Then, in Column 4, we further exclude the top-ten largest banks from the sample and as can be seen from the Table, our findings are also unchanged and robust.

[Insert Table 4 here]

4.6 The impact of strong bank culture on bank performance during crisis times

The recent COVID-19 crisis is similar to the global financial crisis (GFC) 2007–2008 to the extent that both of these two crises happened on a global scale and had a detrimental effect worldwide. However, the main difference distinguished these two crises is that while the COVID-19 pandemic is driven by an exogenous shock, an unprecedented public health crisis, the GFC arising from an endogenous shock in which risks built up in the financial sector due to poor and risky lending practices. After all, a more important question to ask is that in a future crisis, whether it is a financial crisis, a health crisis or any other natural disaster, which banks are expected to withstand better than others? Ultimately is there something unique that makes some banks more resilient in a crisis? As such, in this section, we attempt to answer these questions by demonstrating that it is the strong bank culture built in bank holding companies has allowed them to perform better that their peers without a strong bank culture. To do so, in the first step, we include into our baseline model (2) the dummy variable (*Crisis*), which takes a value of one if our observations are during the financial crisis of 2008-2009 and its interaction term with the bank culture variable (*Strong_Bank_Culture* × *Crisis*). Thus, the coefficient on the interaction term *Strong_Bank_Culture* × *Crisis* will capture the differential impact of bank culture on bank performance during the financial crisis 2008. Then, in the second step, to examine whether banks having a strong culture also perform better during the COVID-19 pandemic, we use the stringency index to proxy for variable *Crisis* and include into the model the interaction term with the bank culture variable and the stringency index (*Strong_Bank_Culture* × *Crisis*), As such, the coefficient of the interaction term *Strong_Bank_Culture* × *Crisis* will now capture the impact of strong culture on bank performance during the COVID-19 pandemic. Our results are provided in Table 5.

Column 1 of Table 5 presents the result of how strong bank culture affects bank profitability during the financial crisis 2008, while Column 2 of the Table shows the result for the Covid-19 pandemic. As can be seen from the table, we find that the coefficient of the interaction terms *Strong_Bank_Culture* × *Crisis* in both Column 1 and 2 of the Table are positive and strongly significant at the 1% level. This result, therefore, further strengthen our earlier finding that in the face of a crisis, banks with a strong culture significantly perform better than their peers without a strong culture.

[Insert Table 5 here]

In order to check the robustness of the link between strong bank culture and bank performance during the COVID-19 crisis, we use some other alternative measures to proxy for the covid crisis. We first use the dummy variable *Covid*, which takes a value of one if our observations are during the COVID-19 crisis and include into the model (2) its interaction term with the strong bank culture variable (*Strong_Bank_Culture*×*Covid*). As such the coefficient of the interaction term *Strong_Bank_Culture*×*Covid* will capture the impact of bank culture on bank profitability during the COVID-19 pandemic. In addition, we use the natural logarithm of the number of new death and new case as other two indicators of covid variable.

Our results are provided in Table 6. Column 1 of the Table 6 presents the result of how strong bank culture affects bank profitability during the COVID-19 crisis when we use the dummy variable Covid, while Column 2 and 3 shows the result when covid variable is measured as the number of new death and the number of new cases, respectively. As can be seen from the table, the estimate coefficients of the interaction term *Strong_Bank_Culture* × *Covid* are still positive and strongly significant at the 1% level across all three models, suggesting that bank holding companies with stronger culture have a higher profitability than their peers with a weak culture during the pandemic.

[Insert Table 6 here]

4.7 Bank culture and bank policies during bad times - Channels analyses

To gain deeper understanding about the role of bank culture as a driving force in leading better bank performance during different crises, in this section, we explore several underlying channels through which bank culture may help banks better deal with crises. Specifically, we examine the linkages between bank culture and some bank policies related to assets growth, dividend, cash holding, cost inefficiency, loans ratio, bank capitalization and employee relation. Our results of bank policies in financial crisis time are provided in Table 7.

First, we examine the asset growth channel to see if banks having strong culture tend to have higher assets growth in crisis times. Our results from Column 1 of Table 7 show that during a financial crisis, banks with a strong bank culture have higher level of assets growth. *Second*, when we investigate the dividend channel, we also find a positive and significant impact of strong bank culture on dividend as indicated by the positive sign of the interaction term *Strong_Bank_Culture*×*Crisis* in Column (2) of the Table. Thus, this result suggests that banks owning a strong culture tend to have higher dividend payout ratio than those owning a weak one.

Third, as suggested by previous studies (i.e., Chang and Noorbakhsh, 2009), in countries where they value the culture of uncertainty avoidance, masculinity and longer-term orientation, companies tend to hold greater cash and liquid assets. In addition, Chen et al. (2015) found that firms operating in states place an emphasis on individualistic culture prefer to hold less cash than those in collectivistic culture. These studies have implied that the national culture of a country does matter in shaping firms' decision-making process, such as the cash holding decisions. It is worth to note that while the prior literature so far has focused only on the national culture, which does not accurately reflect the firm-specific culture, we attempt to assess whether the culture developed by banks matter in shaping the decision of holding cash, especially in times of crisis. As

such, we investigate the relation between banks culture and cash holding activities to examine whether banks having strong culture employ cash holding policies as a strategy to respond to crises, such as the financial crisis and the public health crisis.

Column (3) of the Table 7 show our result for the banks' response in the financial crisis 2008 where our crisis variable is a dummy variable takes the value of one if our observations were during the crisis 2008-2009. We find that banks with a strong culture are more likely to hold more cash during a financial crisis as indicated by the positive and significant coefficient of the interaction term between strong bank culture and crisis (*Strong_Bank_Culture*×*Crisis*).

Fourth, we investigate the cost inefficiency channels to see whether banks having strong culture manage cost more efficiently when they enter a crisis. Our results from Column (4) of the Table show that, banks with a strong culture tend to reduce cost during a crisis since the coefficients of the interaction terms *Strong_Bank_Culture*×*Crisis* is negative and significant in the model where cost inefficiency is used as the dependent variable.

Fifth, we explore the loans channels to see whether banks having strong culture having higher or lower amount of loans during the financial distress. Our results from Column 5 of the Table show that, banks with a strong culture tend to reduce loans ratio during a crisis since the coefficients of the interaction terms *Strong_Bank_Culture*×*Crisis* is negative and significant.

Next, as suggested by Li et al. (2021), firms with a strong culture tend to invest more in their employees since well-treated employees are better motivated and more productive. In addition, previous studies (i.e., Kotter and Heskett, 1992; Gordon and DiTomaso, 1992 and Burt et al., 1994) suggest that the strong culture also help improve the goal alignment between the firm and its employees, enhance coordination among employees and increase employee effort, which ultimately lead to higher performance. In this regard, we examine the employee

relation channel to see whether banks having strong culture can outperform their peers with weak culture or not. Our results are provided in Column 6 of the Table 7. Although we cannot find a significant link between strong bank culture and employee relation, the positive sign of the interaction terms *Strong_Bank_Culture*×*Crisis* indicates that banks with strong culture have regularly invested in their employee's relation, which might enhance bank performance since strong bank culture can help increase the behavioral consistency across individuals in a bank.

Our result from Column 1 have shown that banks having strong culture tend to have higher assets growth in crisis times, however, we are unclear about whether there are variations among subcategory of assets and what types of products that banks with strong culture focus more on in the midst of a crisis. To do so, we further test how banks with strong culture provide different products from both the asset and liability side during the financial crisis to gain deeper insights into what products and business lines drive the performance of banks having strong culture. Our results from Column 7-12 show that, as a response to the financial crisis, banks having strong culture tend to reduce commercial & industrial loans, loans to finance agricultural productions, and illiquid guarantees such as unused commitments, net standby letters of credit, commercial and similar letters of credit. In contrast, these banks have increased the residential real estate loans, goodwill assets, and liquid guarantee such as participations in acceptances acquired by the reporting bank, branch or agency.

Finally, we explore the capital channels to examine whether banks having strong culture tend to hold a higher amount of capital as a response to a crisis. Our result from Column (15) of the Table show that the coefficients of the interaction terms *Strong_Bank_Culture*×*Crisis* are positive and significant. Thus. our result indicates that strong culture banks tend to hold more capital as an effective strategy to withstand the severe financial distress period.

[Insert Table 7 here]

5. Conclusion

Our empirical findings imply that the strong culture in a bank holding company does matter in shaping bank performance. We first find that banks having strong culture experience a higher level of performance, confirming our first hypothesis H1 that there is a positive association between strong bank culture and the performance of banks. This result therefore lends support for the view that since the strong bank culture can help increase the behavioral consistency among employees, goal alignment between the banks and its members, cooperation and control within the banks and the effort of employees, it will lead to higher banks' performance. Our findings are somehow in line with Li et al. (2021b) who found that the corporate culture is associated with higher business outcomes and firm value.

Consistent with our second hypothesis H2, we further find evidence that banks with strong culture exhibit superior performance than their peers with weak culture during bad times. Overall, these results suggest that in volatile environments, the link between strong bank culture and bank performance become stronger. As such, our findings lend support for the argument that in a changing business climate, such as an unexpected crisis, the strong bank culture plays a prominent role in facilitating coordination among employees, guiding appropriate behaviors and right course of actions for employees, and enhancing the goal alignment between the banks and their members. As a result, they can perform better than their peers who owning a weaker bank culture. In this regard, our results are consistent with Li et al. (2021a & 2021b) who find that the corporate culture-firm performance relation is more pronounced in bad times.

The additional analysis of the channels through which banks with a stronger culture have better performance also reveal some key insights. We show that during a financial crisis, banks having strong culture have employed different strategies as a response to the economic shock such as increasing their

assets growths and dividend ratio, holding more cash and capital, reducing loans ratio and cost inefficiency. Finally, we also investigate the channels through which the strong culture in a bank holding company makes it more resilient in the midst of a health pandemic and find that banks having strong culture tend to manage cost more effectively than those owning weak culture.

From the standpoint of regulators, the findings of this study imply that when establishing bank regulation and supervision, policymakers should include bank culture as a key monitoring method. As a result, bank culture should be integrated into supervision and control systems as a powerful instrument to improve the performance of the banking system. From the standpoint of bank management, this research informs a bank's shareholders and board committee about the relevance of bank culture in aligning an organization's operations and performance with its basic principles in order to achieve long-term success.

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Table 1. Summary statistics

Variable	N	Mean	SD	P25	P50	P75	Min
Strong_Bank_Culture	2233	0.4210	0.4938	0	0	1	0
ROE	2233	0.0928	0.0778	0.0743	0.0998	0.1291	-0.3868
Loans_Assets	2233	0.6426	0.1288	0.5831	0.6608	0.7320	0.1826
Bank_Leverage	2233	10.8100	2.8854	8.8970	10.3220	12.1460	5.6750
Deposit_Assets	2233	0.7689	0.0900	0.7214	0.7888	0.8342	0.4591
Loans_Loss_Provision	2233	0.0044	0.0067	0.0011	0.0024	0.0050	-0.0047
Charter_Value	2233	0.9973	0.0063	1	1	1	0.9715
Bank_Dividend	2232	0.0035	0.0023	0.0018	0.0033	0.0049	0
Cost_Inefficiency	2180	0.0280	0.0085	0.0230	0.0272	0.0315	0.0117
Diversification	2180	-10.2743	28.7150	-7.2852	-4.1753	-2.4287	-245.4414

Table 2. Correlation matrix

	Variables	1	2	3	4	5	6	7	8	9
1	*Strong_Bank_Culture*	1								
2	*Loans_Assets*	0.0094	1							
3	*Bank_Leverage*	0.013	-0.1487	1						
4	*Deposit_Assets*	-0.0917	0.2438	-0.1862	1					
5	*Loans_Loss_Provision*	0.0374	-0.0137	0.2316	-0.1113	1				
6	*Charter_Value*	-0.0419	0.0129	-0.2952	0.0631	-0.4277	1			
7	*Bank_Dividend*	-0.1543	-0.0546	-0.291	-0.0698	-0.193	0.2729	1		
8	*Cost_Inefficiency*	-0.0051	-0.0201	0.0937	0.0611	0.2988	-0.1273	-0.1171	1	
9	*Diversification*	0.0092	-0.042	-0.1441	-0.056	-0.2229	0.1301	0.2225	-0.2451	1

-

Table 3. The impact of strong culture on bank profitability

VARIABLES	**Dependent variable: ROE**	
	Baseline	IV-2SLS
	(1)	(2)
Strong_Bank_Culture	**0.0133****	**0.0160****
	(0.0050)	**(0.0058)**
Loans_Assets	-0.0417	-0.0424
	(0.0267)	(0.0274)
Bank_Leverage	0.0058***	0.0057***
	(0.0014)	(0.0014)
Deposit_Assets	0.0455	0.0485
	(0.0499)	(0.0512)
Loans_Loss_Provision	-3.5157***	-3.4718***
	(0.5838)	(0.5553)
Charter_Value	0.2023	0.2295
	(0.5442)	(0.5383)
Bank_Dividend	5.5365***	5.5855***
	(1.4988)	(1.4173)
Cost_Inefficiency	0.4904	0.4640
	(0.5894)	(0.5884)
Diversification	0.0006**	0.0006**
	(0.0002)	(0.0002)
Constant	-0.1967	
	(0.5459)	
Observations	1,024	1,024
R-squared	0.2648	0.1928
State FEs	YES	YES
Cluster level	year	year

Note: This Table reports the regression result of the model to estimate the impact of strong culture on bank performance. The dependent variable is bank performance (*ROE*), and is measured as net income divided by total equity. Column (1) shows the result of the baseline model (2) while Column (2) provides the result after controlling for potential endogeneity issues. The main explanatory variable (*Strong_Culture*) is a dummy variable that equals one if the sum of a bank's seven cultural values is in the top quartile across all banks in a year, and 0 otherwise. The definitions for all other variables are outlined in Table 4 of the Internet Appendix. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Robustness check

Panel A: Alternative measure of strong culture

VARIABLES	(1) Top quantile 4	(2) Top quantile 4 & two-way cluster	(3) Top decile (10%)	(4) Top decile (10%) & Two-way cluster	(5) Culture dominant	(6) Culture dominant & Year FEs & Two-way cluster
Strong_Bank_Culture	**0.0112***	**0.0112****	**0.0317****	**0.0317*****	**0.0182****	**0.0149*****
	(0.0059)	**(0.0050)**	**(0.0138)**	**(0.0115)**	**(0.0088)**	**(0.0056)**
Loans_Assets	-0.0386	-0.0386	-0.0376	-0.0376	-0.0451	-0.0091
	(0.0264)	(0.0255)	(0.0259)	(0.0251)	(0.0279)	(0.0255)
Bank_Leverage	0.0056***	0.0056***	0.0056***	0.0056***	0.0057***	0.0053***
	(0.0014)	(0.0013)	(0.0014)	(0.0013)	(0.0014)	(0.0016)
Deposit_Assets	0.0363	0.0363	0.0384	0.0384	0.0364	-0.0115
	(0.0492)	(0.0344)	(0.0488)	(0.0340)	(0.0495)	(0.0333)
Loans_Loss_Provision	-3.4883***	-3.4883***	-3.5479***	-3.5479***	-3.4152***	-3.6710***
	(0.5867)	(0.8343)	(0.6167)	(0.8388)	(0.5752)	(1.0378)
Charter_Value	0.2075	0.2075	0.1725	0.1725	0.2296	-0.5132
	(0.5294)	(0.5195)	(0.5275)	(0.5152)	(0.5473)	(0.5386)
Bank_Dividend	5.3860***	5.3860***	5.3530***	5.3530***	5.6231***	6.2371***
	(1.4640)	(1.2279)	(1.4538)	(1.2273)	(1.3874)	(1.3316)
Cost_Inefficiency	0.4390	0.4390	0.4025	0.4025	0.4450	0.2753
	(0.5987)	(0.4265)	(0.5869)	(0.4277)	(0.5872)	(0.4060)
Diversification	0.0006**	0.0006***	0.0006**	0.0006***	0.0006**	0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-0.1907	-0.1907	-0.1546	-0.1546	-0.2117	0.5491
	(0.5311)	(0.5215)	(0.5288)	(0.5174)	(0.5507)	(0.5412)
Observations	1,024	1,024	1,024	1,024	1,024	1,024
R-squared	0.2622	0.2622	0.2646	0.2646	0.2654	0.4317
State FEs	YES	YES	YES	YES	YES	YES
Cluster level	year	bank-year	year	bank_year	year	bank-year
Year FEs						YES

Panel B: Alternative measure of bank profitability

VARIABLES	(1) ROA	(2) ROA & Year FEs & Two-way cluster	(3) ROA & Culture (Top Decile 10%)	(4) Market_book ratio & Dominant Culture
Strong_Bank_Culture	**0.0008***	**0.0009*****	**0.0024****	**0.1736*****
	(0.0004)	**(0.0003)**	**(0.0011)**	**(0.0306)**
Loans_Assets	-0.0033	-0.0009	-0.0031	-0.5364**
	(0.0021)	(0.0020)	(0.0020)	(0.2239)
Bank_Leverage	-0.0001	-0.0001	-0.0001	0.0672***
	(0.0001)	(0.0001)	(0.0001)	(0.0154)
Deposit_Assets	0.0055	0.0015	0.0052	0.3767
	(0.0047)	(0.0026)	(0.0047)	(0.2308)
Loans_Loss_Provision	-0.2964***	-0.3103***	-0.2994***	-5.3747
	(0.0489)	(0.0746)	(0.0503)	(3.5764)
Charter_Value	-0.0012	-0.0587	-0.0037	16.2738***
	(0.0523)	(0.0462)	(0.0512)	(4.0914)
Bank_Dividend	0.5495***	0.6511***	0.5419***	130.4087***
	(0.1319)	(0.1118)	(0.1265)	(13.7229)
Cost_Inefficiency	0.0389	0.0299	0.0331	1.7527
	(0.0466)	(0.0333)	(0.0463)	(2.4215)
Diversification	0.0000***	0.0000***	0.0000***	0.0027***
	(0.0000)	(0.0000)	(0.0000)	(0.0007)
Constant	0.0074	0.0660	0.0106	-15.9007***
	(0.0530)	(0.0465)	(0.0519)	(4.1114)
Observations	1,024	1,024	1,024	1,024
R-squared	0.3021	0.4707	0.3035	0.3871
State FEs	YES	YES	YES	YES
Cluster level	year	State-year	year	year
Year FEs		YES		

Panel C: Other robustness tests

VARIABLES	(1) Add Year FEs	(2) Add Year FEs & Bank FEs	(3) Cluster State-year	(4) Cluster Bank-year	(5) Vce robust	(6) State-Year Trend FEs	(7) State-Year Trend FE & Two-way cluster
Strong_Bank_Culture	**0.0151****	**0.0091***	**0.0133*****	**0.0133*****	**0.0133*****	**0.01435****	**0.01435*****
	(0.0059)	**(0.0045)**	**(0.0046)**	**(0.0048)**	**(0.0048)**	**(0.00522)**	**(0.00472)**
Loans_Assets	-0.0079	-0.0182	-0.0417	-0.0417	-0.0417	-0.03744	-0.03744
	(0.0222)	(0.0405)	(0.0253)	(0.0254)	(0.0254)	(0.02567)	(0.02474)
Bank_Leverage	0.0055**	0.0041	0.0058***	0.0058***	0.0058***	0.00416**	0.00416**

	(0.0021)	(0.0029)	(0.0012)	(0.0013)	(0.0013)	(0.00174)	(0.00170)
Deposit_Assets	-0.0015	0.1057*	0.0455	0.0455	0.0455	0.08622**	0.08622***
	(0.0329)	(0.0588)	(0.0344)	(0.0350)	(0.0350)	(0.03839)	(0.03097)
Loans_Loss_Provision	-3.7753***	-3.4452***	-3.5157***	-3.5157***	-3.5157***	-3.59126***	-3.59126***
	(0.6223)	(0.5728)	(0.7288)	(0.8307)	(0.8307)	(0.54461)	(0.84498)
Charter_Value	-0.5267	-0.1928	0.2023	0.2023	0.2023	-0.38098	-0.38098
	(0.3799)	(0.4082)	(0.5254)	(0.5168)	(0.5168)	(0.56292)	(0.54734)
Bank_Dividend	6.3476***	1.3381	5.5365***	5.5365***	5.5365***	4.54282**	4.54282***
	(1.5282)	(1.8729)	(1.2798)	(1.2433)	(1.2433)	(1.65270)	(1.42747)
Cost_Inefficiency	0.3281	-0.5366	0.4904	0.4904	0.4904	0.62122	0.62122
	(0.5184)	(1.0248)	(0.4445)	(0.4233)	(0.4233)	(0.66784)	(0.48250)
Diversification	0.0005**	0.0002	0.0006***	0.0006***	0.0006***	0.00055***	0.00055***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.00019)	(0.00019)
Constant	0.5480	0.1955	-0.1967	-0.1967	-0.1967	0.36705	0.36705
	(0.3856)	(0.4549)	(0.5280)	(0.5187)	(0.5187)	(0.57799)	(0.55236)
Observations	1,024	999	1,024	1,024	1,024	1,024	1,024
R-squared	0.4346	0.5953	0.2648	0.2648	0.2648	0.32581	0.32581
State FEs	YES	YES	YES	YES	YES		
Year FEs	YES	YES					
Cluster level	year	year	State-year	Bank-year		year	Bank-year
Bank FEs		YES					
State-Year Trend FEs						YES	YES

Panel D: Robustness tests with sub-sample

VARIABLES	(1) Exclude crisis 2000-2002	(2) Exclude crisis 2007-2008	(3) Exclude top 5 largest BHCs	(4) Exclude top 10 largest BHCs
Strong_Bank_Culture	**0.0139****	**0.0117****	**0.0131****	**0.0139****
	(0.0057)	**(0.0050)**	**(0.0049)**	**(0.0051)**
Loans_Assets	-0.0462	-0.0157	-0.0310	-0.0388
	(0.0308)	(0.0223)	(0.0279)	(0.0300)
Bank_Leverage	0.0050***	0.0060***	0.0058***	0.0058***
	(0.0016)	(0.0014)	(0.0014)	(0.0014)
Deposit_Assets	0.0713	-0.0154	0.0578	0.0595
	(0.0607)	(0.0344)	(0.0557)	(0.0522)
Loans_Loss_Provision	-3.5471***	-2.6685***	-3.6742***	-3.5328***
	(0.5624)	(0.6284)	(0.6001)	(0.5146)
Charter_Value	-0.0030	0.4309	0.1511	0.1437
	(0.5527)	(0.4081)	(0.5504)	(0.5547)
Bank_Dividend	4.6781**	6.7550***	5.7122***	5.4536***
	(1.6618)	(1.0434)	(1.5157)	(1.5712)
Cost_Inefficiency	0.2355	0.0075	0.5184	0.5127
	(0.6361)	(0.4996)	(0.5840)	(0.5675)
Diversification	0.0006**	0.0005***	0.0006**	0.0007**
	(0.0003)	(0.0002)	(0.0002)	(0.0003)
Constant	0.0062	-0.3829	-0.1645	-0.1523
	(0.5539)	(0.4121)	(0.5588)	(0.5589)
Observations	915	892	993	962
R-squared	0.2518	0.3013	0.2633	0.2584
State FEs	YES	YES	YES	YES
Cluster level	year	year	year	year

Note: This Table reports the results of the robustness checks for the impact of strong culture on bank performance. Panel A of the Table shows the results when we re-run the baseline model (2) using different alternative measures of strong culture while Panel B of the Table shows the results when we use different alternative measures to proxy for bank performance. Panel C of the Table provides the results using different economic specifications, meanwhile Panel D further presents some additional tests to mitigate the potential concerns that our findings are affected by noises from economic crises happened during the studied period. The definitions for all other variables are outlined in Table 4 of the Internet Appendix. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. The impact of strong culture on bank profitability during different crises

	(1)	(2)
	Dependent variable = ROE	
VARIABLES	Crisis 2008	Covid 2019
Strong_Bank_Culture×Crisis	**0.0435*****	**0.0293*****
	(0.0056)	**(0.0095)**
Crisis	-0.1045***	0.0595***
	(0.0200)	(0.0124)
Strong_Culture	0.0085*	0.0121**
	(0.0046)	(0.0048)
Loans_Assets	-0.0185	-0.0333
	(0.0234)	(0.0246)
Bank_Leverage	0.0068***	0.0060***
	(0.0017)	(0.0014)
Deposit_Assets	-0.0006	0.0211
	(0.0410)	(0.0418)
Loans_Loss_Provision	-2.4844***	-3.7955***
	(0.6781)	(0.5208)
Charter_Value	0.1264	0.0488
	(0.4379)	(0.5378)
Bank_Dividend	6.5935***	5.6994***
	(1.2961)	(1.5144)
Cost_Inefficiency	0.3797	0.7061
	(0.5486)	(0.5494)
Diversification	0.0006**	0.0006**
	(0.0002)	(0.0002)
Constant	-0.1064	-0.0407
	(0.4364)	(0.5376)
Observations	1,024	1,024
R-squared	0.3704	0.2774
State FEs	YES	YES
Cluster level	year	year

Note: This Table reports the regression result of the additional analysis to examine the impact of strong culture on bank performance during the bad times. Column (1) reports the result for the financial crisis 2007-2008. Meanwhile, Column (2) shows the result for the pandemic crisis. The dependent variable is bank performance (*ROE*) and is measured as net income divided by total equity. The main explanatory variable (*Strong_Culture*) is a dummy variable that equals one if the sum of a bank's seven cultural values is in the top quartile across all banks in a year, and 0 otherwise. The definitions for all other variables are outlined in Table 4 of the Internet Appendix. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. The impact of strong culture on bank profitability during the Covid pandemic – Alternative measurement of Covid

VARIABLES	ROE		
	Covid (Dummy)	**Covid (New death)**	**Covid (New case)**
	(1)	(2)	(3)
Strong_Bank_Culture ×Covid	**0.0164*** **	**0.0013*** **	**0.0010*** **
	(0.0053)	**(0.0004)**	**(0.0003)**
Covid	0.0334***	0.0026***	0.0020***
	(0.0069)	(0.0005)	(0.0004)
Strong_Culture	0.0121**	0.0121**	0.0121**
	(0.0048)	(0.0048)	(0.0048)
Loans_Assets	-0.0333	-0.0333	-0.0333
	(0.0246)	(0.0246)	(0.0246)
Bank_Leverage	0.0060***	0.0060***	0.0060***
	(0.0014)	(0.0014)	(0.0014)
Deposit_Assets	0.0211	0.0211	0.0211
	(0.0418)	(0.0418)	(0.0418)
Loans_Loss_Provision	-3.7955***	-3.7955***	-3.7955***
	(0.5208)	(0.5208)	(0.5208)
Charter_Value	0.0488	0.0488	0.0488
	(0.5378)	(0.5378)	(0.5378)
Bank_Dividend	5.6994***	5.6994***	5.6994***
	(1.5144)	(1.5144)	(1.5144)
Cost_Inefficiency	0.7061	0.7061	0.7061
	(0.5494)	(0.5494)	(0.5494)
Diversification	0.0006**	0.0006**	0.0006**
	(0.0002)	(0.0002)	(0.0002)
Constant	-0.0407	-0.0407	-0.0407
	(0.5376)	(0.5376)	(0.5376)
Observations	1,024	1,024	1,024
R-squared	0.2774	0.2774	0.2774
State FEs	YES	YES	YES
Cluster level	Year	Year	Year

Note: This Table reports the regression result of the additional analysis to examine the impact of strong culture on bank performance during the pandemic using alternative measure of Covid-19. Column (1) reports the result when the variable *Covid* is measured as a dummy variable that takes value of one if our observations are in the year 2019 and 2020, and 0, otherwise. Column (2) and (3) of the Table shows the result when the variable *Covid* is measured as the natural logarithm of the number of new deaths and new cases, respectively. The dependent variable is bank performance (*ROE*) and is measured as net income divided by total equity. The main explanatory variable (*Strong_Culture*) is a dummy variable that equals one if the sum of a bank's seven cultural values is in the top quartile across all banks in a year, and 0 otherwise. The definitions for all other variables are outlined in Table 4 of the Internet Appendix. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Channels analysis – The Financial crisis 2008

VARIABLES	(1) Asset growth	(2) Dividend	(3) Cash holding	(4) Cost inefficiency	(5) Loans to asset ratio	(6) Employee relation	(7) CI loans	(8) Agricultural loans	(9) Illiquid guarantee	(10) RE loans	(11) Goodwill ratio	(12) Liquid guarantee	(13) Bank Capitalization
Strong_Bank_Culture ×Crisis	**0.0476*** **	**0.0008*** **	**0.0279*** **	**-0.0036*** **	**-0.0210** **	0.0474	**-0.0270*** **	**-0.0026** **	**-0.0189***	**0.0236***	**0.0035***	**0.0000** **	0.4324**
	(0.0158)	**(0.0002)**	**(0.0076)**	**(0.0009)**	**(0.0076)**	(0.0328)	**(0.0070)**	**(0.0012)**	**(0.0098)**	**(0.0130)**	**(0.0018)**	**(0.0000)**	(0.1564)
Crisis	-0.0572***	-0.0003	-0.0134**	0.0035***	-0.0035	-0.0220	0.0034	0.0012	-0.0405***	-0.0123	-0.0044**	-0.0000	-0.2166**
	(0.0134)	(0.0002)	(0.0049)	(0.0008)	(0.0070)	(0.0191)	(0.0054)	(0.0008)	(0.0115)	(0.0087)	(0.0016)	(0.0000)	(0.0987)
Strong_Culture	0.0182**	-0.0006***	-0.0064	-0.0011	0.0047	-0.0052	0.0297***	0.0002	0.0347***	-0.0239**	0.0022*	0.0000	-0.1549
	(0.0086)	(0.0001)	(0.0050)	(0.0007)	(0.0035)	(0.0297)	(0.0072)	(0.0009)	(0.0096)	(0.0093)	(0.0011)	(0.0000)	(0.1162)
Loans_Assets	0.0893*	-0.0017***	-0.1994***	-0.0020	0.9836***	-0.1010	0.1889***	-0.0019	0.0830**	0.7077***	-0.0025	0.0000	1.6141***
	(0.0495)	(0.0006)	(0.0248)	(0.0027)	(0.0161)	(0.1283)	(0.0196)	(0.0021)	(0.0400)	(0.0265)	(0.0043)	(0.0000)	(0.4749)
Bank_Leverage	-0.0001	-0.0002***	-0.0016*	-0.0000	0.0011	-0.0099*	-0.0018*	0.0002	-0.0123***	0.0016	-0.0021***	-0.0000	-0.0398
	(0.0018)	(0.0000)	(0.0010)	(0.0001)	(0.0007)	(0.0046)	(0.0009)	(0.0001)	(0.0012)	(0.0011)	(0.0004)	(0.0000)	(0.0267)
Deposit_Assets	0.0533	-0.0023**	0.1268**	0.0010	-0.0218	-0.1227	-0.0140	0.0250***	-0.0907**	0.0534	-0.0337***	0.0000**	-5.1432***
	(0.0579)	(0.0009)	(0.0528)	(0.0045)	(0.0379)	(0.1037)	(0.0241)	(0.0036)	(0.0392)	(0.0431)	(0.0061)	(0.0000)	(0.7003)
Loans_Loss_Provision	-3.7611***	-0.0221**	0.5056	0.2707***	-1.4821***	-0.9800	0.2242	-0.0234	-0.1547	-0.8139*	0.0590	-0.0000	27.1550**
	(1.0265)	(0.0100)	(0.5268)	(0.0658)	(0.5122)	(0.9843)	(0.4713)	(0.0625)	(0.8850)	(0.4693)	(0.0683)	(0.0002)	(10.9672)
Charter_Value	2.3507**	0.0572***	-0.1932	0.0176	-0.3172	-1.7780*	-0.2779	-0.0703	-2.5167***	-0.2878	0.0242	-0.0000	7.3324
	(0.9006)	(0.0093)	(0.4477)	(0.0472)	(0.3560)	(0.9425)	(0.3187)	(0.0540)	(0.8477)	(0.4326)	(0.0594)	(0.0001)	(8.5510)
Bank_Dividend	-1.1684		-1.2846	-0.1451	0.5602	-9.1255*	-2.4366*	0.8386***	-13.2063***	2.1314	0.5734	-0.0009*	-33.0821
	(2.4312)		(0.7791)	(0.1479)	(0.6465)	(4.8092)	(1.2053)	(0.1763)	(1.7406)	(2.2194)	(0.3666)	(0.0004)	(23.9071)
Cost_Inefficiency	0.1545	-0.0049	0.1039		0.3695	2.9823*	-0.2578	0.0020	-0.4599	-0.1824	-0.1787**	-0.0001	-6.8646
	(0.7555)	(0.0112)	(0.4916)		(0.2881)	(1.6214)	(0.3384)	(0.0396)	(0.3562)	(0.4640)	(0.0785)	(0.0001)	(6.4177)
Diversification	0.0000	0.0000***	-0.0000	-0.0000**	-0.0001	0.0005***	-0.0071***	0.0003	-0.0081**	0.0111***	-0.0007**	0.0000	-0.0749*
	(0.0003)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0002)	(0.0020)	(0.0003)	(0.0033)	(0.0038)	(0.0003)	(0.0000)	(0.0387)
Constant	-2.3235**	-0.0475***	0.3078	0.0105	0.3196	1.9959*	0.3095	0.0526	2.8800***	0.2367	0.0458	-0.0000	-1.6785
	(0.9130)	(0.0095)	(0.4492)	(0.0480)	(0.3528)	(0.9490)	(0.3168)	(0.0536)	(0.8485)	(0.4361)	(0.0606)	(0.0001)	(8.2357)
Observations	1,024	1,024	535	1,024	1,024	260	800	800	800	800	800	800	886
R-squared	0.1383	0.4208	0.3572	0.2293	0.8988	0.3277	0.4054	0.4225	0.4439	0.6621	0.3881	0.0949	0.2833
State FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster level	year	year	year	year	year	year	year	year	year	year	year	year	year

Note: This Table reports the regression result of the model to investigate the channels through which strong culture exerts impact on bank performance. The dependent variable is bank performance (*ROE*) and is measured as net income divided by total equity. The main explanatory variable (*Strong_Culture*) is a dummy variable that equals one if the sum of a bank's seven cultural values is in the top quartile across all banks in a year, and 0 otherwise. The definitions for all other variables are outlined in Table 4 of the Internet Appendix. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.