Financial Stories in the Big Data: Evidence from Textual Analysis and Artificial Intelligence Models

Sirui Cheng

Nottingham University Business School (China)

Supervisors:

Qingfeng Wang, Xiuping Hua, Fumin Zhu

June 2024

Thesis submitted to the University of Nottingham for the degree of Doctor of Philosophy.

ABSTRACT

The digital age has generated vast amounts of data that continue to grow exponentially, and this “big data” revolution is reshaping the financial industry. Complementing text data, a type of big data, textual analysis, and artificial intelligence models have clearly emerged as rather prevalent tools in the empirical study of financial researchers. As the applications of textual analysis continue to expand, it could provide financial researchers with methods to measure relevant economic variables that have traditionally been challenging or even impossible to capture through traditional quantitative data approaches. These new data and methods lead to improvements in research methods and paradigms and enable the exploration of more important research topics.

My thesis consists of three chapters that aim to explore significant questions using big data, textual analysis, and artificial intelligence methods. I look forward to contributing theoretically and empirically to academic research in important fields such as culture, innovation, and ESG. I aspire to study the issues that traditional data and methods cannot address through broader information sources and more diverse analytical methods.

The first chapter of my thesis examines how a stronger corporate culture can provide resilience for enterprises exposed to the Sino-US trade war. Using textual analysis tools such as word embedding models and K-Means, we measure the enterprises' exposure to Sino-US trade war risks and the strength of their corporate culture based on analysts' reports and annual reports' text data. It was found that enterprises with high exposure to the Sino-US trade war suffered more negative impacts

after the war began, and a strong corporate culture mitigated such negative impacts by enhancing operating performance and relieving financial constraints.

The second chapter explores whether political uncertainty affects enterprises' engagement in rapidly evolving technological innovation. A firm can choose to create patents that contribute incremental advancements over existing technologies with limited impact on technological progress or create patents with technologies in their ascending phase, which often lead to widespread dissemination in subsequent development phases, evolution, and refinement. And it is not necessarily related to indicators such as the number of patents and citations. The number of patent applications and citations cannot fairly measure this difference. Using patent text data, we employed textual analysis methods to measure the positioning of a given patent and firms within technology cycles. We also use textual analysis methods and annual report data to measure the firm’s exposure to political uncertainty. Our findings indicate that enterprises facing higher political uncertainty are less inclined to engage in rapidly evolving technological innovation through increasing financing constraints and executive risk aversion. Additionally, we verified the causal relationship through two exogenous shock events: the Sino-U.S. trade war and the COVID-19 pandemic.

The third chapter investigates whether the chairman and CEO's masculinity-femininity culture affect an enterprise's ESG performance. According to Geert Hofstede’s theory, culture acts as a mental program and software of the mind, exerting a subtle and profound influence on people's behaviors and decisions. As a pair of cultural values, masculinity shows features such as assertive, aggressive, achievement-oriented, and confidence, and femininity exhibits features such as nurturance, modesty, caring for others, and focusing on relationships. These differences result in different choices of ESG engagement made by chairpersons and CEOs with different cultural values. To address the limitations of traditional methods such as questionnaires, this paper introduces three artificial intelligence models trained on vast textual data: the word embedding model, ERINE Bot, and ChatGPT to measure masculine-feminine cultural values in various provincial regions in mainland China. We discovered that when the chairman and CEO of a firm come from a masculine region, the enterprise's ESG performance tends to be worse, and vice versa. We verified the causal relationship of this association through the abnormal turnover of the chairman or CEO.

In conclusion, although the study areas are different, the three chapters of my thesis all use big data, textual analysis, and artificial intelligence models to investigate new and significant questions. We contribute to these fields by adding theoretical insights and empirical evidence.

ACKNOWLEDGEMENT

It is my great honor to have studied at the University of Nottingham Ningbo China (UNNC) for the past four years, during which I completed my final thesis under the guidance of my supervisors.

First, I would like to express my gratitude to my supervisors. Without their help, I could not have completed the three research chapters in my final thesis. Professor Xiuping Hua has always supported my exploration and research in financial studies. Under her guidance, I learned how to start research, choose a meaningful topic, and do research with data and theory. In addition, Professor Hua provided me with much data support and opportunities for learning outside of the campus. Dr. Qingfeng Wang gave me a lot of trust, allowing me to explore cutting-edge methods and research directions in the financial field and also providing me with very detailed guidance and help. Dr. Fumin Zhu helped me solve difficulties in learning and life and provided me with many opportunities for learning and development. Moreover, I am deeply grateful to my former supervisor, Professor Xiaping Cao, who gave me a lot of academic guidance and advice and brought me to UNNC to pursue a doctoral degree on this campus and enjoy excellent learning resources.

Moreover, I am grateful to my reviewers, Dr. Hang Zhou, Dr. Kian Howe Ong, and Professor Weiming Liu. I appreciate their patience in listening to my research presentation and for providing me with many objective and valuable suggestions, which helped me improve the quality of my thesis research. I am also grateful to Dr. Yukun Shi for reviewing my thesis and participating in my Viva.

UNNC is an excellent school that provides doctoral candidates with good training, a living environment, rich academic resources, and opportunities, enabling us to conduct research and achieve successful outcomes with the help of the school's resources. I want to thank the faculties of the Graduate School for their hard work in managing my student records and graduation procedures, as well as all the teachers or staff at the university for their contributions and efforts to the students.

Lastly, I am deeply grateful to my parents. Their spiritual and financial support enabled me to complete my doctoral studies. I hope my efforts and future progress can honor my parents, supervisors, and those who have supported or assisted me.

TABLE OF CONTENTS

Chapter 1. Introduction to the Thesis

1.1 Overview

Big data is revolutionizing the finance industry and has the potential to significantly shape future research in finance (Goldstein et al., 2021). With the emergence of big data and improved computing power, textual analysis and artificial intelligence methods have also received more attention in financial research. This thesis explores important corporate finance issues using these new data and methods.

The thesis consists of three studies: “Corporate Culture and Firm Resilience in China: Evidence from the Sino-U.S. Trade War”; “Firm's Political Uncertainty and the Rapidly Involving Technological Innovation: Evidence from China”; “Masculinity, Femininity, and ESG Performance (Environmental, Social, and Governance): Evidence from Artificial Intelligence Models.” The first study investigates how corporate culture provides resilience for enterprises exposed to the Sino-U.S. trade war. The second study examines the influence of a firm’s political uncertainty exposure on enterprises' selection of innovative strategies, namely, whether to innovate in the rapidly evolving technological sector. The third study employs artificial intelligence techniques to measure the regional culture in mainland China and study how the masculinity-femininity cultural values of the chairman and CEOs affect their decision-making on the firm’s ESG activities and performance. In all these studies, we have utilized large volumes of textual data, textual analysis techniques, and artificial intelligence models for variable construction and data analysis.

1.2 Literature review

The accessibility of big data to researchers is increasing, as is the attention it receives in academic research, due to the development of the internet and storage hardware. Compared to the data used in traditional research, big data contains information that structured financial data cannot provide. Goldstein et al. (2021) propose three properties that together can define big data in finance research: large size, high dimension, and complex structure, and they demonstrate that financial economists focus on applying tools to capture, curate, manage, and process data to address interesting economic questions.

In the studies in our thesis, we mainly use a large volume of text data, a type of big data, to address interesting questions in the financial area. In recent studies, big data has been used to study various topics in corporate finance. For example, Li et al. (2021) used conference call data to study corporate culture and find that corporate culture can bring resilience to the enterprise in crisis and affect the success rate of mergers and acquisitions; Kelly et al. (2021) measured the significance of patents by using patenting texts; Cao et al. (2019) use image data to study whether sell-side financial analysts' physical attractiveness is associated with their job performance. Additionally, big data has been applied to asset pricing research. For instance, Cohen et al. (2020) utilize annual report texts and discover that significant year-to-year changes in annual reports indicate a higher possibility of future stock price declines; Jiang et al. (2023) explore the use of machine learning image analysis methods to identify complex and predictive price patterns in stock-level price charts. In our thesis research, we incorporate big data such as the text of annual reports, analyst reports, patents, and news articles. These data are closely related to the research question and provide appropriate measurements, helping to fill in the gaps that cannot be addressed using traditional data.

Textual analysis originated from natural language processing in computers and has gained more applications and developments in financial research. Textual analysis is a method of using textual data for analysis and variable construction. Since the groundbreaking research of Loughran and MacDonald (2011) gained widespread attention, many financial studies have used textual analysis to mine new information from textual data and explore new research topics. For instance, using Textual analysis technology, Hoberg and Phillips (2016) redefine the industry classification of listed firms; Hassan et al. (2019) identified firm's political risk exposure; Sautner et al. (2023) measured climate change risk undertaken by firms; Li et al. (2021) assessed the strength of corporate culture. We use textual analysis in the research of all three studies. We use Chinese data to develop new measures for several different topics. In the first study, we refer to the methods of Li et al. (2021) to define and measure the corporate culture of Chinese firms. In the second study, we use the method of Hassan et al. (2019) to proxy the political risk exposure of enterprises and the method of Bowen et al. (2021) to identify the innovations in rapidly evolving technological areas. In the third study, we adopted the method of Garg et al. (2018) and Kozlowski et al. (2019) and use artificial intelligence models trained on vast textual data to measure the masculinity-femininity culture of the regions within mainland China.

Significant advancements in artificial intelligence have occurred in recent years. Initially, artificial intelligence methods were primarily based on statistical machine learning algorithms, mainly applied to clustering, classification, and predictive tasks. In financial research, for example, Gu et al. 2020) used machine learning algorithms to predict the changes in stock returns; Erel et al. (2021) employ machine learning algorithms to predict corporate board members and utilized the interpretable tool to explain why a certain candidate can become a board member. With the development of deep learning technology, new artificial intelligence models have also been used in research. For instance, Li et al. (2021) constructed corporate culture dictionaries using word embedding models; Huang et al. (2018) classify text and extract topics from analyst reports and conference calls using the Latent Dirichlet Allocation (LDA) algorithm; Kölbel et al. (2024) label text data based on the Bidirectional Encoder Representations from Transformers (BERT). Following the emergence of large language models (LLMs) such as ChatGPT, studies have attempted to use LLMs for Textual analysis and research (e.g., Jha et al., 2024). In our research, we have employed several artificial intelligence models, including the K-Means, word embedding models, and LLMs. In the first study of our thesis research, we use K-Means to identify corporate culture dimensions and construct corporate culture dictionaries for Chinese firms using word embedding models. In the third study, we measure regional culture using word embedding models and LLMs.

1.3 An overview of the first study: Corporate Culture and Firm Resilience in China: Evidence from the Sino-U.S. Trade War

The thesis is comprised of three studies, each addressing a distinct research topic. In the following sections, we briefly introduce the motivations and main contents of these three studies.

The first study investigates how corporate culture can provide resilience to firms exposed to the Sino-U.S. trade war. Previous studies find that soft institutions of enterprises, such as CSR performance (Lins et al., 2017) and corporate culture (Li et al., 2021), can bring resilience to enterprises during financial crises for firms in the U.S. Although the Sino-U.S. trade war has profoundly impacted Chinese enterprises, there is currently a lack of research exploring whether soft institutions such as corporate culture can provide resilience for companies exposed to the trade war. The Sino-U.S. trade war provides a unique scenario for studying this issue. For some Chinese firms, the Sino-U.S. trade war is a serious negative shock since they rely on exports to the U.S., raw materials from the U.S., or the technological support provided by U.S. companies (Caldara et al., 2020). Although Caldara et al. (2020) define the Sino-U.S. trade war by identifying the industries more likely to be exposed to the trade war, there is still a lack of research exploring the trade war exposures of individual Chinese firms and how these exposures influence firms' stock market and business operations performance. This research aims to fill these gaps by exploring the corporate cultural values of Chinese firms and examining whether corporate culture can provide resilience to firms that are more exposed to the Sino-U.S. trade war.

Specifically, we first employ the K-Means algorithm to perform text clustering on the terms from the descriptions of corporate culture from the official websites of listed companies. We calculate the number of the listed firms that mention each corporate cultural value, with the five most frequently mentioned values in the research. We then used the word embedding models to expand the terms of these corporate cultural values and obtained the dictionaries after a manual check. Subsequently, we screen for the terms in annual reports and calculate the ratio of corporate culture terms as a proxy for the strength of corporate culture. Similarly, we measure the firm's exposure to the Sino-U.S. trade war by constructing a Sino-U.S. trade war dictionary using word embedding models and calculating the proportion of analyst reports mentioning the terms about the trade war. In this study, we also provide validations for these newly developed measures.

The empirical results show that companies more exposed to the Sino-U.S. trade war had lower excess returns in the stock market in 2018, the first year of the trade war and a year when the Chinese A-Share market suffered worse performance. Empirical analyses also suggest that a stronger corporate culture mitigates the deteriorating stock returns caused by the trade war exposure. We find two potential influencing mechanisms: stronger corporate culture can enhance operating performance and mitigate financial constraints for trade war-exposed firms, thereby providing resilience to the stock market performance. The results also indicate that corporate culture works more effectively for privately owned enterprises than for their state-owned peers. Furthermore, the individual cultures of innovation, hard work, teamwork, and quality have material effects on the stock performance of the POEs. The evidence of our first study pinpoints that a stronger corporate culture can provide resilience to the firms exposed to the Sino-U.S. trade war.

1.4 An overview of the second study: The Firm's Political Uncertainty and the Rapidly Involving Technological Innovation: evidence from China

The second chapter discusses how a firm's political uncertainty influences its innovation strategy, whether it innovates in rapidly evolving technological areas. Studies have investigated the factors that influence the innovation ability of firms, which is usually measured by the number and citations of patents (e.g., He and Tian, 2013). However, these studies ignore the choice between aggressively pursuing emerging technologies or adopting more conservative approaches based on established techniques when innovating.

While the majority of patents contribute incremental advancements over existing technologies with limited impact on technological progress (Griliches, 1990; Lemley and Shapiro, 2005), a minority introduce radically new technologies and serve as significant reference points for future innovation (Trajtenberg, 1990; Scherer and Harhoff, 2000). More invention patents or higher patent citations are not necessarily associated with a higher significance of the innovation. Some firms may choose to develop more patents, but these patents are merely complementary. On the contrary, other firms can have fewer patents, but the technologies documented in these patents rapidly develop and potentially contribute more to future innovation.

Moreover, technological innovation tends to follow a cyclical pattern. It usually starts with groundbreaking advancements that disrupt prevailing techniques, as Tushman and Aderson (1986) noted. These advancements are frequently followed by a vibrant phase marked by swift progression due to extensive experimentation and iterative trial-and-error processes (Callander, 2011). Technologies in their ascending stage are often radical or even revolutionary, resulting in wide dissemination during subsequent development, evolution, and refinement phases. Eventually, they mature into stable and widely accepted technological domains (Abernathy and Utterback, 1978; Tushman and Anderson, 1986; Callander, 2011). Therefore, in the second study, we examine the factors that encourage or hinder firms from innovating in rapidly developing and evolving technological areas.

The existing research has found that changes in politics and policies can influence business decisions. For example, Julio and Yook (2012) discovered that Economic Policy Uncertainty has a negative impact on corporate investment. Bhattacharya et al. (2017) also show that Economic Policy Uncertainty can affect a company's innovation output. However, current studies overlook the heterogeneity of firms' exposure to political uncertainty. Different industries, regions, state-owned or non-state-owned property rights, and executives' political connections can change the firm's political uncertainty. When a firm faces higher political uncertainty, it can choose conservative innovation strategies for risk avoidance or aggressive innovation strategies for higher market share or risk diversification. Therefore, our research in the second study focuses on the relationship between firms' political uncertainty and their innovation choices, aiming to fill the gaps in the existing research.

Following the methodology outlined by Bowen et al. (2023), we determine the position of a patent within the technological cycle by evaluating the prevalence of its vocabulary among recent and contemporary patents, yielding a continuous variable termed “Rapidly Evolving Technology.” This variable enables us to distinguish between patents that are more closely associated with rapidly evolving technology areas, which are characterized by a surge in the usage of relevant terminology, and those that are more linked to stable technology domains, which are marked by a lack of significant growth in vocabulary usage. For measuring the firm's political uncertainty exposure, we identify the co-occurrence of political terms and terms that signify uncertainty and quantify the ratio of uncertainty terms that are proximal to political terms within each firm's annual report, following the method of Hassan et al. (2019). We also provide validations for these new measures in the second study.

The results of empirical studies show that companies facing greater political uncertainty tend to adopt more conservative innovation strategies, ultimately leading to less innovation in rapidly evolving technological sectors, and these findings remain in multiple robustness checks. To establish a causal relationship, we conducted two quasi-natural experiments centered around the Sino-U.S. trade war and COVID-19 external shocks. The results suggest that financing constraints and executives' risk aversion are the primary mechanisms through which political uncertainty affects innovation in rapidly evolving technologies. This effect is more pronounced among non-state-owned firms, firms operating in highly competitive industries, and firms with a higher proportion of irreversible investments. The research in the second study underscores the hindrance political uncertainty poses to firms' innovation efforts in rapidly evolving technological areas.

1.5 An overview of the third study: Masculinity, femininity, and ESG Performance: Evidence from Artificial Intelligence Models

The third chapter is about how the masculinity-femininity cultural value of the chairman and CEO impacts a firm's ESG performance by drawing on Hofstede's theories. Decision-makers often face trade-offs between the interests of shareholders and ESG activities (Bocquet et al., 2015), and managerial background characteristics can partially predict strategic choices and performance outcomes (Hambrick et al., 1984; 2007). Culture serves as a "mental program" or "software of the mind" and molds the way individuals think, feel, and potentially behave (Hofstede et al., 2005). This cultural imprint also applies to the personal traits of a chairman or CEO, thereby rendering their responses, to a certain extent, foreseeable given their cultural heritage and past encounters. This cultural imprint also applies to the personal traits of a chairman or CEO, thereby rendering their responses, to a certain extent, foreseeable given their cultural heritage and past encounters. Therefore, in this study, we explore whether the masculinity-femininity cultural value of chairmen and CEOs affects the ESG performance of their company.

Numerous studies have shown that the personal characteristics of executives can affect their ESG/CSR decisions and the ESG/CSR performance of the company. For instance, literature documents that companies with CEOs who are married Hegde and Mishra (2019) or have daughters (Cronqvist and Yu, 2017) tend to have better ESG performance due to the prosocial motivation of these CEOs. Furthermore, superior ESG performance is linked to increased levels of local social trust, as indicated by Zhu and Wang (2024), as well as higher social capital, as evidenced by Jha and Cox (2015). A study by Borghesi et al. (2014) reveals that altruistic managers believe that they and their companies are morally obligated to invest in CSR activities. However, the existing research has not yet explored the impact of cultural values on executives' decision-making regarding ESG engagement despite the profound and lasting impact that cultural values have on individuals. Our research fills this gap by investigating the association and causality between the masculinity-femininity cultural values of the chairman and CEO and their firm's ESG performance.

Hofstede (1980) and Hofstede et al. (2005) proposed the theory of masculinity-femininity cultural values. Masculinity is associated with assertive, competitive, and confident behaviors, while femininity is linked to nurturance, concern for relationships, and a tender role. The aggressive, self-centered, and profit-driven motivations linked to masculinity traits tend to motivate chairmen or CEOs to prioritize economic gains at the expense of social responsibilities and potentially disregard legal implications and reputational risks from inadequate ESG performance. Conversely, femininity traits incline chairmen or CEOs to adopt a more socially responsible and altruistic mindset, enabling them to be more mindful of the societal implications of their social responsibility initiatives. Therefore, we hypothesize that firms with chairmen and CEOs from masculine regions are more likely to exhibit poorer ESG performance and vice versa.

In this study, we utilized artificial intelligence models to measure the masculinity-femininity cultural values in various provincial regions of mainland China, including the word embedding models and two LLMs, namely the ERNIE Bot and ChatGPT. These artificial intelligence models are typically trained on large corpora of text that describe regional cultures. This enables them to incorporate information about people's comprehensive perception of regional culture. The reason for using artificial intelligence models is that traditional regional culture values indicators constructed through questionnaires and interviews focus mainly on the national-level cultural values, such as the indicators developed by Hofstede (1980), and lack the measurement of cultural values within a country. Moreover, the limitations of questionnaire surveys and interviews lie in their restricted sample sizes and scopes, which may lead to bias. Individuals' behaviors may not align with their questionnaire responses, necessitating a distinction between stated values and observable actions when analyzing survey data (Hofstede et al., 2005).

We follow the methodologies employed by Garg et al. (2018) and Kozlowski et al. (2019) to employ word-embedding models to identify the masculinity-femininity culture values in different regions. Our approach reveals the association between region names and terms describing masculinity or femininity by computing the averaged embedding distances between the region names and those terms. The regional masculinity-femininity culture index was derived by subtracting the mean embedding distance between region names and masculinity terms from the mean embedding distance between region names and femininity terms. A higher index signifies a stronger masculinity influence in the region, and vice versa. We also query the ERINE Bot and ChatGPT for their descriptions of masculinity-femininity culture in various regions. To account for the inherent randomness in LLMs' responses, we adopt a multi-round approach, repeating the querying process multiple times and averaging the obtained scores. We averaged masculinity-femininity cultural scores of the chairman and CEO's birthplaces for each firm in each year to obtain the firm's masculinity-femininity cultural value variable. The validations of these measurements are presented in the third study.

Our empirical investigation reveals that the firms led by chairmen and CEOs from masculine regions tend to have worse ESG performance, while those from feminine regions tend to perform more positively. These findings persist when we replace the culture measure and ESG performance variable with alternative measures and when we change regression models. To mitigate potential endogeneity issues, we employed the abnormal turnover of the chairman or CEO as a quasi-natural experiment, in which our key findings remained. We identified two primary mechanisms driving these results: more serious financial distress and a higher corporate risk-taking led by the chairman and CEO from masculine regions. Moreover, our observations are more pronounced for firms located in regions with less favorable business environments and lower social trust, as well as for state-owned enterprises.

The third study underscores the significance of the masculinity-femininity cultural value in shaping a company's ESG decision-making. It also introduces a novel cultural analysis approach leveraging artificial intelligence.

In general, the three studies in our thesis have respectively employed different big data and textual analysis methods to investigate three different but equally important topics. These studies not only provide new evidence and methods for the relevant research of big data and textual analysis but also offer new evidence for the theories and empirical studies in their respective fields.

Reference

Abernathy, W.J. and Utterback, J.M., 1978. Patterns of industrial innovation. Technology Review, 80(7), pp.40-47.

Bhattacharya, U., Hsu, P.H., Tian, X. and Xu, Y., 2017. What affects innovation more: policy or political uncertainty?. *Journal of Financial and Quantitative Analysis*, 52(5), pp.1869-1901.

Bocquet, R., Le Bas, C., Mothe, C. and Poussing, N., 2017. CSR, innovation, and firm performance in sluggish growth contexts: A firm-level empirical analysis. *Journal of Business Ethics*, 146, pp.241-254.

Borghesi, R., Houston, J.F. and Naranjo, A., 2014. Corporate socially responsible investments: CEO altruism, reputation, and shareholder interests. *Journal of Corporate Finance*, 26, pp.164-181.

Bowen III, D.E., Frésard, L. and Hoberg, G., 2023. Rapidly evolving technologies and startup exits. *Management Science*, 69(2), pp.940-967.

Caldara, D. and Iacoviello, M., 2022. Measuring geopolitical risk. *American Economic Review*, 112(4), pp.1194-1225.

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A. and Raffo, A., 2020. The economic effects of trade policy uncertainty. *Journal of Monetary Economics*, 109, pp.38-59.

Cao, Y., Guan, F., Li, Z. and Yang, Y.G., 2020. Analysts' beauty and performance. *Management Science*, 66(9), pp.4315-4335.

Cohen, L., Malloy, C. and Nguyen, Q., 2020. Lazy prices. *The Journal of Finance*, 75(3), pp.1371-1415.

Cronqvist, H. and Yu, F., 2017. Shaped by their daughters: Executives, female socialization, and corporate social responsibility. *Journal of Financial Economics*, 126(3), pp.543-562.

Goldstein, I., Spatt, C.S. and Ye, M., 2021. Big data in finance. *The Review of Financial Studies*, 34(7), pp.3213-3225.

Erel, I., Stern, L.H., Tan, C. and Weisbach, M.S., 2021. Selecting directors using machine learning. *The Review of Financial Studies*, 34(7), pp.3226-3264.

Garg, N., Schiebinger, L., Jurafsky, D. and Zou, J., 2018. Word-embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, 115(16), pp.E3635-E3644.

Griliches, Z., 1990. Patent statistics as economic indicators: A survey part I. NBER.

Gu, S., Kelly, B. and Xiu, D., 2020. Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5), pp.2223-2273.

Hambrick, D.C. and Mason, P.A., 1984. Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, 9(2), pp.193-206.

Hambrick, D.C. Upper echelons theory: An update. *Academy of Management Review*, 2007, 32(2): 334-343.

Hassan, T.A., Hollander, S., Van Lent, L. and Tahoun, A., 2019. Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4), pp.2135-2202.

He, J.J. and Tian, X., 2013. The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics*, 109(3), pp.856-878.

Hegde, S.P. and Mishra, D.R., 2019. Married CEOs and corporate social responsibility. *Journal of Corporate Finance*, 58, pp.226-246.

Hoftstede, G., 1980. Culture's consequences: International differences in work-related values. Beverly Hills, Cal., and London: Sage, p.77.

Hoberg, G. and Phillips, G., 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5), pp.1423-1465.

Hofstede, G., Hofstede, G.J. and Minkov, M., 2005. Cultures and organizations: Software of the mind (Vol. 2). New York: McGraw-Hill.

Huang, A.H., Lehavy, R., Zang, A.Y. and Zheng, R., 2018. Analyst information discovery and interpretation roles: A topic modeling approach. *Management Science*, 64(6), pp.2833-2855.

Jha, A. and Cox, J., 2015. Corporate social responsibility and social capital. *Journal of Banking and Finance*, 60, pp.252-270.

Jha, M., Qian, J., Weber, M. and Yang, B., 2024. ChatGPT and corporate policies (No. w32161). National Bureau of Economic Research.

Jiang, J., Kelly, B. and Xiu, D., 2023. (Re-) Imag (in) ing Price Trends. *The Journal of Finance*, 78(6), pp.3193-3249.

Julio, B. and Yook, Y., 2012. Political uncertainty and corporate investment cycles. *The Journal of Finance*, 67(1), pp.45-83.

Kelly, B., Papanikolaou, D., Seru, A. and Taddy, M., 2021. Measuring technological innovation over the long run. *American Economic Review: Insights*, 3(3), pp.303-320.

Kölbel, J.F., Leippold, M., Rillaerts, J. and Wang, Q., 2024. Ask BERT: How regulatory disclosure of transition and physical climate risks affects the CDS term structure. *Journal of Financial Econometrics*, 22(1), pp.30-69.

Kozlowski, A.C., Taddy, M. and Evans, J.A., 2019. The geometry of culture: Analyzing the meanings of class through word-embeddings. *American Sociological Review*, 84(5), pp.905-949.

Lemley, M.A. and Shapiro, C., 2005. Probabilistic patents. *Journal of Economic Perspectives*, 19(2), pp.75-98.

Li, K., Mai, F., Shen, R. and Yan, X., 2021. Measuring corporate culture using machine learning. *The Review of Financial Studies*, 34(7), pp.3265-3315.

Lins, K.V., Servaes, H. and Tamayo, A., 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4), pp.1785-1824.

Loughran, T. and McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1), pp.35-65.

Sautner, Z., Van Lent, L., Vilkov, G. and Zhang, R., 2023. Firm-level climate change exposure. *The Journal of Finance*, 78(3), pp.1449-1498.

Scherer, F.M. and Harhoff, D., 2000. Technology policy for a world of skew-distributed outcomes. *Research Policy*, 29(4-5), pp.559-566.

Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. *The Rand Journal of Economics*, pp.172-187.

Tushman, M.L. and Anderson, P., 1986. Technological discontinuities and

organizational environments. *Administrative Science Quarterly*, pp.439-465.
Zhu, B. and Wang, Y., 2024. Does social trust affect firms' ESG performance?. *International Review of Financial Analysis*, 93, p.103153.

Chapter 2. Corporate Culture and Firm Resilience in China: Evidence from the Sino-US Trade War

ABSTRACT

Prior literature shows that corporate culture matters for firm performance and enhances corporate resilience in crises. We construct a text-based measure of corporate culture for Chinese listed firms and study whether and how strong corporate culture improves corporate resilience during the Sino-U.S. trade war. Empirical analyses suggest that a strong corporate culture mitigates the deteriorating stock returns due to the trade war exposure through two potential influencing mechanisms: enhancing operating performance and mitigating financial constraints. Results also indicate that a strong culture works more effectively for privately owned enterprises (POEs) than their state-owned peers, and individual cultures of innovation, hard work, teamwork, and quality have material effects on the stock performance of the POEs. The evidence pinpoints that a strong corporate culture helps insulate Chinese private firms more from external shocks and achieve more sustainable growth.

Keywords: Corporate Culture, Textual Analysis, Machine Learning, Trade War, Operating Performance

2.1 Introduction

The United Nations has adopted 17 Sustainable Development Goals (SDGs)[1] with 169 targets, including reducing poverty and inequality between countries, providing jobs for higher living standards and sustainable economic growth, and revitalizing strong global partnerships for sustainable development. Research has demonstrated that international commerce is connected to the sustainable advancement of economies (Chen et al., 2009; Bonfatti, 2017; Wang et al., 2017; Xu et al., 2020).

However, certain anti-globalization events have detrimentally affected the economic growth of developing nations in a sustainable manner. The Sino-U.S. trade war started in late 2017 when the former US president, Donald Trump, launched the Section 301 investigation on China. The investigation quickly deteriorated into a trade war, with both countries imposing protectionist policies such as increased trade barriers and tariffs against each other. The unexpected and abrupt rise of trade barriers and disruptions put a heavy toll on the Chinese economy. The Sino-U.S. trade war has been one of China's most serious economic challenges in recent years. In 2018, the first year of this event, the Shanghai Stock Exchange Composite Index, one of the Chinese stock markets, suffered a 32% loss, from 3,587 to 2,441 points.

Given the extraordinary nature of the trade war between the two largest economies in the world, it becomes imperative to study whether corporate culture enhances firms' resilience against external adversities. Corporate culture is one of the most important factors determining value creation and, thus, the ultimate business success of a firm

[1] The 17 Sustainable Development Goals are adopted by all United Nations Member States in 2015. https://unric.org/en/united-nations-sustainable-development-goals/

(Graham et al., 2022). Kreps (1990) defines corporate culture as an intangible asset designed to meet unforeseen contingencies. Corporate culture is the bottom line that firms build over time for survival and competitive advantage. The important survey paper by Graham et al. (2022) of CEOs and CFOs across a wide range of US firms finds that corporate culture is an important value driver of firms, and improving corporate culture can add value to firms.

A major empirical challenge raised by Graham et al. (2022) is how to adequately measure corporate culture using publicly available data. They suggest conference call transcripts and independent datasets as potential sources for empirically measuring corporate culture. Following their suggestion, Li et al. (2021b) construct firm-level corporate culture using a machine-learning approach. Li et al. (2021a) find that the stocks of US firms with strong corporate cultures outperform their counterparts with weak cultures during the Covid-19 pandemic.

Inspired by Graham et al.'s (2022) survey results and following the method introduced by Li et al. (2021a, b), we first identify the most frequently mentioned corporate culture values among listed firms in China: integrity and honesty, innovation and technology, hardworking and performance, product and service quality, and teamwork and cooperation, to be the starting point for us to measure corporate culture. We identify these values by hand-collecting the corporate value content from 2,818 corporate websites and cluster the terms into thematic value categories using the K-Means algorithm, an unsupervised learning technique that groups data into specified clusters based on feature similarity. Next, we score these five corporate culture values by constructing dictionaries for each value using the “word2vec” model (Mikolov et al. 2013). We then count the occurrences of terms from these dictionaries in the annual report to derive scores for the cultural values.

In the preprocessing of textual data, we acknowledge the significant differences in lexical, syntactic, grammatical, and semantic features between English and Chinese as written language (Wang and Chen, 2013). To address these differences, we segment the text while striving to preserve the integrity of the terms by using a pre-trained dictionary to maintain semantic accuracy. Moreover, our construction of the corporate culture measure is based on the textual analysis of firms’ annual reports rather than earnings call scripts, given the low coverage and quality of such scripts in China. To validate our corporate culture measure, we employ markers for the five identified cultural values and examine the association between these values and their corresponding markers.

Next, we measure firms’ exposure to the trade war using their analysts’ reports in which stock analysts analyze the potential risks of their covered firms related to the trade war. Following the existing studies (Hassan et al., 2019, 2020a, b; Sautner et al., 2023), we measure the exposure by screening for the keywords reflecting a firm’s exposure to the Sino-US trade tension. The lexicon of the Sino-U.S. trade war is also constructed with the *word2vec* model, and we keep the terms that have the highest cosine similarity to the seed word “Sino-US Trade War.” We manually cross-checked the relevance of these terms to the trade war. To validate the trade war exposure measure, we use the export and import data between Chinese and American firms from the Chinese customs dataset from 2015 to 2016 and find a significant positive association between the amount of Sino-US business and the trade war exposure.

Based on a sample of 3,688 Chinese listed firms, we find that their abnormal returns for the next month decrease with their exposure to the trade war. Specifically, firms with higher exposure to the trade war on average underperform other firms without any trade war exposure by 1.45% in excess monthly return or 0.89% in DGTW (Daniel et al., 1997) abnormal return. This deterioration in stock performance due to the trade war is robust after controlling for firm characteristics, factor loadings based on the four-factor model of Liu et al. (2019), and firm and month fixed effects. In the multivariate regressions, abnormal stock returns are regressed on corporate culture, trade war exposure, the interaction term of these two variables, and firm characteristics. The interaction term captures the impact of corporate culture on monthly stock returns for a given level of exposure to the trade war. The coefficient of the interaction term is positive and significant at a level of 1%, indicating that firms with a strong corporate culture suffered a smaller loss in returns.

We identify two channels through which culture makes firms more resilient to the trade war, namely enhancing operating performance and releasing financial constraints. In more detail, firms with a strong culture tend to have higher profit margins, higher growth rates, more trading credit, and lower financial constraints, which in turn make them better performers in the Sino-U.S. trade war. We also find that POEs with strong corporate cultures showed stronger resilience to the trade war when we compare the decline in monthly returns between firms with a strong corporate culture and firms with weak ones. Further analyses reveal that there are four most helpful individual cultures for POEs: innovation, hard work, teamwork, and *quality*.

This paper contributes to the three strands of the literature. The first strand examines the impact of corporate culture on firm performance. Previous research has explored the formation and characteristics of corporate culture, demonstrating its positive influence on firm performance (Barney, 1986; Hofstede et al., 1990; O'Reilly and Chatman, 1996; Sørenson, 2002; Zuckerman, 2002). For example, Guiso (2015) identified the most prevalent corporate culture values based on description found on the firm's website, while Li et al. (2021a, b) employed textual analysis to measure corporate culture and show how it can improve stock performance during the Covid-19 pandemic.

Our research utilized machine learning algorithms and textual data to identify the corporate culture values of Chinese firms, from which we constructed a corporate culture dictionary and assessed the intensity of corporate culture. Furthermore, we found that corporate culture can provide resilience for businesses, during crises such as the China-US trade war, facilitating sustainable growth. These innovative methodologies and findings offer new insights and evidence into how corporate culture enhances the intangible value of firms.

The second strand of literature investigates the negative consequences of trade wars. The trade war between the US and China has attracted considerable attention from academia, policymakers, and practitioners (Bown and Kolb, 2022; Amiti et al., 2019, 2020; Besedes et al., 2020; Itakura, 2020). Research has shown that the Sino-U.S. trade war negatively impacts both Chinese and American firms, with particularly severe effects on Chinese firms, leading to a transfer of supply chains and a reshaping of international trade relations. While these studies offer valuable insights into the implications of the trade war, they often overlook the factors that can mitigate its adverse effects, particularly the soft institutions within firms. Our research addresses this gap by demonstrating that a strong corporate culture can significantly ease the negative impact of the Sino-U.S. trade war. Our paper provides further evidence that the relationship between culture and performance is especially pronounced during challenging times. A robust corporate culture fosters unity among employees, management, and stakeholders, ensuring resilience and coherence in the face of severe external shocks. Additionally, our study highlights that while the Sino-U.S. trade war has adversely affected the Chinese stock market, strong corporate culture can help mitigate these negative effects.

The third strand of literature applies textual analysis or machine learning techniques in financial studies. After the pioneering work of Loughran and McDonald (2011), text-based analyses were well used in studies in corporate finance. For example, Backer et al. (2016) and Caldara and Iacoviello (2022) use news information to measure regional political risk and geopolitical risk; Hassan et al. (2019) identify the firm-level political risk by screening the political terms in a specific range around the key words of risk; Bellstam et al. (2021) develop a new measurement of innovation of firms by the LDA model. Li et al. (2021b) introduce the word embedding model to measure firms' corporate culture, a model that captures the semantics rather than merely the syntactic meaning at the expression level. Our research innovatively introduces the word embedding model in measuring corporate culture and the Sino-U.S. trade war exposure of firms in China.

The remainder of this paper proceeds as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data and the methodology used to measure corporate culture scores and firms' exposure to the trade war. Section 4 reports the main findings, explores the heterogeneity and performs robustness tests. Section 5 investigates the potential mechanisms. Section 6 provides further discussions. Section 7 concludes the paper.

2.2 Literature review and hypothesis development

2.2.1 Literature Review

The influence of culture on business operations has consistently been a topic of interest in financial studies. Pioneering research conducted by O'Reilly (1989) posits that culture serves as the pivotal function of "social control," complementing traditional control systems such as incentives (Guiso et al., 2015). Current literature on corporate culture in economics and finance mainly discusses how corporate culture is formed and the transformations it engenders within enterprises. For instance, Bolton et al. (2013) argue that the firm leader help resolve inconsistencies in the followers' motivations that hinder coordination while aligning the organization to adapt to a changing environment. Van den Steen (2010) suggests that corporate culture often emerges unintentionally through processes of screening, self-sorting, and manager-directed joint learning, resulting in shared beliefs and values among employees. Besides, research indicates that corporate culture can foster a positive working atmosphere, ease recruitment, enhance trust between management and staff, improve service quality, and boost overall firm performance (Groysberg et al., 2018; Audit et al., 2016).

While these studies address the origins and roles of corporate culture, early research has often a unified understanding of the commonalities and values associated with corporate culture in financial contexts. It was not until Guiso et al. (2015) analyzed descriptions of corporate culture from the websites of listed companies that a comprehensive and objective classification of corporate culture values emerged. This classification was subsequently adopted by Li et al. (2021b) to measure the strength of corporate culture.

These studies have identified key cultural values and showed that corporate culture can provide vital support to firms during crises such as the COVID-19 pandemic. However, they often rely on subjective human judgment to define corporate culture dimensions, which can lead to inconsistent classification. In developing countries, where firm management is still evolving, further research is needed to accurately assess corporate culture values and their potential positive effect on firms, especially in times of external crises. Our study aims to address this gap by employing the K-Means algorithm for a more objective identification of corporate culture values. We also investigate the role of corporate culture in supporting Chinese enterprises during the Sino-U.S. trade war, contributing new insights to the field and evidence of the positive impact of corporate culture in crisis situations.

Economic globalization has promoted the flow and optimal allocation of global resources, technology, capital, and information, bringing widespread benefits such as economic growth, increased employment opportunities, improved living standards, and enhanced cultural exchange. However, trade protectionism has led to the emergence of trade wars prompting financial research to examine their impacts. Current literature on trade predominantly focuses on the ramifications of the U.S.-China trade war on both nations and the global economy.

Research indicates that the U.S.-China trade war is likely to reduce the amount of Chinese firms' exports to the United States, resulting in three main effects. First, while the trade volume between the two countries has decreased, trade has shifted to other countries (Jiao et al., 2022). Second, the transfer of industrial chains has benefited other countries through increased production and exports (Fajgelbaum et al., 2024). Lastly, the market performance and valuation of Chinese enterprises may suffer (Huang et al., 2023). Moreover, studies have identified which enterprises are particularly vulnerable to trade wars. For example, Benguria et al. (2022) developed the Trade Policy Uncertainty index (TPU), and found that Chinese enterprises in sectors such as Industrial and Commercial Machinery, Computer Equipment, and Electronic Equipment are more susceptible to the trade wars. Huang et al. (2023) further noted that companies with higher R&D investment and those purchasing more homogeneous inputs are less sensitive to trade frictions.

These studies provide valuable theoretical perspectives and empirical evidence on the effects of the U.S.-China trade war from multiple dimensions, they largely focus on its impact and fail to explore mitigating factors. Given that the U.S.-China trade war is an exogenous negative event with profound implications for enterprises, especially those in developing countries, understanding how to promote sustainable development and reduce wealth disparities is essential. Our research seeks to investigate whether the soft institutions of corporate culture can alleviate the negative impacts on affected Chinese enterprises, thereby filling the theoretical gap on what factors can mitigate the impact of trade wars.

2.2.2 Hypothesis Development

The Sino-US trade frictions present immense challenges for cross-border trade or investment. Han et al. (2022) find that US sanction causes worse innovation and stock performance of Chinese firms in the sectors being sanctioned. Tariffs can slow down technology adoption by foreign exporting firms (Crowley, 2006). China is one of the largest export markets for US goods and services. The US firms that depend more on importing from or exporting to China experience worse stock performance (Huang et al., 2023). The United States imports more from China than from any other country. The exposure to the trade conflict between China and the US presents a significant challenge for these firms that are deeply rooted in the global supply chain. Thus, our first hypothesis is as follows:

Hypothesis 1. Chinese firms exposed to the Sino-US trade war suffer worse stock performance.

Culture shapes economic activities (Weber, 1930), as it determines people's decision-making dictated by preferences and beliefs (Hofstede, 2001; Talhelm et al., 2014) during different economic development stages across regions (Guiso et al., 2003; Algan and Cahuc, 2010; Nunn, 2008). Cultural perspectives are also considered important determinants of corporate financial decisions (Bertrand and Schoar, 2003;

Guiso et al., 2008; Chui et al., 2010; Eun et al., 2015; Pursiainen, 2022).

Kreps (1990) argues that corporate culture plays a vital role in firms' dealing with unforeseen contingencies that surface during crises or in a challenging operational environment. Schein (1990) suggests that corporate culture, as an intangible asset, functions via shared assumptions, values, and beliefs that help employees understand which behaviors are appropriate. Similarly, several studies (Guiso et al., 2015; Graham et al., 2022; Grennan, 2019) emphasize the importance of corporate culture in strengthening the employees' sense of worth in workplaces. Lin et al. (2017) find that the firms with high corporate social responsibility intensity have higher stock returns during the 2008-2009 financial crisis. Li et al. (2021a) provide evidence that corporate culture helps mitigate adverse shocks of Covid-19 on stock performance. Li et al. (2021b) report that a strong corporate culture can mitigate the negative impact of bad times, such as the 2008 financial crisis and BP's oil spill.

All these studies suggest that a strong corporate culture enhances firms' resilience during a crisis. In such environments, firms with sound corporate culture are equipped with stronger employees, better operating performance, and more trust from investors, enabling them to face and navigate great uncertainties (Lin et al., 2017; Li et al., 2021a, b). Hence, we contemplate that a strong corporate culture should play an important role in strengthening Chinese firms' resilience to the Sino-U.S. trade war.

Hypothesis 2a. A strong corporate culture helps Chinese listed firms to be more resilient during the Sino-US trade war.

The literature on international trade conflicts focuses on the economic impacts of hostilities between countries or regions. Trade conflicts often result in severe economic and financial consequences. For example, Guiso et al. (2009) find that lower bilateral trust leads to less trade between two countries, less portfolio investment, and less direct investment. Glick and Taylor (2010) identify the effects of military hostility with severe disruptions in international business. Fisman et al. (2014) provide direct evidence that the deterioration of Sino-Japanese relations harms the inter-trading between these two countries and the stock performance of Japanese firms that are highly exposed to the Chinese market. Itakura (2020) estimates that the escalating of the Sino-U.S. trade war reduces gross domestic product (GDP) by 1.41% and 1.35% for China and the US, respectively. Huang et al. (2023) show that the stock return and default risk of US firms were adversely influenced by the Sino-U.S. trade war. Moreover, firms with negative risk exposure but have strong corporate cultures were generally more resilient in crises (Li et al., 2021a, b). So, we hypothesize that the firms exposed to the trade war but with a strong corporate culture suffered a smaller decrease in abnormal returns compared to the firms with a weaker corporate culture.

Hypothesis 2b. Exposed firms in China with a strong corporate culture experienced a smaller drop in their stock returns compared with exposed firms with a weak one.

2.3 Data and variable construction

2.3.1 The sources of data

We collect the annual reports from the Shenzhen and Shanghai Stock Exchange websites and the analyst reports of listed firms from the WIND database. We obtain the firm characteristics, financial information, and stock trading data from the China Stock Market Accounting Research Database (CSMAR). To identify the most-mentioned cultures in China, we manually collect the corporate culture statement from the corporate websites of the Chinese A-Share market stocks. The primary data set used in the analysis contains corporate culture measure, trade war exposure measure, firm characteristics, and stock performance. The process of generating the corporate culture measure and the trade war exposure measure is described in section 3.2. The explanation of the main variables is presented in Appendix 2-1.

2.3.2 Measuring corporate culture

2.3.2.1 Corporate culture values and seed words

Building on the work of Li et al. (2021b) and Guiso et al. (2015), we first identify the corporate culture values adopted by Chinese listed firms. Then, we proxy corporate culture by comparing the five most popular cultural values and measuring their strength.

To identify these corporate culture values and their associated seed words, we hand-collected descriptions from the corporate culture statements on the 2,818 websites of Chinese listed firms. Typically, these corporate websites include a dedicated section outlining the core values of the company, which are often articulated through mission and goal statements emphasizing specific keywords. We segment these descriptions into individual terms and group them based on their semantic meaning using the K-Means algorithm.

K-Means is an unsupervised machine learning algorithm that classifies and partitions data into a predetermined number of clusters. The algorithm works by iteratively assigning each data point to the cluster with the nearest mean value and recalculating the mean of each cluster based on its assigned points. This process continues until there are no significant changes in the cluster assignments.

In our analysis, we first assign 200-dimensional word vectors to the terms extracted from the corporate culture description. Then, we use K-Means to semantically classify these terms based on their word vectors, resulting in the automatic division of terms into 200 categories[2]. At this stage, some terms may belong to multiple categories corresponding to the same corporate culture value. Therefore, we manually verify the cultural values associated with each category and designate these terms as seed words for their respective values based on their categorical classification. This process leads to the identification of eleven distinct corporate culture topics.

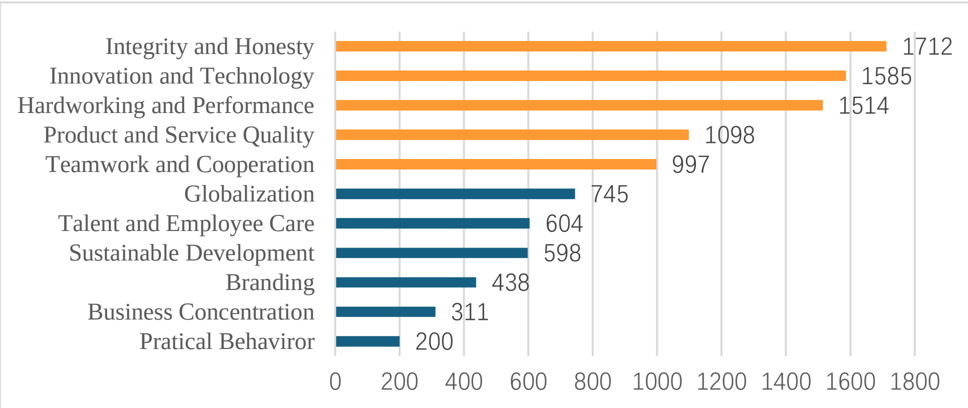


Figure 2-1 An overview of corporate culture topics of Chinese firms listed as A-Share in the stock market

[2] The choice of 200 categories balances the computational cost of the model with the level of classification granularity. When using the K-Means algorithm, if too few categories are used, it may fail to distinguish the semantic differences between terms and is more likely to group terms belonging to two distinct cultural categories into the same category. However, excessively numerous categories also pose challenges. On the one hand, an excessive number of categories results in significant computational load and manual recognition costs. On the other hand, it can make it difficult for humans to accurately interpret the meanings represented by the vocabulary within a category when defining the value of terms, leading to misinterpretation. Therefore, after careful consideration, we opted for 200 categories to perform the K-Means clustering.

Figure 2-1 presents the extracted corporate culture topics and reports the number of firms that have mentioned each of the topics. “Integrity and Honesty” is the most popular topic that has been mentioned by 1,712 firms (about 60% of our sample), then followed by “Innovation and Technology” (56%). About 1,514 firms (53%) used the terms “Hardworking and Performance,” and 1,098 firms mentioned the terms “Product and Service Quality” in their mission statements, while 997 (35%) of firms mentioned the terms “Teamwork and Cooperation.” Our reported distribution of corporate values is similar to those reported in Guiso et al. (2015)[3] for S&P 500 firms. We identified “Integrity and Honesty” (*Integrity*), “Innovation and Technology” (*Innovation*), “Hardworking and Performance” (*Hardworking*), “Product and Service Quality” (*Quality*), and “Teamwork and Cooperation” (*Teamwork*) as the five most important cultural values for Chinese firms[4].

2.3.2.2 Generating the culture dictionary

Following Li et al. (2021b), we used a trained *word2vec* model to create a “culture dictionary” by computing the cosine similarity between the vectors of seed words and the terms in the annual report. This method allows us to identify terms that are most similar to the keywords representing corporate culture values. *word2vec* is a neural network-based algorithm designed to represent words in a high-dimensional vector space. It operates by predicting the context of a given word within a text corpus using a simplified neural network architecture. Through this predictive process, word2vec

[3] S&P 500 firms are innovation (80%), integrity (70%), Quality (60%), respect (70%), and teamwork (50%).
[4] There were identified as the most important cultural values Li et al. (2021b) for 2,894 US firms over the period Jan. 22, 2020-Apr. 30, 2020.

learns semantic relationships between words, resulting in vectors that effectively capture these relationships. Instead of training our own *word2vec* model, we use a model developed by the Tencent Artificial Intelligence Lab[5] (The Tencent AI Lab model) (Song et al., 2018). The model boasts extensive coverage of Chinese terms and is trained on a large corpus of articles from diverse sources. Consequently, the vectors generated by this model more accurately and efficiently represent the meanings of terms, enhancing our ability to measure the semantic similarities between seed words and unique terms in annual reports.

To construct the corporate culture dictionary using *the word2vec model, first,* we first derive an averaged vector representing the semantic meaning of each cultural value. This is achieved by averaging the vectors of terms associated with each cultural value topic identified in section 2.3.2.1. For example, suppose that we categorize n terms to the corporate value "Product and Service Quality" in the last section. Let the first term in the group "Product and Service Quality", to be the vector $V^{\{1\}} = [x_1{}^{\{1\}}, x_2{}^{\{1\}}, \dots, x_{200}{}^{\{1\}}]$, and the last term to be $V^{\{n\}} = [x_1{}^{\{n\}}, x_2{}^{\{n\}}, \dots, x_{200}{}^{\{n\}}]$. Then we average the vectors of these terms, $\bar{V}^{\{Product\ and\ Service\ Quality\}} = \frac{1}{n}\sum_{i=1}^{n}[x_1{}^{\{i\}}, x_2{}^{\{i\}}, \dots, x_{200}{}^{\{i\}}]$.

Next, we identify the terms that are most semantically similar to the keywords. To do so, we calculate the cosine similarity between the vector of each unique term in the

[5] The Tencent *word2vec* model covers a large-scale of news, webpage text, and novels in model training so it has much better topic and word coverage and probably higher accuracy in finding associations between the words than the model trained by limited text data. The model contains 12,287,936 unique words or phrases in Chinese and English, each of which has a 200 dimensions vector. The downloading link and the other information about this model are available on: https://ai.tencent.com/ailab/nlp/en/embedding.html

annual report and the averaged vector of seed words for each cultural value, for example $\bar{V}^{\{Product\ and\ Service\ Quality\}}$. Then we keep 3,000 unique terms with the highest similarity score. Finally, we manually inspect the terms in the auto-generated dictionary and keep the terms that truly fit the corporate value.

Another use of this *word2vec* model is in text segmentation. Unlike English, the Chinese language does not naturally have space between words, and the effort to segment a text can be more challenging. For example, the Chinese term with the meaning of "Fintech" will be separated to the two terms meaning "Finance" and "Technology". To avoid information loss in the segmentation of text, we train a pre-defined lexicon, a list of 12.2 million terms extracted from the Tencent AI Lab model. With this enhancement, the terms in the lexicon will be kept in the text segmentation process. For example, the text with the meaning of "Fintech" will now be transformed to not only the terms meaning "Finance" and "Technology" but also the term meaning "Fintech."

2.3.2.3 Scoring the corporate culture

Next, we score each of the cultural values at the firm-fiscal year level. We screen and count the culture dictionary terms in the *Discussion and Analysis of the Operation* section in the annual report.[6] Our defense of the use of the annual report is as follows. The existing studies use the earning conference call for the textual analysis (e.g., Li et al., 2021a, b; Hassan et al., 2023; Sautner et al., 2023). However, for the online earning conference in China, questions and responses are of low quality due to the absence of

---

[6] In this section, managers discuss essential issues in operation, such as business strategy, product development, new technology research, social responsibility, employee care, etc.

restrictions on the qualification of participants. For another alternative text data source, the conference record of analyst investigation, only 2,470 (53%) Chinese A-share market-listed firms have disclosed this record from 2012 to 2020. For example, ZTE Corporation, one of the most famous communications equipment companies in China, did not disclose any analyst conference report until November 2020, following the temporary sanctions issued by the US government in 2018. Therefore, rather than using conference calls or analyst investigation records, we use the annual report to score the corporate culture of the firm. Moreover, annual reports contain higher information quality and better firm coverage since the disclosure is under the supervision of the regulator and is required to be released annually, a feature that makes annual reports more suitable for our research.

To measure the corporate cultures score, we use the weighted counts of the number of terms associated with each corporate culture value divided by the total number of terms in the document. The weight is determined using the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm. The model is shown as follows:

$$W_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right) \quad (2\text{-}1)$$

where the $W_{x,y}$ is the weight of word x in the document y, $tf_{x,y}$ is the frequency of x in y, df_x is the number of documents containing x, and the N is the total number of documents. For each document, the TF-IDF algorithm gives greater weight to the terms that appear more frequently in a specific document and less frequently in others.

This method balances the significance of a word in a document and its importance within the corpus. Figure 2-2 presents the word cloud graph for each topic of value[7].

We validate our cultural measure by regression between the corporate culture scores and the markers. To validate the cultural value of "Integrity and Honesty," we use a degree of real earnings management (*EarningsManagement*) and the number of times the firm has violated regulation and has been punished by the regulators (*Fault*). To validate the cultural value of "Innovation and Technology," we use both the ratio of research and development expense to the total asset (*R&D*) and the number of patents (*Patents*). To validate the cultural value of "Hardworking and performance," we use annual change in earnings (*EarningGrowth*). To validate the cultural value of "Product and Service Quality," we use the number of contract-related lawsuits that the firm involved as a defendant (*LawSuit*) and the certification of ISO9001 (*ISO9001*). To validate the cultural value of "Product and Service Quality", we use the number of joint ventures in which the firm has participated (*JointVenture*). The validation results are presented in Appendix 2-2.

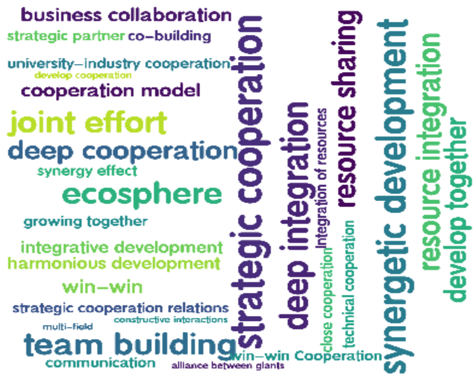
[7] We use the *wordcloud* package in python to generate these word-cloud graphs automatically. The algorithm chooses the word automatically according to the frequency of these terms. The higher frequency of appearance of the term in the text data, the larger size the term is shown in the graph.

Integrity and Honesty

Innovation and Technology

Hardworking and Performance

Product and Service Quality



Teamwork and Cooperation

Figure 2-2 Word Clouds for Different Topics

2.3.3 Estimating firm-level exposure to trade war

2.3.3.1 Method and text data source

In this section, we describe how we estimate the firms' exposure to the trade war. The measurement of the firm's exposure to a particular event is a key issue in the financial study, especially in the study of the impact of the event on the performance of the financial market. Fisman et al. (2014) investigate the Sino-Japanese conflict and its impact on the stock market. The exposure of a Japanese firm in this event is calculated as a ratio between the sales of a Japanese firm in China and the total sales. Huang et al. (2023) measure the Sino-US exposure by using the tariffs expense of firms collected from an unpublic supply chain database.

We measure the exposure of firms to the Sino-US trade war by constructing a Sino-US trade war dictionary. Then, following the recent studies (Hassan et al., 2019; 2023, b; Sautner et al., 2023; Caldara et al., 2020; Benguria et al., 2022) that use the lexicon method, we count the number of terms from the trade war dictionary and determining the proportion of these Sino-US trade war terms in the analyst report. The reasons we use the analyst report in determining firms' exposure to trade war are as follows: Analyst reports usually provide profound studies for the firms, including the issue of the extent to which the firm's business is exposed to trade war. Because analysts are professionals, they conduct more detailed research on companies, and their opinion on the impact of the Sino-U.S. trade war can be more reliable than other sources, such as news or online stock forums (Huang et al., 2018).

2.3.3.2 Generating trade war dictionary and measuring trade war exposure

To measure firm exposure to the trade war, we first generate a Sino-U.S. dictionary by identifying the most relevant terms that are most associated with the Sino-U.S. trade war. Again, we use the Tencent AI Lab *word2vec* model to identify and retain the first

1,000 terms with their *word2vec* vector that have the greatest cosine similarity to the word vector for "Sino-US trade war" (Appendix 2-3 shows the dictionary). Each of the sentences in 295,024 analyst reports is screened, and the sentences containing the words/phrases in the dictionary are counted. Moreover, in order to avoid a mistaken inclusion of the Sino-Europe business conflict statement, we leave out the sentences that suggest no trade war exposure, such as a sentence with the terms meaning "no influence" or "the risk has been moderated," and the sentences with terms related to Europe are also eliminated. Finally, we keep 8,044 sentences, corresponding to 3,275 firm-month observations. We measure the Sino-US exposures in two ways: by identifying the existence of trade war-related sentences and by calculating the proportion of trade war-related sentences for each firm in each month.

2.3.3.3 Validating the trade war exposure

We examine the validation of our newly constructed trade war exposure by identifying whether the trade war exposure measured from 2017 is associated with the actual trade war exposure from 2015 to 2016 through a cross-sectional regression. To measure the real Sino-US trade war exposure, we use a unique customs dataset of listed firms from 2015 to 2016[8], which contains the quantity of goods or services exported to and imported from the U.S. Appendix 2-4 presents the results of our validation tests. The dependent variable is a dummy variable that is equal to one if the word/phrase in the Sino-US trade war dictionary is mentioned in the analyst report, from 2017 to 2020,

[8] The data is provided by the UNNC-NFTZ Blockchain Laboratory: http://nottingchain.com/cn/index.html. According to this institution, the data is processed from the exporting and importing data of Chinese Custom. The data is only available from 2015 to 2016.

otherwise zero. The independent variable is the quantity of goods or services exported to the US or the amount of imports. We show that the measures of trade with the US are positively and significantly associated with the trade war exposure after controlling for firm characteristics and industrial fixed effects. This result indicates that the more businesses with the US, the greater the probability the firm will be exposed to the Sino-US trade war in the future.

2.3.4 Sample window of the analysis

In our baseline study, we chose 2018 as the sample window for the following reasons. First of all, 2018 marks the first year that Chinese companies faced a serious challenge from the Sino-US trade war. In 2018, more than fifty trade war-related events took place, including a sanction to the ZTE Corporation, a Chinese high-tech telecom firm listed in April 2018[9]. According to Weber's Law[10], after a strong stimulus, people tend to underreact to the following new stimulus. So, it is likely that, after the striking start of the Sino-U.S. trade war in 2018, shareholders and investors may underreact to the new tariffs or sanctions in the following years. In addition, the company exposed to the trade war may have better preparation in the following years, e.g., by transferring the market from the US to other countries.

Second, the Chinese stock market experienced a typical bear market in 2018: "It's *been the worst in a decade*." The unsuccess of the market in 2018 can be partially attributed to the Sino-US trade war and the policy reaction of the Chinese government,

[9] https://www.forbes.com/sites/ywang/2018/06/18/chinas-zte-faces-long-lasting-damage-from-u-s-trade-sanctions/?sh=279486e430ac

[10] Weber's Law explain the psychological effect that the stronger the stimulus people receive at the beginning, the slower they will respond to the stimulus in the future. The introduction page is available at: https://en.wikipedia.org/wiki/Weber%E2%80%93Fechner_law

as in this news: "*Beijing's ongoing trade war with Washington dominated headlines for much of the year, with the Chinese markets taking hits throughout as authorities undertook a string of measures, such as cutting the amount of reserves held by banks, with limited success in calming traders*." Li et al. (2021a, b) and Lins et al. (2017) indicate that a strong corporate culture and higher corporate social responsibility intensity help the stock performance of companies to be resilient in the negative shock and bear market. Therefore, 2018 is probably the best time to observe the impact of the Sino-U.S. trade war on stock performance.

2.4 Main results

2.4.1 Summary Statistics

This section presents our main results. Our empirical strategy is following Li et al. (2021a). We first examine the impact of trade war exposure on firms' performance. Next, we investigate whether a strong corporate culture alleviates the negative impact of trade war exposure on firms' stock returns. We document a sharp divergence in the impact of trade war exposure on firms with strong corporate cultures from those without strong cultures, with the firms with strong corporate cultures suffering a smaller drop in their stock returns. Before exhibiting the empirical results, we provide summary statistics in Table 2-1.

Table 2-1 Summary statistics for the variables in main regressions

Varibles	N	Mean	SD	Min	Max
ExcessReturn	42,255	-0.0032	0.1110	-0.7675	4.0407
DGTWReturn	40,067	0.0000	0.0913	-0.6754	1.2445
TradeWar	42,364	0.0206	0.1419	0.0000	1.0000
TradeWar_Count	42,364	0.0004	0.0037	0.0000	0.1671

CultureScore	35,385	5.6748	2.8537	1.0000	10.0000
Integrity	35,385	5.8010	2.4802	3.0000	10.0000
Innovation	35,385	5.5208	2.8711	1.0000	10.0000
Hardworking	35,385	5.5016	2.8688	1.0000	10.0000
Quality	35,385	5.5229	2.8692	1.0000	10.0000
Teamwork	35,385	5.5070	2.8780	1.0000	10.0000
ROE	41,069	0.0154	1.7032	-176.3802	1.5932
Size	42,224	22.3110	1.51218	17.6958	30.9703
Leverage	42,224	0.4208	0.2189	0.0093	2.9220
Tobin's Q	39,970	1.9094	1.7264	0.6927	44.0052
SalesGrowth	40,831	3.4033	367.6049	-11.9245	42,879
FixedGrowth	41,219	0.1334	1.3934	-1.0000	65.7210
CEOChair	40,314	0.6915	0.4619	0.0000	1.0000
BoardIndependence	40,866	0.3762	0.0547	0.1000	0.8000
BoardSize	40,878	8.5111	1.7849	0.0000	18.0000
BoardOwnership	39,431	0.4180	0.7867	0.0000	8.0462

In this table, we provide the summary statistics. We report the mean, median, standard deviation, minimum number, and maximum number.

2.4.2 The Sino-US trade war exposure and abnormal stock returns

First, we estimate the regression from model (2-1) with fixed effects to identify the influence of the Sino-US trade war exposure on firms' abnormal stock returns:

$$Abnormal\ Ret_{i,m+1} = \alpha + \beta_1 TradeWar_{i,m} + \beta_4 FirmCharacteristics_{i,q-1} + \beta_5 FactorLoadings_{i,m} + FirmFixedEffect + MonthFixedEffect + \varepsilon_{i,t} \quad (2\text{-}2)$$

where $Abnormal\ Ret_{i,m+1}$ is the monthly abnormal return, $TradeWar_{i,m}$ is the monthly trade war exposure, $FirmCharacteristics_{i,q-1}$ is the quarterly firm characteristics known to affect stock returns frequency, and the $FactorLoadings_{i,m-1}$ is the monthly factor loading estimated for stock i[11]. For robustness checking, we

[11] The factor loading is based on the 4-factors model developed by Liu et al. (2019). The four factors are are the market factor, value minus growth (VMG), small minus big (SMB), and the pessimistic minus optimistic (PMO).

define abnormal return as excess return (*ExcessReturn*) or as DGTW abnormal return (*DGTWReturn*). In our model (2-1), we control for firm-month fixed effects.

Table 2-2 presents the results. The coefficients of trade war exposure are all negative and significant. Our findings strongly suggest that the exposure to the trade war reduced the affected firm monthly returns, on average, by about 1%. For example, column (3) reports the firms exposed to the trade war on average suffered a drop in monthly returns of 1.17%, when compared to the market. The result in column (6) indicates that the exposed firms suffered a 1.10% loss of DGTW abnormal return.

Table 2-2 The Sino-US trade war exposure and stock returns

	ExcessReturn			*DGTWReturn*		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TradeWar	-0.0145***	-0.0132***	-0.0117***	-0.0089***	-0.0105***	-0.0110***
	(0.0038)	(0.0041)	(0.0042)	(0.0034)	(0.0039)	(0.0039)
ROE		0.1017***	-0.0196		-0.0293**	-0.0078
		(0.0147)	(0.0165)		(0.0126)	(0.0146)
Size		-0.0628***	-0.0458***		-0.0173**	-0.0178**
		(0.0106)	(0.0097)		(0.0074)	(0.0074)
Leverage		0.0838***	0.0387*		0.0170	0.0249
		(0.0209)	(0.0204)		(0.0183)	(0.0184)
Tobin's Q		-0.0179***	-0.0288***		-0.0145***	-0.0165***
		(0.0020)	(0.0025)		(0.0018)	(0.0022)
SalesGrowth		0.0083***	0.0054***		0.0038***	0.0044***
		(0.0011)	(0.0011)		(0.0010)	(0.0010)
FixedGrowth		0.0152***	0.0052*		0.0063**	0.0069***
		(0.0030)	(0.0028)		(0.0025)	(0.0025)
Factor Loadings	NO	YES	YES	NO	YES	YES
Month FE	NO	NO	YES	NO	NO	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	42,255	27,269	27,269	40,067	26,955	26,955
Pseudo/Adj. R^2	0.0004	0.0258	0.1329	0.0002	0.0199	0.0225

Factor loadings are re-estimated each month based on the previous 60 months data. The factor data is available in the website: https://finance.wharton.upenn.edu/~stambaug/..

This table presents the panel data regressions estimates of the relation between the trade war exposure and abnormal stock return over 2018. The dependent variables are two measures of abnormal return, the excess return and DGTW abnormal return. The key independent variable is the trade war exposure proxied by the textual analysis from analyst reports. The control variable consists of firm feature variables and the factor loadings in the last available period. The fixed effects (FE) used in each specification are at the firm-month level and are noted in the table. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *p<.1; **p<.05; ***p<.01.

2.4.3 Corporate culture, Sino-US trade war exposure, and abnormal stock performance

In this section, following Li et al. (2021a), we examine whether strong corporate culture reduce firms' monthly return drop by the following model:

$$Abnormal\ Ret_{i,2018} = \alpha + \beta_1 CultureScore_i + \beta_2 FirmCharacteristics_{i,2016to2017} + \beta_3 FactorLoadings_i + IndustryFixedEffect + \varepsilon_{i,t} \qquad (2\text{-}3)$$

In model (2-3) the $Abnormal\ Ret_{i,2018}$ is the yearly abnormal return in 2018, which is also defined in terms of excess return (*ExcessReturn*), and the DGTW abnormal return (*DGTWReturn*). The indicator variable $CultureScore_i$ takes value from 1 to 10 according to the sum of the firm's five cultural value scores from 2016 to 2017[12]. We control for firm characteristics known to affect stock returns and a firm's factor loadings estimated over the previous 60 months prior to 2018. Following Li et al. (2021a, b), we include industry-fixed effects for this model. Panel A in Table 2-3 shows

[12] We use the corporate culture score in 2016 to 2017, the most recent two years before 2018, to eliminate the concern that firms changed their culture due to serious consequence of trade war.

that firms with a strong culture have aignificantly better stock performance during 2018, and the findings are robust across different model specifications. For example, column (1) in Panel A indicates that a unit increase in $CultureScore_i$ is associated with a 0.4-percentage-point increase in the yearly excess return during 2018 on average.

Moreover, if the corporate culture is correlated with governance, it is possible that corporate culture is simply proxying for corporate governance, resulting in an omitted variable bias. To address this concern, following Lins et al. (2017), we include four corporate governance control variables (*BoardIndependence*, *CEOChair*, *BoardSize* and *BoardOwnership*) in the model to ensure that our findings persist after we control for the corporate governance proxies. Columns (3) and (6) in Panel A show that the effect of corporate culture on abnormal returns persists after control the corporate governance variables.

We also investigate whether the positive relation between strong corporate culture and stock performance is unique to our research time window, 2018, or is common to most periods before the trade war, a scenario under which the relation can be attributed to omitted risk factors related to corporate culture. To address this concern, following Lins et al. (2017), we implement a difference-in-difference model. Specifically, we construct regression model (2-4), with a year frequency panel data from 2016, two years prior to the onset of the crisis, to the end of 2018. $Crisis_t$ is a dummy variable set to one in 2018 otherwise zero, while $PreCrisis_t$ is a dummy variable set to one in 2016 otherwise zero. For robustness check, we also set $PreCrisis_t$ to one in period from 2016 to 2017. The firm's *CultureScore*, $Crisis$ and $PreCrisis$ terms are omitted due to multicollinearity.

$$Abnormal\ Ret_{i,t+1} = \alpha + \beta_1 CultureScore_{i,t} \times Crisis_t + \beta_2 CultureScore_{i,t} \times PreCrisis_t + \beta_2 FirmCharacteristics_{i,t} + \beta_3 FactorLoadings_{i,t} + IndustryFixedEffect + YearFixedEffect + \varepsilon_{i,t} \quad (2\text{-}4)$$

The results are presented in Panel B in Table 2-3. Columns (1) and (2) show the results in the model that $PreCrisis_t$ is set to one in 2016 otherwise zero, and columns (3) and (4) show the results in the model that $PreCrisis_t$ is set to one in period from 2016 to 2017. The coefficients of the crisis interaction term are positive and significant, indicating that strong corporate culture firms exhibit superior performance during 2018; before 2018, the relation between corporate culture and abnormal returns becomes insignificant. These results indicate that the excess abnormal return earned by a stronger corporate culture is limited to 2018, consistent with our suggestion that Chinese listed companies with a stronger corporate culture have been more capable of withstanding the impact of the Sino-U.S. trade war.

Table 2-3 Corporate Culture and Abnormal Stock Returns

Panel A: Corporate culture and abnormal returns during the crisis

	ExcessReturn			*DGTWReturn*		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CultureScore	0.0040***	0.0030**	0.0026**	0.0034**	0.0040**	0.0035**
	(0.0013)	(0.0013)	(0.0013)	(0.0017)	(0.0017)	(0.0017)
ROE		0.0018***	0.0021***		0.0033***	0.0031***
		(0.0004)	(0.0004)		(0.0006)	(0.0005)
Size		0.0174***	0.0173***		-0.0113**	-0.0132**
		(0.0033)	(0.0036)		(0.0048)	(0.0053)

Leverage		-0.1070***	-0.1152***		-0.0551	-0.0772**
		(0.0233)	(0.0248)		(0.0343)	(0.0355)
BoardIndependence			0.0602			0.0687
			(0.0799)			(0.1075)
CEOChair			0.0111			0.0280**
			(0.0088)			(0.0114)
BoardSize			0.0035			0.0046
			(0.0025)			(0.0033)
BoardOwnership			0.0213**			-0.0087
			(0.0098)			(0.0124)
FactorLoadings	NO	YES	YES	NO	YES	YES
Industry FE	NO	YES	YES	NO	YES	YES
Observations	3,040	2,904	2,747	2,980	2,856	2,718
Pseudo/Adj. R^2	0.0032	0.1138	0.1158	0.0014	0.0934	0.0968

Panel B: Corporate culture and abnormal returns surrounding the crisis

	PreCrisis: 2016		PreCrisis: 2016-2017	
	ExcessReturn	*DGTWReturn*	*ExcessReturn*	*DGTWReturn*
Variables	(1)	(2)	(4)	(5)
Culture×Crisis	0.0041***	0.0057***	0.0043***	0.0057***
	(0.0014)	(0.0017)	(0.0013)	(0.0017)
Culture×PreCrisis	-0.0041**	-0.0018	0.0017	0.0002
	(0.0019)	(0.0018)	(0.0014)	(0.0012)
FirmCharacteristics	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Culture×(Crisis- PreCrisis)	0.0082	0.0075	0.0026	0.0055
p-Value	(0.0024)	(0.0055)	(0.1767)	(0.0191)
Observations	2,980	2,856	3,040	2,904
Pseudo/Adj. R^2	0.0854	0.0318	0.0850	0.0317

Panel A in this table presents baseline cross-sectional estimates of the relation between culture score and abnormal stock returns in 2018. The key independent variable is the ten decile levels of the corporate culture score. Panel B presents comparison between baseline panel estimates in the period from 2016 to 2017 and the estimate in 2018. The key independent variables are interaction terms consisting of corporate culture score and the dummy variables indicating the periods in 2016, from 2016 to 2017, or 2018. The dependent variables are two measures of abnormal return, the excess return and DGTW abnormal return. The control variables are the firm characteristics and the factor loadings. The fixed effects (FE) used in each specification are at the industrial level. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *p<.1; **p<.05; ***p<.01.

We next investigate whether the positive corporate culture-abnormal return relationship is unique to the firm exposed to trade war by following Li et al. (2021a). Meanwhile, we investigate how much a strong corporate culture can mitigate the negative impact of trade war on firms' abnormal returns during the crisis. The interaction term $TradeWar_{i,m-1} \times CultureScore_i$ in Model (2-4) captures the differential impact of corporate culture on monthly abnormal returns in 2018, for a given level of overall exposure to the Sino-US trade war.

$$Abnormal\ Ret_{i,m} = \alpha + \beta_1 TradeWar_{i,m-1} + \beta_2 TradeWar_{i,m-1} \times CultureScore_i + \beta_3 CultureScore_i + \beta_4 FirmCharacteristics_{i,y-1} + \beta_5 FactorLoadings_{i,m-1} + FirmFixedEffect + MonthFixedEffect + \varepsilon_{i,t} \tag{2-4}$$

Table 2-4 presents the results. Similar to the results in table 2-2, coefficients of $TradeWar_{i,m-1}$ remaining negative and significant. Moreover, the positive and significant coefficients on the interaction term indicate that firms with a strong culture are associated with a smaller drop in abnormal returns. Columns (3) and (4) in Table 2-4 present the results with industrial fixed effect controls versus firm fixed effect, and these results are similar to those models controlled for firm fixed effect in columns (1) and (2). These results suggest that, during the Sino-U.S. trade war, exposed firms with a strong culture experienced a significantly smaller drop in abnormal returns than their exposed peers without a strong culture.

Table 2-4 Test with interaction term: the effect of the corporate culture

	ExcessReturn	*DGTWReturn*	*ExcessReturn*	*DGTWReturn*

Variables	(1)	(2)	(3)	(4)
TradeWar	-0.0325***	-0.0334***	-0.0204***	-0.0212***
	(0.0093)	(0.0084)	(0.0077)	(0.0072)
TradeWar ×				
CultureScore	0.0031**	0.0034***	0.0024**	0.0023**
	(0.0014)	(0.0012)	(0.0011)	(0.0010)
CultureScore			0.0005***	0.0004***
			(0.0002)	(0.0001)
FirmCharacteristics	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Firm FE	YES	YES		
Industry FE			YES	YES
Observations	26,217	25,907	26,217	25,907
Pseudo/Adj. R^2	0.1389	0.0232	0.1227	0.0146

This table presents the panel data regression estimates of the relationship between abnormal stock return and the interaction term, consisting of trade war exposure and culture score over 2018. The dependent variables are two measures of abnormal return, the excess return, and DGTW abnormal return. The key independent variable is the intersect term multiplied by the exposure to the trade war and the culture score level. The control variable consists of firm feature variables and the factor loadings in the last available period. The fixed effects (FE) used in each specification are at firm and month levels for columns (1) and (2) or are at industry and month levels for columns (3) and (4). Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *p<.1; **p<.05; ***p<.01.

2.4.4 Robustness checks

We conduct several robustness checks on our main findings. First, we perform robustness checks on our main regression results by dividing firms into two groups based on their culture scores. Specifically, we select the firms that have the top 20% (30%) as the strong culture group, and the bottom 20% (30%) as the weak culture group.

Panel A in Table 2-5 shows that the coefficients for the strong culture group (firms in the top 20% of culture scores) are positive and insignificant, while the coefficients for the weak culture group are all negative and significant (firms in the bottom 20% of culture scores). Similar results hold in panel B for different specifications of strong and weak culture groups. Our findings show that the firms with weak cultures suffered more abnormal stock return losses in 2018, while the firms with strong cultures suffered almost no losses. All these confirm our early findings that a strong culture can mitigate the adverse impact of the trade war on stock returns.

Table 2-5 Tests in groups: The effect of the corporate culture

Panel A. Strong culture in the top 20% and weak culture in the bottom 20%

	ExcessReturn		*DGTWReturn*	
	Strong	Weak	Strong	Weak
Variables	(1)	(2)	(3)	(4)
TradeWar	0.0009	-0.0317***	0.0022	-0.0295***
	(0.0079)	(0.0098)	(0.0072)	(0.0085)
FirmCharacteristics	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	6,417	5,142	6,374	5,068
Pseudo/Adj. R^2	0.1385	0.1396	0.0349	0.0234
Difference in coeff.	0.0317***		0.0326***	
statistic (p-value)	6.63 (0.0100)		7.79 (0.0052)	

Panel B. Strong culture in the top 30% and weak culture in the bottom 30%

	ExcessReturn		*DGTWReturn*	
	Strong	Weak	Strong	Weak
Variables	(1)	(2)	(3)	(4)
TradeWar	-0.0007	-0.0250***	0.0023	-0.0234***
	(0.0068)	(0.0074)	(0.0063)	(0.0067)
FirmCharacteristics	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	8,781	8,143	8,715	8,040
Pseudo/Adj. R^2	0.1332	0.1410	0.0278	0.0233
Difference in coeff.	-0.0243**		-0.0257**	
statistic (p-value)	5.32 (0.0211)		5.82 (0.0158)	

This table presents panel data regressions that estimate the relation between trade war exposure and abnormal returns under different groups of strong or weak aggregated corporate culture observations. Panel A presents the results with the definition of strong or weak culture as being top or bottom 20% of the culture score. Panel B presents the results with the definition of strong or weak culture as being top or bottom 30% of the culture score. The key independent variable is the trade war exposure proxied by the textual analysis from analyst reports. The control variables are the firm feature variables and the factor loadings. The fixed effects (FE) used in each specification are at firm and month level and are noted in the table. Heteroscedasticity-consistent standard errors are clustered at the firm level and reported in parentheses. R^2 values are given in the table. The table also reports the results of the χ^2 tests on the difference in the coefficients between the groups of strong or weak culture scores for firms. *p<.1; **p<.05; ***p<.01.

Second, we perform the robustness check by converting the measure of exposure to the trade war from a dummy variable to a continuous variable, which is defined as the ratio of the number of sentences with terms in the trade war dictionary to the total number of sentences in analyst reports of each company for each month. Table 2-6 reports the results. The findings in Panel A and B are not qualitatively different from those in Tables 2-2 and 2-4, respectively, suggesting that our empirical findings are consistently robust across alternative definitions of key explanatory variables.

Table 2-6 Different definitions of text-based trade war exposure

Panel A: the Sino-US trade war exposure and stock returns – defining trade war exposure variable as the ratio of related sentences

	ExcessReturn			*DGTWReturn*		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TradeWar_Count	-0.2739*	-0.3091*	-0.3625**	-0.1873	-0.3095*	-0.3550**
	(0.1571)	(0.1780)	(0.1798)	(0.1328)	(0.1612)	(0.1631)
FirmCharacteristics	NO	YES	YES	NO	YES	YES
FactorLoadings	NO	YES	YES	NO	YES	YES
Month FE	NO	NO	YES	NO	NO	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	42,255	23,193	23,193	40,067	22,942	22,942
Pseudo/Adj. R^2	0.0001	0.0260	0.1180	0.0000	0.0188	0.0213

Panel B: Test with an interaction term for the effect of the corporate culture-defining trade war exposure variable as the ratio of related sentences

	ExcessReturn		DGTWReturn	
Variables	(1)	(2)	(3)	(4)
TradeWar_Count	-0.9561**	-1.1832***	-0.9320**	-1.2103***
	(0.4164)	(0.4408)	(0.3726)	(0.4015)

	(1)	(2)	(3)	(4)
TradeWar_Count × CultureScore	0.0988*	0.1231**	0.1043**	0.1334***
	(0.0543)	(0.0578)	(0.0478)	(0.0516)
FirmCharacteristics	NO	YES	NO	YES
FactorLoadings	NO	YES	NO	YES
Month FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	35,385	26,217	34,866	25,907
Pseudo/Adj. R^2	0.1091	0.1335	0.0007	0.0191

In this table, we present the panel data regression estimates of the relation between the trade war exposure and abnormal stock return over 2018. The dependent variables are two measures of abnormal return, the excess return, and DGTW abnormal return. The control variable consists of firm feature variables and factor loadings. The fixed effects (FE) used in each specification are at firm and month level and are noted in the table. Heteroscedasticity-consistent standard errors are clustered at the firm level and reported in parentheses. R^2 values are given in the table. *p<.1; **p<.05; ***p<.01.

We also conduct a robustness test by replacing the trade war exposure variable from the text-based measurement with a dummy variable that is set to one of the industries in China that are more likely to be exposed to the trade war in 2018. To identify the exposed Chinese industries in 2018, we look into the industries in which the firms had goods exported to the US and targeted by the tariffs announced by the US government in 2018. Specifically, the US government's tariffs mainly target electrical equipment, industrial equipment, machinery goods, airplanes, motor vehicle equipment, etc.[13] Benguria et al. (2022) identified the Chinese industries that were most subjected to uncertainty in the trade policy in 2018 and found similar industries.

Based on these identifications, we label the trade war-exposed industries, replace the key variable 'text-based exposure' with the trade war-exposed industry dummy variable (*TradeWarInd*), and repeat the regression of the model (2-4). Table 2-7 shows

[13] The Chinese industries targeted by US tariff in 2018 are analyzed and exhibited by CNBC: https://www.cnbc.com/2018/07/05/global-trade-war-ramps-up-as-us-tariffs-on-china-kick-in.html

a result similar to the result in Table 2-4, that the interaction terms are all positive and significant. These results suggest that our finding persists using an alternative definition of trade war exposure. During the Sino-U.S. trade war, exposed firms with a strong culture experienced a significantly smaller drop in abnormal returns than their exposed peers.

Table 2-7 Alternative definition of trade war exposure: Industry based

	ExcessReturn		*DGTWReturn*	
Variables	(1)	(2)	(3)	(4)
TradeWarInd × *CultureScore*	0.0005***	0.0005**	0.0004***	0.0004**
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
CultureScore	0.0005***	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
FirmCharacteristics	NO	YES	NO	YES
FactorLoadings	NO	YES	NO	YES
Month FE	NO	YES	NO	YES
Industry FE	NO	YES	NO	YES
Observations	35,337	24,604	34,837	24,502
Pseudo/Adj. R^2	0.0008	0.1209	0.0006	0.0116

In this table, we present the panel data regression estimates of the relation between the trade war exposure and abnormal stock return over 2018. The dependent variables are two measures of abnormal return, the excess return, and DGTW abnormal return. The control variable consists of firm feature variables and factor loadings. The fixed effects (FE) used in each specification are at the industry and month level and are noted in the table. Heteroscedasticity-consistent standard errors are clustered at the firm level and reported in parentheses. R^2 values are given in the table. *p<.1; **p<.05; ***p<.01.

2.5 Mechanisms

Thus far, we have documented that a strong corporate culture helps alleviate the negative impact of the Sino-U.S. trade war on firms' stock returns. In this section, we investigate potential channels through which a strong culture keeps firms resilient during the bear market. We conduct mediating effect tests following the procedure of

Baron and Kenny (1986), which is widely used by financial scholars (e.g., Chen et al., 2021; Francis et al., 2021). Specifically, following Lai et al. (2023), we construct a recursive model to explore the influencing mechanisms. To estimate the statistical significance of the indirect effect, we follow Chen et al. (2021) and Xiong et al. (2021) and conduct the Sobel test in mediating effect. We identify two distinct mechanisms. These mechanisms are operating performance enhancement and financial constraints relieving.

First, we examine the channel of operating performance. Lins et al. (2017) and Li et al. (2021a) find that operating performance is a mechanism behind the association between high-ESG performance or strong culture and higher stock return in crisis. We examine this channel by testing the mediating mechanism of two performance measures: profit margin (*ProfitMargin*) and earnings growth (*EarningGrowth*), proxying for profitability and growth, respectively. The results are shown in Panel A of Table 2-8. The coefficients are all positive and significant, indicating that the strong culture significantly promotes firm profitability and growth, which in turn causes better stock performance.

Second, we examine the mediating effect of financial constraints relieving. The relationship between soft information and financial constraint relief has been discussed in several studies. Wu et al. (2014) provide Chinese evidence that higher regional social trust helps local firms obtain more trade credit, an important source of financing. El Ghoul and Zheng (2016) point out that the four macro-level cultural dimensions constructed by Hofstede (2001) - individualism and collectivism, power distance, avoidance of uncertainty, masculinity, and femininity - can all affect the business credit supply decisions of enterprises. Soft information at the firm level also relieves information ambiguity and convinces investors or credit providers (Lin et al., 2017), resulting in better financial status and stock performance.

Table 2-8 Mechanisms analyses

Panel A: the operating performance enhancement channel

	(1)	(2)	(3)	(4)
Variables	*ProfitMargin*	*DGTWReturn*	*EarningGrowth*	*DGTWReturn*
Culture	0.0062***	0.0032***	0.1636**	0.0021*
	(0.0021)	(0.0011)	(0.0736)	(0.0012)
ProfitMargin		0.054***		
		(0.0100)		
EarningGrowth				0.0015***
				(0.0003)
Indirect effect	0.0003		0.0002	
Sobel test	2.5580**		2.0230**	
FirmCharacteristics	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	2,753	2,753	2,787	2,787
Pseudo/Adj. R^2	0.4868	0.0930	0.2865	0.0513

Panel B: the financial constraints reduction channel

	(1)	(2)	(3)	(4)
Variables	*TradeCredit*	*DGTWReturn*	*KZ*	*DGTWReturn*
Culture	0.0018***	0.0038**	-0.0441***	0.0031***
	(0.0004)	(0.0012)	(0.0116)	(0.0012)
TradeCredit		0.1323***		
		(0.0579)		
KZ				-0.0055***
				(0.0019)
Indirect effect	0.0002		0.0002	
Sobel test	2.0400**		2.2700**	
FirmCharacteristics	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	2,709	2,709	2,636	2,636
Pseudo/Adj. R^2	0.3796	0.0461	0.4495	0.0807

This table presents the results of the mechanism tests of the effect of corporate culture on abnormal returns. The dependent variable is the DGTW abnormal return, and the mediator variables are profit margin (*ProfitMargin*), earning growth (*EarningGrowth*), trading credit (*TradeCredit*), and financial constraints Index (*KZ*). The key independent variables are the corporate culture score (*CultureScore*) and mediator variables. The control variables are the firm characteristics variables and the factor loadings. The fixed effects (FE) used in each specification are at the industrial level. Heteroscedasticity-consistent standard errors are clustered at the firm level and reported in parentheses. R^2 values are given in the table. *p<.1; **p<.05; ***p<.01.

We examine this channel by testing the mediating mechanism of two kinds of financial constraint measures. The first is trading credit (*TradeCredit*). The results are in the columns (1) and (2) in Panel B of Table 2-8. The coefficients are all positive and significant, indicating that the strong culture exhibits more available trading credit and lower financial constraints which in turn relate to higher abnormal return of stocks.

Following Buehlmaier and Whited (2018), the second measures are the KZ Index (KZ), developed by Kaplan and Zingales (1997), and the WW index (WW), developed by Whited and We (2006). *KZ* results are shown in columns (3) and (4) in Panel B of Table 2-8. The coefficient in column (3) is negative and significant, indicating that the strong culture is significantly negatively associated with the KZ financial constraint index. The coefficients in column (4) are positive for the culture score variable and negative for the KZ Index variable, indicating that stock performance increases with lower financial constraints. For robustness checking, the mediating effect of *WW* is also examined, and the results are similar to those of *KZ*.

2.6 Further discussions

2.6.1 The heterogenous impacts on SOEs and POEs

It is recognized that government officials exercise control over state-owned enterprises (SOEs) for their own objects (Shleifer and Vishny, 1994; Shleifer, 1998) rather than maximizing shareholder value. Therefore, corporate governance in the SOEs, including corporate culture development, can be intervened by the government for political purposes. In China, SOE is essential to the economy and accounted for over 60% of market capitalization in 2019. Xie et al. (2022) point out that SOEs in China have an alternative model of governance compared to private-owned enterprises (POE); for example, SOEs may legitimize a governing system that authorizes the government over the board of directors. Moreover, the main incentive for SOE managers is the chance of promotion to higher-level government positions after tenure rather than the payment or performance bonuses, a motivation that essentially eliminates the need for incentive-based compensation at SOEs (Jiang et al. (2015)). Consequently, rather than promoting the firm's performance, managers in Chinese SOEs are more likely to employ corporate culture to achieve political goals, such as policy response or propaganda.

We, therefore, examine the heterogeneity of the mitigation effects of strong corporate culture to the negative impact of the trade war on the firm valuation across the SOEs and POEs. The comparison of corporate cultures between POEs and SOEs is reported in Table 2-9. The culture scores in all dimensions in SOEs are higher than in POEs, except for the cultural value of "Product and Service Quality" (see columns (2) and (3)). The differences in each cultural value between SOEs and POEs are all significant at the 1% level in column (3).

Table 2-9 Comparisons of the mean corporate culture scores between SOE and POE

Culture	Group	Number of Observations	Mean	Diff
		(1)	(2)	(3)
Overall	POE	22,186	5.4556	0.6400***
	SOE	12,109	6.0956	

Integrity	POE	22,186	5.6273	0.4951***
	SOE	12,109	6.1224	
Innovation	POE	22,186	5.2531	0.7557***
	SOE	12,109	6.0088	
Hardworking	POE	22,186	5.0213	1.4101***
	SOE	12,109	6.4314	
Quality	POE	22,186	5.8162	-0.8394***
	SOE	12,109	4.9768	
Teamwork	POE	22,186	5.4036	0.2854***
	SOE	12,109	5.6890	

This table compares the mean corporate culture scores between the POE and SOE subgroups in the t-test. The results of overall and individual cultures are all presented in this table. Column (3) presents the difference between mean values and the p-statistics of the t-test with the hypothesis that the mean value in the POE group is not equal to the value in the SOE group. *p<.1; **p<.05; ***p<.01.

We run the regressions in the specification of equations (2) and (4) for SOEs and POEs, respectively. Results in Table 2-10 show that POEs with a strong culture performed significantly better than SOEs with a strong culture during the crisis period. These results suggest that a strong corporate culture matters only for POEs but not for SOEs during the trade war.

Table 2-10 Test in groups: SOE and POE

Panel A: the Sino-US trade war exposure and abnormal stock returns: SOE and POE

	ExcessReturn		*DGTWReturn*	
	POE	SOE	POE	SOE
Variables	(1)	(2)	(3)	(4)
CultureScore	0.0036**	-0.0021	0.0052**	-0.0033
	(0.0018)	(0.0024)	(0.0024)	(0.0031)
FirmCharacteristics	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	1,828	919	1,805	913

Pseudo/Adj. R^2	0.1725	0.3657	0.1595	0.3352

Panel B: the effect of the corporate culture: SOE and POE

	DGTWReturn			
	POE	SOE	POE	SOE
Variables	(1)	(2)	(3)	(4)
TradeWar	-0.0322***	-0.0160	-0.0384***	-0.0169
	(0.0104)	(0.0109)	(0.0119)	(0.0111)
TradeWar × *CultureScore*	0.0032**	0.0015	0.0040**	0.0020
	(0.0016)	(0.0017)	(0.0018)	(0.0017)
FirmCharacteristics	NO	NO	YES	YES
FactorLoadings	NO	NO	YES	YES
Month FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	22,947	11,919	14,983	9,954
Pseudo/Adj. R^2	0.0026	0.0144	0.0250	0.0386

Panel A in this table presents cross-sectional data regressions that estimate the relation between trade war exposure and abnormal returns under the SOE and POE subgroups over 2018. Panel B presents regression estimates of panel data on the relationship between the interaction term, which consists of trade war exposure and culture score, and abnormal stock return under the SOE and POE subgroups over 2018. The dependent variables are two measures of abnormal return, the excess return and DGTW abnormal return. The key independent variable is the trade war exposure proxied by the textual analysis from analyst reports in panel A, and the interaction term consists of the trade war exposure and culture score in panel B. The control variables are the firm feature variables and the factor loadings. In panel A, industry fixed effects (FE) are used. The fixed effects (FE) used in each specification are at the firm and month level in panel B. Standard errors consistent with Heteroscedasticity are clustered at the firm level and reported in parentheses. R^2 values are given in the table. *p<.1; **p<.05; ***p<.01.

2.6.2 Impact of individual cultures

To understand how a strong culture helps firms during the trade war, we further examine the contribution of each individual corporate cultural value to the resilience of SOEs and POEs in the trade war. Panel A of Table 2-11 shows that the coefficients of interaction terms with the score of cultures of "Product and Service Quality," "Hardworking and Performance," and "Innovation and Technology" are positive and significant, while the coefficients of interaction terms with the cultures of "Integrity and

Honesty" and "Teamwork and Cooperation" are positive but not significant. These results suggest that the company's cultures of improvement of product or service, creativity, and firm performance are the keys to resilience during the trade war. Panel B shows the results of POEs. The results are comparable to those in Panel A except that the coefficients in Panel B of the interaction term with the "Teamwork and Cooperation" variable are also positive and significant, and the coefficient of the term with "Innovation, and Technology" variable is positive and significant at 5% level instead of 10%. These results suggest that being creative and cooperative are more important for POEs in crisis than for SOEs.

Table 2-11 Tests of the impact of individual cultures

Panel A: Corporate culture and abnormal stock returns: single cultures

			DGTWReturn		
Variables	(1)	(2)	(3)	(4)	(5)
TradeWar	-0.0243**	-0.0258***	-0.0295***	-0.0332***	-0.0233***
	(0.0101)	(0.0086)	(0.0093)	(0.0074)	(0.0082)
TradeWar × Integrity	0.0020				
	(0.0016)				
TradeWar × Innovation		0.0022*			
		(0.0013)			
TradeWar × Hardworking			0.0028**		
			(0.0014)		
TradeWar × Quality				0.0037***	
				(0.0013)	
TradeWar × Teamwork					0.0019
					(0.0013)
FirmCharacteristics	YES	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Observations	25,907	25,907	25,907	25,907	25,907
Pseudo/Adj. R^2	0.0230	0.0230	0.0231	0.0232	0.0230

Panel B: Corporate culture and abnormal stock returns: single cultures (POE)

	DGTWReturn				
Variables	(1)	(2)	(3)	(4)	(5)
TradeWar	-0.0326**	-0.0436***	-0.0422***	-0.0550***	-0.0436***
	(0.0143)	(0.0128)	(0.0130)	(0.0125)	(0.0117)
TradeWar × Integrity	0.0025				
	(0.0023)				
TradeWar × Innovation		0.0044**			
		(0.0020)			
TradeWar × Hardworking			0.0043**		
			(0.0019)		
TradeWar × Quality				0.0059***	
				(0.0019)	
TradeWar × Teamwork					0.0044**
					(0.0020)
FirmCharacteristics	YES	YES	YES	YES	YES
FactorLoadings	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Observations	14,650	14,650	14,650	14,650	14,650
Pseudo/Adj. R^2	0.0266	0.0269	0.0269	0.0271	0.0269

This table presents the panel data regression estimates of the relationship between abnormal stock return and the interaction term, consisting of trade war exposure and individual culture score over 2018. Panel A presents the relation between abnormal return and interaction terms consisting of trade war exposure and individual culture scores for all samples. Panel B presents the results for the subsample of POEs. The dependent variable is DGTW abnormal return. The key independent variable is the interaction terms, which consist of trade war exposure and individual culture scores. The control variables are the firm feature variables and the factor loadings. The fixed effects (FE) used in each specification are at firm and month level and are noted in the table. Heteroscedasticity-consistent standard errors are clustered at the firm level and reported in parentheses. R^2 values are given in the table. *p<.1; **p<.05; ***p<.01.

2.7 Conclusion

In this research, we study whether a strong corporate culture can provide resilience and mitigate the negative impact of the Sino-U.S. trade war on the listed Chinese companies. First, we introduce a new semi-supervised machine learning approach to generate a corporate culture dictionary in Chinese and obtain corporate culture measurement for the top five most popular corporate culture values of the Chinese A-Share listed firms. Then, we quantify the corporate exposure to the Sino-US trade war using the lexicon method. We find that the firms exposed to the trade war significantly suffered adverse valuation effects in 2018.

Empirical analyses suggest that firms with stronger cultures had better stock performance in 2018 compared to their peers with weaker cultures, and the stronger culture helps mitigate the negative impacts of trade war exposure. Two potential influencing mechanisms are operating performance enhancement and financial constraint mitigation. Moreover, the corporate culture provides more resilience to POEs than SOEs in the trade war. Further analyses reveal that individual cultures of "Quality," "Hardworking," "Teamwork," and "Innovation" have more material effect on the firm performance of POEs.

Our research has important implications. Firstly, the Sino-U.S. trade war represents a substantial economic burden for Chinese companies, threatening their sustainable development. Secondly, we provide evidence that corporate culture helps mitigate these negative impacts, fostering a more sustainable future, especially for POEs that benefit most from a strong corporate culture. These findings underscore the critical role of corporate culture as a soft institution in helping firms navigate crises and enhance operational performance. They also validate the economic value of corporate culture, which extends beyond mere managerial improvements.

Given these insights, firms in developing countries, where management systems tend to be less sophisticated and more vulnerable to external shocks, should prioritize nurturing corporate culture. Top managers need to identify cultural values that resonate with their organizations and integrate them into management and operations through regulation, behavioral practices, and employee education. Training employees to understand and embrace these values is essential. Additionally, government agencies should support firms in building and reinforcing their corporate culture through initiatives such as advocating their soft power and facilitating the sustainable development of both firms and the broader economy.

While our research aims to demonstrate how a sound corporate culture can foster resilience among firms adversely impacted by the Sino-U.S. trade war, it is important to acknowledge potential limitations that could be addressed in future studies. Firstly, our measure of corporate culture and firms' exposure to the China-U.S. trade war relies on textual analysis due to the limited availability of public data, such as annual reports or analyst reports. While alternative data sources, such as actual import-export figures or internal corporate culture materials, may exist, they are often not publicly accessible. This constraint necessitated the use of textual analysis to indirectly measure corporate culture and trade war exposure. Future research could address more suitable data becomes available, leading to more precise conclusions. Secondly, our study does not conduct a detailed examination of endogeneity issues, in which may result in omitted variable bias or other concerns. To mitigate these issues, future research should consider including instrumental variables for endogeneity testing.

Reference

Algan, Y. and Cahuc, P., 2010. Inherited trust and growth. *American Economic Review*, *100*(5), pp.2060-2092.

Amiti, M., Redding, S.J. and Weinstein, D.E., 2019. The impact of the 2018 tariffs on prices and welfare. *Journal of Economic Perspectives*, *33*(4), pp.187-210.

Amiti, M., Redding, S.J. and Weinstein, D.E., 2020, May. Who's paying for the US tariffs? A longer-term perspective. In *AEA Papers and Proceedings* (Vol. 110, pp. 541-546).

Audi, R., Loughran, T. and McDonald, B., 2016. Trust, but verify: MD&A language and the role of trust in corporate culture. *Journal of Business Ethics*, 139, pp.551-561.

Baker, S.R., Bloom, N. and Davis, S.J., 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), pp.1593-1636.

Barney, J.B., 1986. Organizational culture: can it be a source of sustained competitive advantage?. *Academy of Management Review*, *11*(3), pp.656-665.

Bellstam, G., Bhagat, S. and Cookson, J.A., 2021. A text-based analysis of corporate innovation. Management Science, 67(7), 4004-4031.

Benguria, F., Choi, J., Swenson, D.L. and Xu, M.J., 2022. Anxiety or pain? The impact of tariffs and uncertainty on Chinese firms in the trade war. *Journal of International Economics*, *137*, p.103608.

Bertrand, M. and Schoar, A., 2003. Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, 118(4), 1169-1208.

Besedes, T., Kohl, T. and Lake, J., 2020. Phase out tariffs, phase in trade?. *Journal of International Economics*, 127, 103385.

Baron, R.M. and Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), p.1173.

Bolton, P., Brunnermeier, M.K. and Veldkamp, L., 2013. Leadership, coordination, and corporate culture. *Review of Economic Studies*, 80(2), pp.512-537.

Bonfatti, R., 2017. The sustainability of empire in a global perspective: The role of international trade patterns. *Journal of International Economics*, 108, 137-156.

Bown, C.P. and Kolb, M., 2022. Trump's trade war timeline: An up-to-date guide.

Buehlmaier, M.M. and Whited, T.M., 2018. Are financial constraints priced? Evidence from textual analysis. *Review Financial. Studies*, 31(7), 2693-2728.

Caldara, D. and Iacoviello, M., 2022. Measuring geopolitical risk. *American Economic Review*, 112(4), 1194-1225.

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A. and Raffo, A., 2020. The economic effects of trade policy uncertainty. *Journal of Monetary Economics*, *109*, pp.38-59.

Chen, D., Newburry, W. and Park, S.H., 2009. Improving sustainability: An international evolutionary framework. *Journal of International Management*, *15*(3), pp.317-327.

Chen, J., Chen, X., Hou, Q. and Hu, M., 2021. Haste doesn't bring success: Top-down amplification of economic growth targets and enterprise overcapacity. *Journal of Corporate Finance*, 70, 102059.

Chui, A.C., Titman, S. and Wei, K.J., 2010. Individualism and momentum around the world. *Journal of Finance*, 65(1), 361-392.

Crowley, M.A., 2006. Do safeguard tariffs and antidumping duties open or close technology gaps?. *Journal of International Economics*, 68(2), 469-484.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, 52(3), 1035-1058.

El Ghoul, S. and Zheng, X., 2016. Trade credit provision and national culture. *Journal of Corporate Finance*, 41, 475-501.

Eun, C.S., Wang, L. and Xiao, S.C., 2015. Culture and R2. *Journal of Financial Economics*, 115(2), 283-303.

Fajgelbaum, P., Goldberg, P., Kennedy, P., Khandelwal, A. and Taglioni, D., 2024. The US-China trade war and global reallocations. *American Economic Review: Insights*, 6(2), pp.295-312.

Fisman, R., Hamao, Y. and Wang, Y., 2014. Nationalism and economic exchange: Evidence from shocks to sino-japanese relations. *Review of Financial Studies*, 27(9), 2626-2660.

Francis, B., Hasan, I., Liu, L., Wu, Q. and Zhao, Y., 2021. Financial analysts' career concerns and the cost of private debt. *Journal of Corporate Finance*, 67, 101868.

Glick, R. and Taylor, A.M., 2010. Collateral damage: Trade disruption and the economic impact of war. *The Review of Economics and Statistics*, *92*(1), pp.102-127.

Graham, J.R., Grennan, J., Harvey, C.R. and Rajgopal, S., 2022. Corporate culture: Evidence from the field. *Journal of Financial Economics*, 146(2), 552-593.

Grennan, J., 2019. A corporate culture channel: How increased shareholder governance reduces firm value. Working paper.

Groysberg, B., Lee, J., Price, J. and Cheng, J., 2018. The leader's guide to corporate culture. *Harvard Business Review*, 96(1), pp.44-52.

Guiso, L., Sapienza, P. and Zingales, L., 2003. People's opium? Religion and economic attitudes. *Journal of Monetary Economics*, 50(1), 225-282.

Guiso, L., Sapienza, P. and Zingales, L., 2008. Trusting the stock market. *Journal of Finance,* 63(6), 2557-2600.

Guiso, L., Sapienza, P. and Zingales, L., 2009. Cultural biases in economic exchange?. *The Quarterly Journal of Economics*, 124(3), 1095-1131.

Guiso, L., Sapienza, P. and Zingales, L., 2015. The value of corporate culture. *Journal of Financial Economics*, 117(1), 60-76.

Han, P., Jiang, W. and Mei, D., 2022. Mapping US-China technology decoupling, innovation, and firm performance. Working paper.

Hassan, T.A., Hollander, S., Van Lent, L. and Tahoun, A., 2019. Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4), 2135-2202.

Hassan, T.A., Hollander, S., Lent, L.V. and Tahoun, A., 2024. The global impact of Brexit uncertainty. *The Journal of Finance*, *79*(1), pp.413-458.

Hassan, T.A., Hollander, S., Van Lent, L., Schwedeler, M. and Tahoun, A., 2023. Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1. *The Review of Financial Studies*, *36*(12), pp.4919-4964.

Hofstede, G., Neuijen, B., Ohayv, D.D. and Sanders, G., 1990. Measuring organizational cultures: A qualitative and quantitative study across twenty cases. *Administrative Science Quarterly*, pp.286-316.

Hofstede, G.H. and Hofstede, G., 2001. Culture's consequences: Comparing values, behaviors, institutions and organizations across nations. Sage.

Huang, A.H., Lehavy, R., Zang, A.Y. and Zheng, R., 2018. Analyst information discovery and interpretation roles: A topic modeling approach. *Management Science*, 64(6), 2833-2855.

Huang, Y., Lin, C., Liu, S. and Tang, H., 2023. Trade networks and firm value: Evidence from the US-China trade war. Journal of International Economics, 145, p.103811.

Itakura, K., 2020. Evaluating the impact of the US–China trade war. *Asian Economic Policy Review*. 15(1), 77-93.

Jiang, F. and Kim, K.A., 2015. Corporate governance in China: A modern perspective. *Journal of Corporate Finance*, 32, 190-216.

Jiao, Y., Liu, Z., Tian, Z. and Wang, X., 2022. The impacts of the US trade war on Chinese exporters. *Review of Economics and Statistics*, pp.1-34.

Kaplan, S.N. and Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints?. *The Quarterly Journal of Economics*, 112(1), 169-215.

Kreps, D.M., 1990. Corporate culture and economic theory. *Perspectives on Positive Political Economy*, *90*(109-110), p.8.

Lai, K.M., Khedmati, M., Gul, F.A. and Mount, M.P., 2023. Making honest men of them: Institutional investors, financial reporting, and the appointment of female directors to all-male boards. *Journal of Corporate Finance*, 78, 102334.

Li, K., Liu, X., Mai, F. and Zhang, T., 2021. The role of corporate culture in bad times: Evidence from the COVID-19 pandemic. *Journal of Financial and Quantitative Analysis*, *56*(7), pp.2545-2583.

Li, K., Mai, F., Shen, R. and Yan, X., 2021. Measuring corporate culture using machine learning. *The Review of Financial Studies*, *34*(7), pp.3265-3315.

Lins, K.V., Servaes, H. and Tamayo, A., 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4), 1785-1824.

Liu, J., Stambaugh, R.F. and Yuan, Y., 2019. Size and value in China. *Journal of Financial Economics*, *134*(1), pp.48-69.

Loughran, T. and McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1), 35-65.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G.S. and Dean, J., 2013. Distributed representations of words and phrases and their compositionality. *Advances in Neural Information Processing Systems*, *26*.

Nunn, N., 2008. The long-term effects of Africa's slave trades. *The Quarterly Journal of Economics*, 123(1), 139-176.

O'Reilly, C., 1989. Corporations, culture, and commitment: Motivation and social control in organizations. *California Management Review*, 31(4), pp.9-25.

O'Reilly, C.A. and Chatman, J.A., 1996. Culture as scial control: Corporations, cults,

and commitment.
Pursiainen, V., 2022. Cultural biases in equity analysis. *The Journal of Finance,* 77(1), pp.163-211.
Sautner, Z., Van Lent, L., Vilkov, G. and Zhang, R., 2023. Firm-level climate change exposure. *The Journal of Finance*, *78*(3), pp.1449-1498.
Schein, E.H., 1990. Organizational Culture: What it is and How to Change it. In Human resource management in international firms (pp. 56-82). Palgrave Macmillan, London.
Shleifer, A. and Vishny, R.W., 1994. Politicians and firms. *The Quarterly Journal of Economics*, 109(4), 995-1025.
Shleifer, A., 1998. State versus private ownership. *Journal of Economic Perspectives*, *12*(4), pp.133-150.
Song, Y., Shi, S., Li, J. and Zhang, H., 2018, June. Directional skip-gram: Explicitly distinguishing left and right context for word embeddings. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2, 175-180.
Sørensen, J.B., 2002. The strength of corporate culture and the reliability of firm performance. *Administrative Science Quarterly*, *47*(1), pp.70-91.
Talhelm, T., Zhang, X., Oishi, S., Shimin, C., Duan, D., Lan, X. and Kitayama, S., 2014. Large-scale psychological differences within China explained by rice versus wheat agriculture. *Science*. 344(6184), 603-608.
Van den Steen, E., 2010. On the origin of shared beliefs (and corporate culture). *The RAND Journal of Economics*, 41(4), pp.617-648.
Wang, Y. and Chen, J., 2013. Differences of English and Chinese as Written Languages and Strategies in English Writing Teaching. *Theory & Practice in Language Studies (TPLS)*, *3*(4).
Wang, Y., Wang, Y. and Lee, S.H., 2017. The effect of cross-border e-commerce on China's international trade: An empirical study based on transaction cost analysis. *Sustainability*. 9(11), 2028.
Weber, M., 1930. The Protestant ethic and the spirit of capitalism, tr. Talcott Parsons. New York: Charles Scribner's Sons. 1(0).
Whited, T.M. and Wu, G., 2006. Financial constraints risk. *The Review of Financial Studies*, *19*(2), pp.531-559.
Wu, W., Firth, M. and Rui, O.M., 2014. Trust and the provision of trade credit. *Journal of Banking & Finance*, *39*, pp.146-159.
Xie, S., Lin, B. and Li, J., 2022. Political Control, Corporate Governance and Firm Value: The Case of China. *Journal of Corporate Finance*, 72, 102161.
Xiong, J., Ouyang, C., Tong, J.Y. and Zhang, F.F., 2021. Fraud commitment in a smaller world: Evidence from a natural experiment. *Journal of Corporate Finance*, 70, 102090.
Xu, Z., Li, Y., Chau, S.N., Dietz, T., Li, C., Wan, L., Zhang, J., Zhang, L., Li, Y., Chung, M.G. and Liu, J., 2020. Impacts of international trade on global sustainable development. *Nature Sustainability*, *3*(11), pp.964-971.

Zuckerman, A., 2002. Strong corporate cultures and firm performance: are there tradeoffs?. *Academy of Management Perspectives*, *16*(4), pp.158-160.

Appendix

Appendix 2-1. Variables definitions

Variables	Definition
Variables of corporate culture	
CultureScore	The culture score level aggregated from the culture scores level of innovation, integrity, teamwork, and honest, in 2016.
Integrity	The culture score of integrity and honesty.
Innovation	The culture score of innovation and technology.
Hardworking	The culture score of hardworking and performance.
Quality	The culture score of product and service quality.
Teamwork	The culture score of teamwork and cooperation.
Variables of the trade war exposure	
TradeWar	The trade war exposure variable equals to 1 if the analyst reports for a specific firm in specific month have the sentence containing the words of trade war.
TradeWar_Count	The trade war exposure variable equals to the ratio of the number of sentences containing the words of trade war to number of all sentences in the analyst reports for a specific firm in specific month, taking logarithm.
Control variables	
ROE	Earning return divided by the total equity.
Size	The amount of market size of stock, taking logarithm.
Leverage	Debt to equity ratio.
Tobin's Q	The market value of a company divided by its assets' replacement cost.
SalesGrowth	The growth of sales.
FixedGrowth	The growth of fixed asset.
CEOChair	A dummy variable equals to 1 if CEO is not the Chairman of board.
BoardIndependence	Fraction of board consisting of independent director.
BoardSize	The number of members of board.
BoardOwnership	Fraction of outstanding shares owned by board members.
Variables for validating the corporate culture scores	
EarningsManagement	The degree of real earnings management
Fault	The number of times that the firm violated regulation and punishment by the regulators
R&D	The ratio of research and development expense amount to total asset
Patents	The number of patents
EarningGrowth	The percentage change of earnings
LawSuit	The number of lawsuits related to the business contract
ISO9001	The pass of ISO9001 (dummy variable)
JointVenture	The number of joint ventures that the firm has participated in

Appendix 2-2. Validating our measure of the corporate culture

	EarningsManagement	*Fault*	*R&D*	*Patents*	*EarningGrowth*	*LawSuit*	*ISO9001*	*JointVenture*
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Integrity	-1.0941**	-3.1798***						
	(0.4883)	(0.6583)						
Innovation			0.2257***	12.6757***				
			(0.0226)	(1.8012)				
Hardworking					0.7765***			
					(0.1449)			
Quality						-4.5137***	20.4824***	
						(0.8523)	(3.8168)	
Teamwork								74.6280***
								(20.9120)
ROE	-0.7183***	-1.0273***	0.0340***	0.7087***	0.0940***	-0.5579***	0.6084	-3.9220***
	(0.0387)	(0.0679)	(0.0033)	(0.1873)	(0.0130)	(-9.10)	(0.3926)	(1.1054)
Size	0.0022	-0.0184***	-0.0011***	0.1026***	-0.0028***	-0.0260***	-0.0501*	2.9059***
	(0.0020)	(0.0029)	(0.0002)	(0.0160)	(0.0005)	(-4.37)	(0.0266)	(0.1547)
Leverage	0.0190	0.1162***	-0.0058***	-0.0934	0.0093**	0.3721***	-0.1606	-1.9003***
	(0.0127)	(0.0216)	(0.0012)	(0.0752)	(0.0040)	(8.39)	(0.1643)	(0.5546)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	20,558	22,847	22,847	22,847	19,362	22,847	21,295	16,262
Pseudo/Adj. R^2	0.0872	0.0578	0.3776	0.0643	0.0280	0.0690	0.0543	0.2923

This table validates our main measure of corporate values based on the *Discussion and Analysis of the Operation* section of the annual report, from 2012 to 2020. In columns (1) to (2), *EarningManagement* and *Fault* are used to validate the culture score of "Integrity and Honesty". In columns (3) and (4), *R&D* and *Patents* are used to validate the culture score of "Innovation and Technology". In column (5), *EarningGrowth* is used to validate the culture score of "Hardworking and Performance". In columns (6) and (7), *LawSuit* and *ISO9001* are used to validate the "Product and Service Quality". In column (8), *JointVenture* is used to validate the culture score of "Teamwork and Cooperation". Logistic regressions are used for dummy dependent variables in column (7). Industry fixed effects (FE) are used. R^2 values are given. Heteroscedasticity-consistent standard errors are clustered at the firm level and reported in parentheses. *p<.1; **p<.05; ***p<.01.

Appendix 2-3. List of the words of the Sino-U.S. Trade War

Words of Sino-US Trade War (in English)	Words of Sino-U.S. Trade War (in English)
"Double Reverse" investigation	Sino-U.S. trade friction
301 Investigation	Sino-U.S. trade disputes
337 Investigation	Sino-U.S. trade relations
American "double reverse"	Tariff
American ITC	Trade agreement
Anti-dumping investigation	Trade conflict
Anti-trust investigation	Trade dispute
Countervailing investigation	Trade friction
Federal register	Trade investigation
Federal Trade Commission	Trade protection
Protectionism	Trade protectionism
Protective tariff	Trade remedy
Punitive tariff	Trade sanctions
Retaliatory tariff	Trade War
Section 301	Great Trade War
Sino US conflict	Trump administration
Sino US economic and trade	Unfair trade
Sino US friction	US Department of Commerce
Sino US trade	American Government Department of Commerce
Sino-US trade disputes	US export regulations

Appendix 2-4. Validating our measure of the Sino-US trade war exposure

	TradeWar					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Export	0.0636***	0.0602***	0.0422***			
	(0.0050)	(0.0060)	(0.0070)			
Import				0.0734***	0.0635***	0.0399***
				(0.0056)	(0.0067)	(0.0075)
Controls	NO	YES	YES	NO	YES	YES
Industry FE	NO	NO	YES	NO	NO	YES
Observations	4,604	3,141	3,140	4,604	3,141	3,140
Pseudo/Adj. R^2	0.0332	0.1165	0.1940	0.0344	0.1142	0.1913

This table validates our main measure of the Sino-U.S. trade war exposure based on the analyst report. Columns (1) to (3) show the association between the export amount from 2015 to 2016 and the trade war exposure from 2017 to 2020 for the listed firms. Columns (4) to (7) show the association between import amounts from 2015 to 2016 and the trade war exposure from 2017 to 2020 for the listed firms. Logistic regressions are used in these regressions. Industry fixed effects (FE) are used. R^2 values are given. Heteroscedasticity-consistent standard errors are clustered at the firm level and reported in parentheses. *p<.1; **p<.05; ***p<.01.

Chapter 3. Political Uncertainty and the Rapidly Involving Technological Innovation of Firms: Evidence from China

ABSTRACT

In this paper, we examine the impact of individual firms' political uncertainty on their rapidly evolving technology innovation. Technological areas tend to follow cycles. Using patent text data, we determine the positioning of a given patent and firms within technology cycles. We also adapt simple tools from computational linguistics to construct a new measure of political uncertainty faced by individual Chinese firms: the share of their annual reports that they devote to political uncertainty. Empirical analyses suggest that firms facing higher political uncertainty tend to adopt more conservative innovation strategies, resulting in less innovation in rapidly evolving technological areas. These findings remain robust after adding control variables and fixed effects. To address potential endogeneity issues, we employ two quasi-natural experiments involving the Sino-U.S. trade war and COVID-19 shocks to establish causality. Our results indicate that increased financing constraints and executive risk aversion are the primary channels through which political uncertainty affects innovation in rapidly evolving technological areas. The effect is more pronounced for non-state-owned enterprises, firms in highly competitive industries, and those with more irreversible investments. Our research pinpoints that political uncertainty impedes firms' innovation in rapidly evolving technological areas.

Keywords: Political Uncertainty, Rapidly Evolving Technology, Textual Analysis

3.1 Introduction

Technological innovation is not only considered a source of national economic growth and competitiveness (Solow, 1957) but is also regarded as an important issue of enterprise performance (Koellinger, 2008; Hall, 2015; Wadho and Chaudhry, 2018). The creation of new technologies is vital for firm productivity and economic growth (Romer, 1990).

Technological innovation follows a cyclical pattern, typically beginning with breakthroughs that disrupt existing techniques (Tushman and Aderson, 1986). These breakthroughs are often succeeded by a dynamic phase characterized by rapid evolution through widespread experimentation and trial and error (Callander, 2011). Technologies in their ascending phase are often groundbreaking or even revolutionary, leading to widespread dissemination in subsequent development phases, evolution, and refinement, ultimately maturing into stable and widely adopted technological fields (Abernathy and Utterback, 1978; Tushman and Anderson, 1986; Callander, 2011). While the majority of patents contribute incremental advancements over existing technologies with limited impact on technological progress (Griliches, 1990; Lemley and Shapiro, 2005), a minority introduce radically new technologies and serve as significant reference points for future innovation (Trajtenberg, 1990; Scherer and Harhoff, 2000). Our research is focused on investigating the factors that either encourage or hinder firms from rapidly developing evolving technology, as well as understanding the underlying reasons behind these dynamics.

Political uncertainty is known to significantly impact business operations (Brogaard and Detzel, 2015; Handley and Limão, 2017) by creating an unpredictable environment that complicates strategic planning and investment decisions. Recent studies have shown that political uncertainty can negatively affect a firm's research and development (R&D) investment and patent creation (Xu, 2020; Liu and Ma, 2020; Cong and Howell, 2021). While identifying a relationship between regional political uncertainty and innovation intensity, recent studies overlook the heterogeneity of political uncertainty exposure faced by individual enterprises, as well as the diversity of marginal technological contributions and the decision-making process of firms regarding the development of rapidly evolving versus complementary technologies. This gap is critical because different enterprises face different political uncertainty exposures, and the type and impact of innovation can vary significantly. Firms under high political uncertainty might avoid high-risk, high-reward innovations and instead focus on incremental improvements, thereby affecting the overall trajectory of technological progress. Understanding these decisions is essential for comprehensively assessing how political uncertainty shapes technological landscapes and influences long-term economic growth and competitiveness.

In this paper, we study how political uncertainty exposure influences the innovation strategies of individual firms to develop rapidly evolving technology. Unlike previous studies focusing solely on patent creation intensity, we study how political uncertainty exposure affects firms' choices between aggressively pursuing emerging technologies or adopting more conservative approaches based on established techniques in innovation. Our analysis centers on two competing hypotheses: the influence of risk aversion and market competition. We focus on firms listed on the A-Share stock market in China from 2007 to 2021. The findings provide evidence that higher political uncertainty exposure leads to a shift towards more conservative innovation strategies. This shift, characterized by a reluctance to embrace rapidly evolving technologies and innovation, ultimately translates into fewer groundbreaking advancements in the technological sphere. These effects persist even after controlling for patent outputs, R&D expenditure, firm characteristics, and macroeconomic factors.

Building on the methodology outlined by Bowen et al. (2023), we leverage firms' patent text data to discern the trajectory of technological innovation within rapidly evolving spheres. Our approach involves tracking the evolution of technology domains using textual analysis of patents filed with the State Intellectual Property Office of China (SIPO). To determine the position of a patent within the technological cycle, we evaluate the prevalence of its vocabulary among recent and contemporary patents. This assessment yields a continuous variable termed "Rapidly Evolving Technology" (RETech), allowing us to capture the positioning of patents within the technology cycle: those associated more with rapidly evolving technology areas, characterized by a surging in the usage of relevant terminology, and those linked more to stable technology domains, marked by a lack of significant growth in vocabulary usage.

To ensure the robustness of our findings, we develop an alternative RETech measure and three patent significance measures. The alternative RETech measure relies on the percentage change of the patents that contain specific terms, offering an additional perspective on technological evolution. The first patent significance measure, inspired by Kelly et al. (2021), gauges a patent's significance based on textual similarities with prior and subsequent patents. This approach identifies patents with distinct descriptions from prior art but shares similarities to subsequent innovations, indicating their transformative potential. Moreover, drawing from Bowen et al. (2023) and Owen-Smith (2016), we develop another patent significance measure assessing a patent's likelihood of substituting its cited predecessors. Lastly, we incorporate a citation measure to capture the influence and relevance of patents within the broader technological landscape. Our analysis establishes positive and statistically significant associations between our main measure, RETech, and these alternative indicators of technological significance. This convergence lends credence to the validity and reliability of our main RETech measure, bolstering its utility in uncovering the dynamics of rapidly evolving technological domains.

We adopt simple tools from computational linguistics to construct a new measure of political uncertainty faced by individual Chinese firms: the share of their annual reports that they devote to political uncertainty. First, we construct Political and Uncertainty Dictionaries by using the word2vec model. By assigning vectors to each word and calculating their similarities to seed words related to politics and uncertainty, we identify and manually verify relevant terms for inclusion in the dictionaries. Subsequently, within each firm annual report, we identify the co-occurrence of political terms and terms meaning uncertainty and quantify the ratio of uncertainty terms that are proximate to political terms, following Hassan et al. (2019). To validate our political uncertainty measure, we aggregate individual firm-level measures into a macro-level index and compare it against the EPU index developed by Baker et al. (2016). The high correlation and close proximity between the two indices lend credibility to our measure.

In the empirical study, we conduct panel regressions to test our hypotheses. The results reveal a significant negative association between political uncertainty exposure and firms' RETech. Specifically, a one-standard-deviation increase in the political uncertainty exposure corresponds to a 2.3% standard deviation decrease in the RETech. These findings remain robust even after controlling for various firm characteristics, macroeconomic factors, and fixed effects for year, industry, and province.

In the robustness check, we undertake several sensitivity analyses to validate the robustness of our main findings. Initially, we substitute the original political uncertainty variable with three alternative measures derived by varying the distance range parameters used in screening for the co-occurrence of political terms and terms meaning uncertainty within the annual report. Moreover, we replace the dependent variable with alternative metrics, such as the alternative RETech measure or the patent significance measures aggregated for each firm. Finally, we restrict our analyses to observations with recorded patent applications, thereby focusing exclusively on firms actively engaged in innovation activities. This step helps ensure that our results are not unduly influenced by firms that may not be directly involved in technological innovation. All these results consistently align with our main findings.

We conduct two quasi-natural experiments and introduce instrumental variables to alleviate the endogeneity issue. First, we use the Sino-U.S. trade war and the COVID-19 pandemic as exogenous shocks to test the causal relationship between political uncertainty and the RETech innovation of firms. By implementing the DID model, we examine whether firms that were more exposed to the Sino-U.S. trade war or had higher supply chain concentration during the COVID-19 pandemic suffered higher political uncertainty exposure after the initiation of the events and had fewer RETech innovations. We find that these firms experienced greater increases in political uncertainty due to these shocks, and our DID regressions demonstrate that such firms exhibit lower RETech innovation in response to exogenous shocks and higher political uncertainty. Second, we use the averaged location-industry value of the firm's RETech innovation as an instrumental variable to conduct a two-stage IV regression. We also employ a difference model to address the endogeneity issue. This instrumental variable strategy helps ensure that our results are not driven by omitted variable bias or reverse causality. Overall, the combination of these methodologies—quasi-natural experiments, IV regression, and difference model — provides robust evidence that political uncertainty causally affects firms' innovation strategies, leading to a reduction in rapidly evolving technological advancements. These findings effectively address the concerns about endogeneity and reinforce the validity of our main results.

We identify two channels through which political uncertainty exposure leads to a decrease in RETech innovation: aggravation of financing constraints and an increase in executive risk aversion. Specifically, firms exposed to higher political uncertainty tend to face more severe financial constraints and are less likely to implement Employee Stock Ownership Plans, which raises executive risk aversion. This heightened risk aversion subsequently results in less rapidly evolving technological innovation. Our findings also reveal that the effect of political uncertainty exposure on firms' innovation in rapidly evolving technological areas is more pronounced for non-state-owned enterprises (non-SOE), firms in highly competitive industries, and firms with more irreversible investments. These results align with our hypotheses and are consistent with existing literature.

This paper contributes to three strands of literature. The first strand explores the relationship between political uncertainty and firm innovation. Previous studies have shown that political uncertainty negatively impacts firms' innovation outputs, typically measured by the number of patent applications and granted. For instance, Xu (2020) shows that government political uncertainty increases a firm's cost of capital, thereby reducing its R&D and patent output. Liu and Ma (2020) use China's accession to the World Trade Organization in 2001 as a quasi-natural experiment to show that reduced trade political uncertainty promotes patent output. Cong and Howell (2021) investigate the suspension of IPO in China as a quasi-natural experiment and find that political uncertainty discourages firm innovation and decreases the number of patent applications and patents granted.

Literature also demonstrates that most patents make minor improvements over existing technologies, having little impact on technological progress. However, a few patents introduce groundbreaking technologies that significantly influence subsequent technological developments (Griliches, 1990; Trajtenberg, 1990; Scherer and Harhoff, 2000; Lemley and Shapiro, 2005). Existing research fails to explore what drives firms to innovate in rapidly evolving technological areas, especially from the perspective of political uncertainty. The primary difference between our research and existing studies is that we focus on how political uncertainty impacts firms' innovation strategy choices, especially whether to explore technology in its rapidly evolving stage or to pursue complementary innovations with mature and stable technology.

The second strain of literature we contribute to is the study of political uncertainty. Political uncertainty is a widely discussed issue in the current literature. Scholars mainly use regional-level EPU indices to study the impact of political uncertainty on corporate investment (Julio and Yook, 2012), acquisition (Cao et al., 2019), and asset pricing (Brogaard et al., 2020). The study most similar to ours is by Bhattacharya et al. (2017), which uses the regional EPU indices to examine a firm's innovation capabilities and finds that political uncertainty, rather than the policy itself, depresses the firm's innovation activities. However, the limitation of these studies is that regional EPU indices only capture macro-level political uncertainty, overlooking the heterogeneity of political uncertainty experienced by individual enterprises. These differences arise due to variations in their specific business operations, political connections, and ownership structure. Our research addresses this gap by focusing on the impact of firm-specific political uncertainty on innovation activities rather than relying on region EPU indices. By doing so, we provide new evidence that the heterogeneity of political uncertainty significantly influences a firm's innovation strategies.

The third strand of studies involves the application of textual analysis and machine learning in financial research. Various studies have developed text-based proxies to measure innovation activities or firm performance. Baker et al. (2016) introduced a news-based regional EPU index for assessing political uncertainty. Bellstam et al. (2021) establish a novel measurement of firm innovation using the LDA model. Kelly et al. (2021) devised an approach to measure patent significance based on pairwise forward and backward textual similarity of patents. Bowen et al. (2023) assessed the position of patents in the technological cycle using the frequency of across-year percentage change in terms of patent descriptions. Additionally, Caldara and Iacoviello (2022) developed geopolitical risk indices for several countries using textual news data. Hassan et al. (2019) used conference call textual data in the U.S. to construct firm-level political uncertainty measures. Our study contributes to this body of literature by developing new text-based measures for RETech, patent significance, and firm-level political uncertainty exposure in China.

The remainder of this paper is structured as follows. Section 2 develops the main hypotheses. Section 3 introduces data and the construction of main variables. Section 4 presents the methodology and main results. Section 5 addresses endogeneity issues. Sections 6 shows the mechanisms and heterogeneities. Section 7 concludes the paper.

3.2 Literature review and hypothesis development

3.2.1 Literature review

The risks stemming from the political systems and their impacts on investment strategies, employment levels, and various aspects of corporate behavior have become a central point of discussion among economists, corporate executives, and policymakers (Hassan et al., 2019). A key question is which dimensions of political decision-making contribute to disruptions in business operations.

Since Baker et al. (2016) pioneered research on measuring economic and political uncertainty using news text data, financial studies have increasingly focused on this important topic. These studies largely employ the Economic Policy Uncertainty index (EPU) developed by Baker et al. (2016), which is widely recognized for demonstrating that increased EPU heightens corporate uncertainty, raises volatility, and diminishes business performance (Liu and Zhang, 2020; Xu, 2020; Phan et al., 2021). In response to rising uncertainty, firms tend to adopt risk-avoidance strategies, curtail trade credit, and scale back investments (D'Mello and Toscano, 2020; Liu and Zhang, 2020). While these studies offer valuable insights into the broader effects of political uncertainty, the

EPU focused primarily on policy uncertainty at the regional level, particularly regarding economic policy, does not account for firm-specific political uncertainties that directly influence corporate decision making.

In contrast, Hassan et al. (2019) introduced a measure of political uncertainty at the firm level. Their findings revealed that firm-specific political uncertainty also leads to reduced investment and hiring, but with significant heterogeneity across firms in terms of political risk exposure. Furthermore, Hassan et al. (2023) demonstrated that although Brexit affected 8,177 firms across 81 countries, the extent of risk exposure varied considerably, underscoring the importance of examining political uncertainties on a firm-by-firm basis. Despite these advances, existing research has yet to investigate how firms' political uncertainty shapes their innovation strategies, particularly their choice of innovation direction.

When making R&D investment decisions, firms not only decide how many patents to file but also the direction of their technological development. A critical consideration is the pace of technological change in areas they pursue. Firms can opt for incremental innovation, which enhances existing technologies, or engage in more radical innovations, exploring groundbreaking technologies. Recent studies have examined firms' preferences for radical technological innovation. For instance, firms without independent director-led boards, private firms, or those with limited exposure to technology spillovers are more likely to pursue radical innovation (Balsmeier et al., 2017; Gao et al., 2018; Byun, 2021). Given the profound influence of policy and political environments on corporate strategies, it is essential to explore how political uncertainty affects firms' adoption of rapidly evolving technologies. However, this topic remains underexplored, and our research seeks to fill this theoretical gap.

3.2.2 Hypothesis development

Innovation involves discovering superior actions through experimentation and learning, with exploration activities often risking more time on inferior actions compared to exploitation (Manso, 2011). Policy changes significantly impact a firm's innovation decisions because shifts in policy and regulation can alter the economic conditions in which innovative firms operate, ultimately affecting their innovation choices.

Political uncertainty and policy changes are known to impact a firm's operating performance (Jens, 2017; Jeong, 2002). Bhattacharya et al. (2017) show that political uncertainty adversely impacts innovation performance, whereas the policy itself does not significantly affect innovation activity. Similarly, Cong and Howell (2021) provide evidence from China that corporate innovation accumulates over time and is adversely impacted by political uncertainty. However, when faced with high political uncertainties, firms have multiple options for their innovation activities. They can choose to engage in conservative innovation to avoid risks or pursue innovation in rapidly evolving technological areas to secure an advanced position. This complexity makes it unclear how political uncertainty influences a firm's preference for innovation in rapidly evolving technological areas in their R&D investments, specifically regarding the choice between radical and complementary patent creation.

In this article, we propose two competing hypotheses regarding firms' relative preference for radical evolving or conservative innovation within a policy-uncertain environment. Our first hypothesis is the "risk avoidance hypothesis," which states that firms tend to adopt a conservative innovation strategy when confronted with greater political uncertainty. Innovation involves exploring unknown technologies and untested approaches (Manso, 2011), and failure due to misjudgment of policies and economic conditions can be costly, especially in a high political uncertainty environment. Responding to uncertainty by waiting or delaying investment is considered a value-increasing strategy for firms (Aghion and Tirole, 1994; Weeds, 2002; Ferreira et al., 2014), especially for those with investment projects that are not fully reversible (Bernanke, 1983; Bloom et al., 2007; Bloom et al., 2016). Consequently, political uncertainty can motivate firms to delay the rapidly evolving technological innovation activities until the uncertainty is resolved.

In addition, innovation, as a form of research and development investment (Weeds, 2002), is closely tied to various forms of financing, including equity financing (Martinsson, 2010; Atanassov, 2016), enterprise and entrepreneurial financing (Fulghieri and Sevilir, 2009; Chemmanur et al., 2014), credit financing (Chang et al., 2019; Mello and Toscano, 2020), and loan financing (Atanassov, 2016; Lee et al., 2015). Evolving technological innovation may require more financial support compared to complementary innovation, as it involves experimentation in uncharted technological territories and necessitates trial and error. However, political uncertainty hampers firm financing and leads to financial constraints (Duong et al., 2020; Xu, 2020). Therefore, under the theory of precautionary savings, firms might reduce investments in rapidly evolving technological innovation to mitigate risks due to uncertainties.

Based on the foregoing discussion, we hypothesize that firms' exposure to political uncertainty will negatively influence their preference for innovation in rapidly evolving technological areas.

Hypothesis 1a. A firm's exposure to political uncertainty is negatively associated with its engagement in rapidly evolving technological areas of innovation.

Our second hypothesis, "market competition hypothesis," states that firms may pursue rapidly evolving technological areas innovation in the face of greater political uncertainty to gain a competitive edge. Bloom (2007) notes that R&D investment may respond differently to uncertainty compared to other types of investments due to varying adjustment costs. Van Vo and Le (2017) provide evidence supporting the "strategic growth option theory," which suggests that firms in highly competitive markets are more likely to engage in preemptive R&D expenditure expansion strategies. Additionally, competition can drive innovation by reducing pre-innovation rents more than post-innovation rents, thereby increasing the incremental profit from innovation and encouraging R&D investments to outpace competitors (Aghion et al., 2005). As political uncertainty can intensify industry competition, firms can be more motivated to increase their R&D investments and focus on cutting-edge innovations to secure a more favorable position in the evolving competitive landscape.

Additionally, firms may conduct pioneering research and innovation for the purpose of technology diversification, especially under high uncertainty. Growing uncertainty can cause technology imitation and a lack of breakthrough innovations to be sources of obsolescence. Diversifying innovation efforts can mitigate the variability in innovation investments (Garcia-Vega, 2006) and economic outcomes (Gambardella and Torrrisi, 1998). Firms often choose diversification in response to declining returns

(Gomes and Livdan, 2004). This rationale explains why risk-averse managers might prefer investing in innovative but risky research projects (Nelson, 1959). Under significant uncertainty, firms may diversify their innovation strategies by pursuing groundbreaking projects to avoid the negative lock-in effect of specific technologies (Garcia-Vega, 2006) and stay aligned with the most promising technological trends.

Considering the previous discussion, we propose the competing hypothesis that firms' political uncertainty exposure will be positively linked to their preference for rapidly evolving technological innovation.

Hypothesis 1b. A firm's political uncertainty exposure is positively associated with innovation in rapidly evolving technological areas.

3.3 Data and key variables

3.3.1 The key dependent variable

3.3.1.1 The positioning of a given patent or a firm within technology cycles

Following Bowen et al. (2023), we track the evolution of technology areas using the text from all patents filed with the State Intellectual Property Office of China (SIPO) between 2007 and 2020. To determine the position of a specific patent within the technological cycle, we assess the degree to which its vocabulary is gaining popularity among recent and contemporary patents. We refer to this continuous variable as "RETech" and classify a patent as higher RETech technology if it relies on terminology that exhibits a more rapid growth in usage across the entire patent corpus. Conversely, we categorize a patent in a more stable technology area if it utilizes terms that are not experiencing rapid growth. We use the "description" section in the patenting file, which outlines the technical content of the patent.

We first pre-treat the textual data. Unlike English, Chinese does not naturally have spaces between its words, making text segmentation more challenging. Following Cheng et al. (2023), we use the vocabulary list from the pre-trained Tencent AI-Lab word2vec model as a pre-determined dictionary, and we forcibly retain terms according to this dictionary when segmenting the text using the Jieba package in Python. Then, following Bowen et al. (2023), we eliminate the terms that appear in more than 5% of patents and less than five times across all patents. After the pre-treatment, 301,139 unique terms are kept in patent text data.

Next, we calculate the RETech for each patent (*RETech*). Our measure is constructed in two steps. In the first step, we calculate the percentage change of the terms in each year:

$$Z_t = \frac{1}{|P_t|}\sum_{k=1}^{P_t}\frac{V_{k,t}}{V_{k,t}\cdot\mathbf{1}} \tag{3-1}$$

$$\Delta_t = \frac{Z_t - Z_{t-1}}{Z_t + Z_{t-1}} \tag{3-2}$$

Specifically, for each patent k, we convert its text data to a word vector $V_{k,t} = [v_{1,t}, v_{2,t}, \dots, v_{N,t}]$, where N is the number of unique words across all patents in year t, and $v_{n,t}$ is the frequency of word n in patent k. To reduce the influence of patent length, we standardize the vector $V_{k,t}$ by dividing it by the total number of words in patent k. This can be expressed as $\frac{V_{k,t}}{V_{k,t}\cdot\mathbf{1}}$, where $\mathbf{1}$ is a vector of ones and "·" denotes the dot product. Next, we add up the vectors across all patents in the year t and standardize the aggregated vector by the number of patents in that year, $|P_t|$, to account for differences in the number of patents across years. This aggregated and standardized vector is denoted as Z_t.

By following these steps, we ensure that the influence of individual patent length and the varying number of patents per year are mitigated, allowing for a more accurate assessment of the degree to which specific terminologies are gaining popularity over time.

Then, we compute the relative difference between the aggregate vector Z_t in year t and the vector in year $t-1$. This difference is represented as $\Delta_t = [\Delta_{1,t}, \Delta_{2,t}, \dots, \Delta_{N,t}]$, where $\Delta_{n,t}$ is the percentage frequency change of word n in year t. Intuitively, the vector Δ_t tracks the emergence, disappearance, and development of specific technological vocabularies across all patents over time while controlling for the length and number of patents.

In the second step, we measure the position of a given patent k in the technology cycle, or the RETech of patent k:

$$RETech_{k,t} = \left(\frac{B_{k,t}}{B_{k,t} \cdot \mathbf{1}} \cdot \Delta_t\right) \times 10000 \qquad (3\text{-}3)$$

To do so, we first define the Boolean vector $B_{k,t} = [b_{1,t}, b_{2,t}, \dots, b_{N,t}]$ for each patent k, where the element $b_{n,t}$ equals one if the word n is in the patent k in year t. The dot product $B_{k,t} \cdot \mathbf{1}$ represents the number of unique words in patent k. Next, we calculate the dot product of $B_{k,t}$ and Δ_t and divided this by $B_{k,t} \cdot \mathbf{1}$.. This assigns the values of words' frequency change in vector Δ_t to the corresponding word in the patent, and these assigned values are averaged for each patent. The resulting value is standardized within a year to obtain the RETech of the patent k, $RETech_{k,t}$.

We construct the RETech measures for each listed firm in each year by averaging the $RETech$ of the patents developed by the firms. Our research aims to explore the impact of political uncertainty on enterprises' preference for innovative strategies, rather than merely focusing on its effect on enterprises' innovative capabilities. The data of enterprises' patent applications can better reflect their intentions in innovation compared to the data of their patents granted. Therefore, we use the data of patent applications and variables developed from this data for our research, and we also provide results using the data of patents that were finally granted, referring to Beladi et al. (2022) and Cong and Howell (2021). We construct RETech indicators of firms based on both patent application data (*FRETech*) and the data of patents eventually granted (*FRETech_Grant*). By following Bowen et al. (2023), we set these variables to be zero when firm i has no patent application in year t.

Similar to Bowen et al. (2023) and our research, Kelly et al. (2021) define the significance of a patent based on its textual similarity to previous and subsequent patents. The idea is that a significant patent should be distinct from earlier patents but similar to the later ones, which may represent innovation following the given patent.

Compared to the method of Kelly et al. (2021), our measure has two advantages. First, it can quantify the significance of a patent ex-ante without relying on forward-looking information. This feature not only provides more patent significance observations but also enables practical applications in business, such as measuring the value of patents during acquisitions, where timely identification of a patent’s worth is crucial.

Second, our method is more practical from a calculation perspective than the method proposed by Kelly et al. (2021). For instance, calculating the cosine similarity for each pair of 610,000 patents of Chinese listed firms would require more than 372.1 billion such calculations. In contrast, our measures the significance of patents by simply calculating the change in word frequency of nearly 300,000 words.

3.3.1.2 Alternative Measure: The RETech based on the frequency of patent

We provide an alternative measure of the RETech and use this measure for robustness check in our empirical result session. The alternative measure is constructed using the percentage change in the number of patents that contain certain terms (*RETech_Pat*). Repetition of Terms within patents may cause biased measurements of the RETech. For instance, consider two scenarios. In the first scenario, a single patent mentions Virtual Reality (VR) one hundred times throughout the year. In the second scenario, one hundred patents each mention VR once during the same year. While the total number of times the term VR is mentioned remains the same in both cases, the level of engagement and interest in VR-related technology differs significantly between these two scenarios.

To address the issue of term repetition, we provide an alternative measurement of the degree of rapidly evolving patents (*RETech_Pat*). Specifically, for each unique term, we identify the patents containing the term and calculate the percentage change in the frequency of these patents across years. First, for each patent k in each year t, we convert the patent from text data to word vector $V_k = [v_1, v_2, \dots, v_N]$, where N is the number of unique words appearing across all patent applications from listed firms, and v_n is a Boolean value equal to one if the word n is in the patent. We then add up the word vector V_k for all patents in year t to compute the aggregate vector z_t:

$$Z_t = \sum_{k=1}^{P_t} V_k \tag{3-4}$$

where P_t is the number of patents in year t.

Similar to our first measurement of RETech, $Z_t = [z_{1,t}, z_{2,t}, \dots, z_{N,t}]$ describes the frequency of terms in patents. The vector Δ_t tracks the relative difference between the aggregate vector Z_t in year t and the vector in year $t-1$:

$$\Delta_t = \frac{Z_t - Z_{t-1}}{Z_t + Z_{t-1}} \tag{3-5}$$

Intuitively, although Δ_t is based on the frequency change of the number of patents containing a certain word, it actually measures the change in terms frequencies.

In the second step, we measure the RETech of a given patent k in the technological cycle. Similar to the initial measurement process, the values of frequency changes of terms in Δ_t are assigned to the patent. Instead of using Boolean vector, we use the word frequency vector to calculate $RETech\_Pat$ for each patent.

$$RETech\_Pat_{k,t} = \frac{V_{k,t}}{V_{k,t} \cdot \mathbf{1}} \cdot \Delta_t \tag{3-6}$$

3.3.1.3 Validation of RETech measure

We validate our RETech measure by using three measures that identify the significance of a given patent based on patent similarity, substitution, and patent citation.

3.3.1.3.1 The patent significance based on patents' pairwise similarity.

The first indicator for validation is based on a method of measuring the patent significance (*Significance*) developed by Kelly et al. (2021). In this method, a patent is considered more significant if it is more distinct from existing patents and related to subsequent patents. For a given patent, we calculate the pairwise similarity of the text between this patent and others.

[1] We then measure the "backward similarity" (BS) and "forward similarity" (FS) based on the similarity calculations. The "backward similarity", BS_j, reflects how distinct the patent is from earlier patents, while the "forward similarity" reflects its relation to subsequent patents.

The backward similarity (BS_k) is calculated as the sum of pairwise similarities between patent k and all patents (j) filed in the preceding year. Mathematically, it is expressed as:

$$BS_k = \sum_{j \in B_k} \rho_{k,j} \tag{3-7}$$

where the $\rho_{k,j}$ is the pairwise similarity of patent k and j, and B_k is the set of patents filed in the year before patent k. Intuitively, the "backward similarity" reflects the averaged similarity between patent k and its preceding patents. A lower "backward similarity" indicates higher novelty for patent k. The forward similarity (BS_k) is calculated as the sum of pairwise similarities between patent k and all patents (j) filed in the subsequent years. Mathematically, it is expressed as:

---

[1] We keep only the pairs of patents that the patent's listed-companies-applicant are from the same industry.

$$FS_k = \sum_{i \in F_k} \rho_{k,j} \tag{3-8}$$

where the $\rho_{k,j}$ is the pairwise similarity of patent k and j, and B_k is the set of patents filed in the year after the patent k. Intuitively, the "forward similarity" (FS_k) measures the impact of patent k by evaluating its similarity to patents filed in subsequent years. It is computed as:

The significance of a patent k is determined by combining "backward similarity" and "forward similarity" as follows:

$$Significance_k = \frac{FS_j}{BS_j} \tag{3-9}$$

Intuitively, the formula indicates that a patent is more significant if it has lower backward similarity (indicating higher novelty relative to its predecessors) and higher forward similarity (signifying greater influence on subsequent research).

3.3.1.3.2 The degree of substitution

To measure the degree of substitution of a focal patent, we follow the approach outlined by Funk and Owen-Smith (2016). First, for each focal patent, we collect the predecessor patents cited by the focal patent and the follow-on patents that cite the focal patent. We then identify the follow-on patent that cites the focal patent but not any of its predecessors. The degree of substitution is computed by dividing the number of these following patents by the total number of follow-on patents.

For the degree of complementarity, we calculate a number of follow-on patents that simultaneously cite the focal patent and at least one of its predecessors. This number is divided by the total number of follow-on patents.

In essence, a focal patent with a high degree of substitution is more likely to replace its predecessor patent, as indicated by follow-on patents citing the focal patent while disregarding its predecessors. Conversely, if the focal patent is complementary to its predecessor, the follow-on patent will also cite the predecessor patent for comprehensive referencing. We operationalize this concept by measuring the degree of substitution for patents that have predecessor patents. Figure 3-1 illustrates the citation relationship diagram between the focal patent, its predecessor, and its follow-ons.

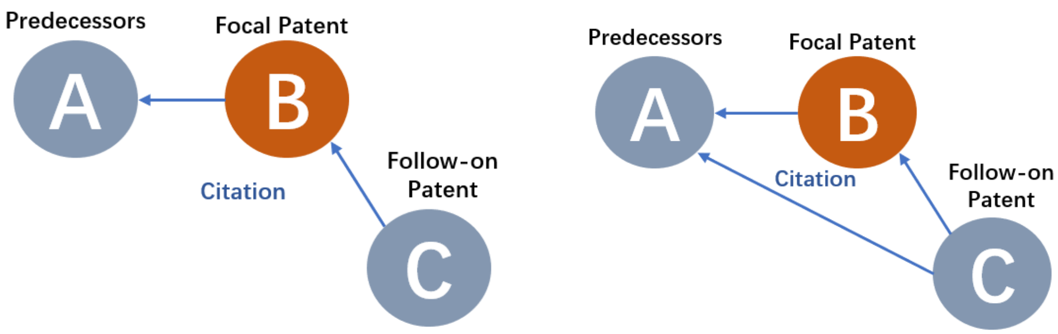


Figure 3-1 Citation Relationship Diagram between Focal Patent, Its Predecessor, and Its' Follow-ons

3.3.1.3.3 Validations of the RETech measure

To validate our RETech measure, we regress patent significance (*Significance*), degree of substitution (*Substitution*), and patent citation (*Citation*) on the RETech measure of patents, controlling for year-fixed effects and IPC classification-based technology fixed Effects. Table 3-1 presents the results.

All coefficients in the table are positive and significant at the 1% level, which indicates a strong positive relationship between *RETech* and other patent significance indicators. In summary, the validation tests in Table 3-1 reassure us that our measure effectively proxies the RETech of patents in the technological cycle.

Table 3-1 Validation of the RETech measure

	(1)	(2)	(3)
Variables	*Substitution*	*Citation*	*Significance*
RETech	0.022***	0.191***	0.069***
	(0.005)	(0.053)	(0.001)
Year FE	YES	YES	YES
Technology FE	YES	YES	YES
Observations	313,595	607,382	553,894
R^2	0.025	0.245	0.555

This table presents the regression estimates of *RETech* on validation indicators. The sample is cross-sectional data of patents of the listed firms in China. The dependent variable is the patent substitution degree, the natural logarithm number citations, and the significant degree. The key independent variable is the *RETech*. Fixed effects are included based on a patent's application year and IPC category (technology). Standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.3.2 Measuring of individual firm's political uncertainty

In this section, we outline our approach to using textual analysis to measure the firm-level political uncertainty exposure of individual listed firms in China. While prior research has attempted to construct measures for political uncertainty, existing efforts like Baker et al. (2016) in the U.S. and Caldara and Iacoviello (2022) have primarily focused on constructing macroeconomic indices or news-based indicators. However, these approaches overlook the unique characteristics of individual firms, such as their business type, corporate governance, and exposure to industrial policies.

Following the approach of Hassan et al. (2019), we adopt a strategy to assess the individual firms' risk exposure annually through textual analysis. This methodology, also applied by Hassan et al. (2023) and Hassan et al. (2024) to measure the firms' pandemic and Brexit exposures, involves identifying specific policy and uncertainty terms. We construct Policy and Uncertainty Dictionaries and analyze the co-occurrence of political and uncertainty-related terms within firm disclosures. The ratio of uncertainty terms in proximity to political terms is then quantified, offering a detailed measure of political uncertainty. This approach leverages computational linguistics to develop a firm-level metric that reflects the actual discourse in corporate filings. By quantifying the proportion of language dedicated to political risks, it captures the immediacy and relevance of these concerns as expressed by firm management and analysts. This method's key strength lies in its ability to differentiate political discussions from broader uncertainties, providing a more accurate and objective assessment of how political events and policy uncertainties impact business operations and strategic decision-making. Moreover, the dynamic nature of this analysis allows for real-time tracking of political risk exposure, ensuring the measure evolves with changing corporate concerns.

We use the Manager Discussion and Analysis (MD&A) section of the annual report instead of other textual data sources, such as analyst reports, analyst investigation Q&A records, or online conference calls. This choice is motivated by the higher quality of information provided in annual reports, which are regulated by the China Securities Regulatory Commission and mandated to be released annually. Unlike other sources, annual reports ensure comprehensive coverage of listed firms. Comparatively, the coverage of analyst reports for Chinese listed firms averaged only 68% since 2007, and the disclosure rate of analyst investigation Q&A records stands at only 53%. Additionally, online earnings conference calls in China often lack restrictions on the qualification of participants, leading to lower-quality questions and responses.

We use the Word2Vec model to generate the Policy Dictionary and Uncertainty Dictionary, which contain terms indicative of discussion on political or uncertain topics. Each term in the textual data is represented by a 200-dimensional word vector, enabling the calculation of pairwise word similarity. We select the 100 terms most similar to the word "Policy" or "Uncertainty" to form the initial "candidate terms" lists. After manually reviewing these candidate terms, we retain the relevant ones to create the final Policy Dictionary and Uncertainty Dictionary. The terms in these two dictionaries are presented in Appendix 3-1.

Next, we count the occurrences of terms from the Uncertainty Dictionary within a 40-character window surrounding terms from the Policy Dictionary and divide this count by the total number of terms in the transcript. Specifically, we first identify the position of policy terms from the Policy Dictionary in the MD&A text. Let $\mathbb{U}$ be the set of terms from the Uncertainty Dictionary and $\mathbb{p}$ be the set of terms from the Policy Dictionary. For the MD&A text of firm j in year t, we count the number of occurrences ($nr_{j,t}$) of the uncertainty terms ($r \in \mathbb{U}$) within a distance D characters of any policy terms ($p \in \mathbb{p}$). The term set $R_{j,t}$ consists of all uncertainty terms $r \in \mathbb{U}$ in the MD&A text of firm j in year t. Then, we calculate the ratio of occurrence frequencies to the length of MD&A text data ($L_{j,t}$). This ratio is summed for each of the uncertainty terms:

$$UncertaintyRatio_{j,t} = \sum_{r}^{R_{j,t}} \frac{nr_{j,t}[r \in \mathbb{U}] \times \mathbb{1}[|r-p|<D]}{L_{j,t}} \quad ,for\ p \in \mathbb{p} \qquad (3\text{-}10)$$

Intuitively, formula (3-10) shows how we compute the ratio of the number of occurrences of the terms from the Uncertainty Dictionary within a certain range around terms from the Policy Dictionary to the total number of words or terms in the MD&A text. We adjust the $UncertaintyRatio$ using the TF-IDF algorithm, which gives more weight to terms that appear frequently in a specific document and less frequently across other documents. This adjustment yields the political uncertainty indicator, $Uncertainty$.

In our main regression models, we set the distance parameter to $D = 40$ for the variable $Uncertainty$. In Hassan et al. (2019), this parameter is set to 10 when using bigrams in English, and one such bigram corresponds to four characters in Chinese, generally. For robustness checks, we also provide three additional $Uncertainty$ indicators with different distance parameters: $D = 50$ (*Uncertainty_50*), $D = 30$ (*Uncertainty_50*), or $D = 20$ (*Uncertainty_20)*.

We compare our political uncertainty measure with the news-based regional EPU index developed by Baker et al. (2016). Figure 2 plots the aggregated individual political uncertainty exposure ($Uncertainty$) across firms for each year alongside the EPU index. The yearly averaged frequency of uncertainty terms ($Uncertainty\_Count$) is also provided. The correlation between the yearly averaged uncertainty indicator and the EPU index is 0.489. Figure 3-2 shows a visibly similar trend between the aggregated uncertainty measure and the EPU index.

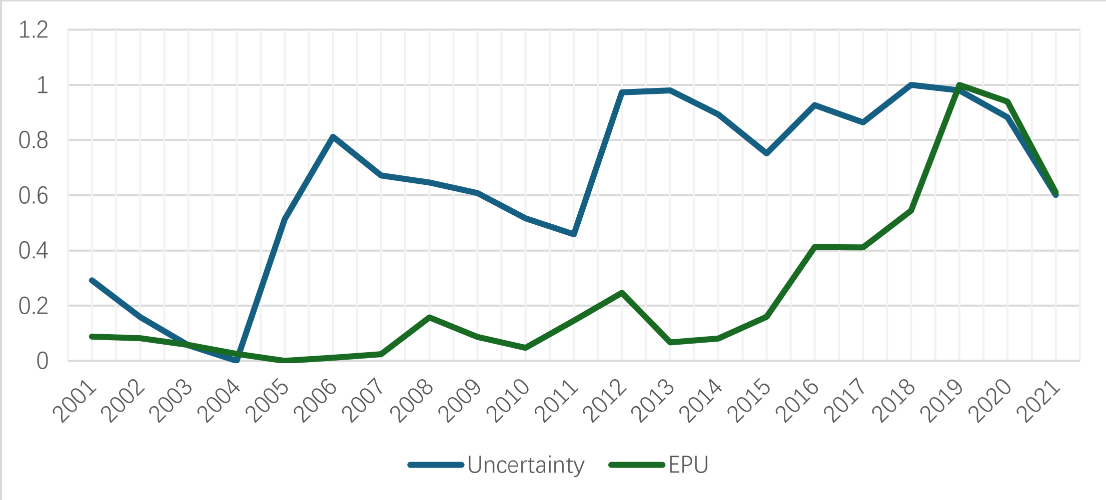


Figure 3-2 Comparison of Trends between the Aggregated Individual Political Uncertainty Exposure and the EPU Index

3.4 Methodology and main results

In this section, we use our RETech measure and political uncertainty exposure measures from 2007 to 2020 to evaluate the impact of political uncertainty exposure on firms' innovation in rapidly evolving technological areas. To ensure the comprehensiveness of patent data, our sample data is cut off at 2020, as there is a usually two- or three-year lag from preparation of patent document to patent's disclosed or granted. In addition to subjecting our main hypothesis to regression analysis, we conduct several robustness checks and endogeneity analyses to validate this relationship.

3.4.1 Methodology and data

We estimate the relationship between the firm-level political uncertainty exposure (*Uncertainty*) in year t and the firm's RETech (*FRETech* or *FRETech_Grant*) in year $t+1$ using the specification:

$$FRETech_{i,t+1}/FRETech\_Grant_{i,t+1} = \alpha + \beta_1 Uncertainty_{i,t} + \beta_2 Controls_{i,t} +$$

$$\beta_3 GDP_t + \gamma_t + \delta_i + \varphi_{i,t} + \varepsilon_{i,t} \tag{3-11}$$

The dependent variable $FRETech_{i,t+1}$ and *FRETech_Grant* are the measures of RETech for firm i in year $t+1$, based on the data of patent application and patent granted. The independent variable $Uncertainty_{i,t}$ is the political uncertainty exposure for firm i in year $t+1$. $Controls_{i,t}$ is a vector of firm-characteristics, including ROA (*ROA*), firm size (*Firmsize*), firm leverage (*Lev*), Tobin's Q (*Tobin'sQ*). One concern is that the relationship between political uncertainty and rapidly evolving technology innovation may also be influenced by other innovation performance indicators, such as the number of patents or R&D expenditure. To address this, we control for the natural logarithm of a firm's number of patents (*PatNum*) and R&D expenditure (*R&D*). Additionally, we include GDP growth rate (GDP_t) to account for the aggregate economic environment. Our baseline specification also includes the year-, industry-, and province-fixed effects (γ_t, δ_i and $\varphi_{i,t}$). To account for correlated errors, we cluster standard errors by firm.

Table 3-2 provides descriptive statistics for our main variables. Due to the lack of disclosure of *R&D* data for some firms, there are missing observations for the *R&D* variable. Appendix 3-2 contains the definitions of all variables. Table 3-3 presents the autocorrelation matrix for *Uncertainty* across different periods. The high autocorrelation of our measure reflects the gradual changes in political uncertainty over time. Therefore, following Li et al. (2021 a, b), we include industry fixed effect for our regression models.

Table 3-2 Summary statistics

	(1)	(2)	(3)	(4)	(5)
Variable	N	Mean	SD	Min	Max
FRETech	31,502	0.251	0.266	0.000	1.000
FRETech_Grant	31,502	0.216	0.228	0.000	1.000
Uncertainty	31,502	0.103	0.124	0.000	2.505
ROA	31,502	0.042	0.407	-64.819	20.788
Firmsize	31,502	22.045	1.343	11.348	28.543
Lev	31,502	0.460	1.532	-0.195	178.345
TobinQ	31,502	2.769	84.310	0.674	14,810.306
GDP	31,502	0.104	0.050	0.027	0.231
PatNum	31,502	1.041	1.337	0.000	8.990
R&D	23,148	17.699	1.609	0.000	25.025

In this table, we provide the summary statistics. We report the number of observations, mean, standard deviation, minimum number, and maximum number.

Table 3-3 Correlation matrix for variable uncertainty

Year	t	t-1	t-2	t-3	t-4	t-5
t	1.000***					
t-1	0.534***	1.000***				
t-2	0.409***	0.528***	1.000***			
t-3	0.319***	0.414***	0.531***	1.000***		
t-4	0.258***	0.313***	0.413***	0.507***	1.000***	
t-5	0.213***	0.248***	0.304***	0.381***	0.483***	1.000***

This table presents the autocorrelation matrix for the key independent variable *Uncertainty* in the baseline regression. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4.2 Baseline Results

We first evaluate the association between firm political uncertainty exposure and rapidly evolving technology innovation. Columns (1) to (5) in Table 3-4 present the results from the estimating equation (3-11). The coefficients are all negative and significant. Across specifications, the estimates imply that a one-standard-deviation increase in the political uncertainty exposure is associated with a decrease in $FRETech$ ranging from 0.004 to 0.006, or between 0.015 and 0.023 standard deviations of the $FRETech$. This estimated effect remains robust when including year, industry, and province fixed effects (columns (2) and (3)), with the magnitude of coefficient estimates staying consistent despite the addition of these fixed effects. Due to missing observations for the firm R&D expenditure (R&D), we also regressed the model with this control variable individually. Column (4) shows the result that consists of the results in columns (1) to (3).

The results in Table 3-4 suggest that political uncertainty exposure negatively impacts the firms' rapidly evolving technological innovation measured by using the data of patent application or by using the data of patent granted. This relationship persists even after controlling for unobservable time-varying factors at the industry and provincial levels, indicating the observed effect is not driven by these factors.

Table 3-4 Political uncertainty and firm's RETech innovation

	(1)	(2)	(3)	(4)	(5)
Variables	*FRETech*	*FRETech*	*FRETech*	*FRETech*	*FRETech_Grant*
Uncertainty	-0.048***	-0.056***	-0.035***	-0.030**	-0.029**
	(0.011)	(0.010)	(0.010)	(0.013)	(0.014)
ROA		0.174***	0.175***	0.203***	0.057***
		(0.020)	(0.020)	(0.026)	(0.015)
Firm size		-0.008***	0.004**	-0.012***	0.001
		(0.002)	(0.002)	(0.003)	(0.002)
Lev		-0.078***	-0.059***	-0.047***	-0.008
		(0.009)	(0.009)	(0.012)	(0.007)
TobinQ		-0.003***	-0.003***	-0.003**	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
GDP		-0.433***	-0.379***	-0.318***	1.177***
		(0.030)	(0.031)	(0.072)	(0.110)
PatNum		0.088***	0.077***	0.075***	0.062***
		(0.001)	(0.002)	(0.002)	(0.001)
R&D				0.012***	0.009***
				(0.002)	(0.001)
Year FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	YES	YES
Province FE	NO	NO	YES	YES	YES
Observations	31,502	31,502	31,502	23,148	23,148
Pseudo/Adj. R^2	0.072	0.429	0.470	0.396	0.342

This table presents the regression estimates of a firm's innovation in rapidly evolving technological areas on political uncertainty exposure. The sample is a yearly panel of listed firms of the A-Share market in China from 2007 to 2021. The dependent variables are the *FRETech* and *FRETech_Grant*. The key independent variable is the firm-year level textual-based political uncertainty exposure. The control variable consists of firm features and macroeconomy variables. Year, industry, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4.3 Robustness checks

We test the robustness of our main results to the choice of RETech measure, political uncertainty measure, and sample compositions.

First, we conduct robustness checks on the main regressions with three alternative, independent variables. As mentioned in section 3.2, the choice of the distance parameter in the formula (3-10) follows Hassan et al. (2019) and assumes that one English bigram corresponds to four Chinese characters. We construct three additional political uncertainty exposure variables with variations in the distance parameter (*Uncertainty_50*, *Uncertainty_30*, and *Uncertainty_20*). We replace the independent variable *Uncertainty* in the model (3-11) with these new variables and re-estimate the regression. The results, shown in Panel A of Table 3-5, indicate that the coefficients of the new independent variables are all negative and significant at the 1% level, consistent with the results in Table 3-4.

Secondly, we address concerns regarding the representativeness of the dependent variable, the firm's RETech indicator *FRETech*, by replacing it with the firm-level average from the alternative measure from session 3.1.1 and the patent significance measure introduced in section 3.1.2. Column (1) of Panel B presents the regression results with *FRETech_Pat* as the dependent variable, while Column (2) shows the results for the significance measure. Both columns indicate negative and significant coefficients for the key independent variable, similar to the results in Table 3-5.

Thirdly, we conduct a robustness check by considering only the firm-year observations that have patent applications. Column (3) of Panel B shows results consistent with the main finding in Table 3-4.

Table 3-5 Robustness checks

Panel A

Variables	(1) *FRETech*	(2) *FRETech*	(3) *FRETech*
Uncertainty_50	-0.030***		
	(0.010)		
Uncertainty_30		-0.031***	
		(0.011)	
Uncertainty_20			-0.043***
			(0.012)
Observations	31,502	31,502	31,502
Controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Province FE	YES	YES	YES
Pseudo/Adj. R^2	0.470	0.470	0.470

Panel B

Variables	(1) *FRETech_Pat*	(2) *Significance*	(3) *FRETech*
Uncertainty	-0.027***	-0.005**	-0.013**
	(0.009)	(0.002)	(0.006)
Controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Province FE	YES	YES	YES
Observations	31,502	15,428	15,995
Pseudo/Adj. R^2	0.450	0.288	0.632

This table presents the robustness check. In Panel A, the dependent variable is the *FRETech*. The independent variables are the variant variables of political uncertainty with the distance parameters equal to 50, 30, and 20. In Panel B, the dependent variable is the firm's innovation in rapidly evolving technology areas calculated based on the change of frequencies of patents, the patent significance, and the original firm's innovation in rapidly evolving technology areas. The independent variable is the firms' political uncertainty. The key independent variable is the firm-year level textual-based political uncertainty exposure. The control variable consists of firm features and macroeconomy variables. Year, industry, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.5 Endogeneity issue

Another concern in our empirical analyses is the potential endogeneity resulting from omitted variables, measurement errors, or the simultaneous determination of variables. To alleviate these concerns, we control for various firm and country-level characteristics, as well as year-, industry- and province-fixed effects. However, there may still be unobserved factors that simultaneously affect political uncertainty exposure and the firm's RETech innovation. In such cases, our main OLS estimate regression may either understate or overstate the true effect of political uncertainty on a firm's RETech innovation, depending on how the unobserved factors affect these two variables. To address this issue, we employ the instrumental variables approach and utilize two settings of quasi-natural experiments. These methods help us better isolate the causal effect of political uncertainty on a firm's RETech innovation, accounting for potential endogeneity concerns.

3.5.1 Quasi-natural experiments and difference-in-difference model

Following the methods of Baghdadi et al. (2023), we start our analysis with two quasi-natural experiment settings by using the difference-in-differences (DID) model to examine how political uncertainty affects rapidly evolving technology innovation in general. In China, the Sino-U.S. trade war and the COVID-19 pandemic were characterized by significant policy fluctuations, resulting in heightened risk exposure for impacted firms. The level of policy uncertainty stemming from these events varied across industries and enterprises. Leveraging these two exogenous shocks as quasi-natural experiments, we designed two DID models based on the heterogeneity of their impacts on enterprises to conduct our tests.

Firstly, we examine the impact of political uncertainty on the RETech innovation of firms using the Sino-U.S. trade war as an exogenous shock. The trade war commenced in 2018 when former U.S. president Trump announced tariffs on imports from China worth 100 billion dollars[2]. Subsequently, both countries introduced a series of tariff policies, causing higher political uncertainty to the exposed enterprises. According to Benguria et al. (2022) and Cheng et al. (2023), industries such as electrical equipment, industrial equipment, machinery goods, airplanes, and motor vehicle equipment in China are most vulnerable to the Sino-US trade war. Enterprises in these industries are expected to bear more negative impacts of political uncertainty arising from the trade war. Since the Sino-U.S. trade war is mainly caused by political issues, the political uncertainty it induces is exogenous to enterprises, making it suitable for testing causal relationships between political uncertainty and the RETech innovation of firms. In line with the studies of Cheng et al. (2023), we define enterprises in the industries with higher exposure to the trade war as the treatment group, while the remaining firms constitute the control group.

The premise for this quasi-natural experiment to hold true is that the enterprises that have received greater impact from the China-U.S. trade war are indeed exposed to higher political uncertainty after the start of the trade war. Therefore, we compare the change in political uncertainty before and after the initiation of the Sino-U.S. trade war between the enterprises in industries with higher trade war exposure and those with lower exposure. Calculating the change in political uncertainty helps to mitigate the impact of inherent differences in the level of political uncertainty across these industries. Column (4) in Panel A of Table 3-6 demonstrates the difference in the change in political uncertainty between more- and less-exposed firms, along with the significance level

[2] https://www.latimes.com/business/la-fi-trump-tariffs-china-20180405-story.html

from the t-test. The results show that following the initiation of the trade war, the increase in political uncertainty for more-exposed enterprises was significantly higher than that for less-exposed ones, confirming that the trade war has indeed brought higher political uncertainty to the more-exposed enterprises.

Column (1) in Panel B of Table 3-6 shows the result of the DID regression. The coefficient of the interaction term is negative and significant, suggesting that firms with greater exposure to trade wars experienced significantly lower RETech innovation following the onset of the trade wars. This test indicates a causality between policy uncertainty and the RETech innovation of firms.

Table 3-6 Results of difference-in-difference models: the Sino-U.S. trade war

Panel A Comparison of political uncertainty exposure change before and after events

(1)	(2)	(3)	(3)
Events	Groups	Number of Observations	Differences of Political Uncertainty Change before and after Events
Trade war	Exposed	9,060	0.009***
	Not Exposed	8,364	

Panel B Result of difference-in-difference model

	(1)
Variables	*FRETech*
Trade war	0.036***
	(0.005)
*Tradewar*TradewarPost*	-0.010**
	(0.005)
TradewarPost	-0.130***
	(0.017)
Controls	YES
Year FE	YES
Industry FE	YES
Province FE	YES
Observations	31,502
Pseudo/Adj. R^2	0.045

Panel A in this table shows the value and comparison of changes in political uncertainty between the firms in the treatment group and the control group. Column (1) shows the exogenous shock events, column (2) shows the types of groups, column (3) shows the number of observations in each type of group, and Column (4) shows the differences in political uncertainty change before and after events. Panel B in this table presents the results of DID model regressions. The dependent variables are *FRETech*. The key independent variables are the treatment group, post, and the product of these two variables, the DID indicators. The control variable consists of firm features and macroeconomy variables. Year, industry, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

Next, we employed the COVID-19 pandemic as another exogenous shock to investigate the impact of political uncertainty on the RETech innovation of firms. Since COVID-19's onset and rapid spread in China beginning in early 2020, the Chinese government implemented a three-year "dynamic zero-COVID" policy, enforcing lockdowns and quarantines in areas with confirmed COVID-19 cases. These lockdowns and quarantine policies introduced political uncertainty for enterprises, as the unpredictable nature of lockdowns disrupted supply chains and adversely affected enterprises' investment and employment in affected areas (Hassan et al., 2023). Additionally, COVID-19 and the "dynamic zero-COVID" policy exacerbate policy uncertainty for enterprises with higher supply chain concentration, as such concentration indicates a greater reliance on a limited number of suppliers and distributors. This limitation hindered their ability to diversify risks from supply chain disruptions caused by the unpredictable lockdown policies through alternative channels, leading to higher political uncertainty.

Therefore, we designate firms with higher supply chain concentration as the treatment group and others as the control group. Using the onset of COVID-19 in early 2020 as an exogenous shock, we use the DID model to examine the causal relationship between political uncertainty and enterprises' rapidly evolving technology innovation.

Both COVID-19 and the following "dynamic zero-COVID" policy are unrelated to the firm's operation, rendering them exogenous shocks for enterprises.

Similar to the endogeneity test using the Sino-U.S. trade war as an exogenous shock, we found that COVID-19 significantly increased political uncertainty for enterprises with higher supply chain concentration, as shown in Column (4) in Panel A of Table 3-7. As indicated in the study results presented in Column (1) in Panel B of Table 3-7, following the COVID-19 shock, enterprises with higher supply chain concentration experienced significantly lower RETech innovation, suggesting that political uncertainty impairs enterprises' rapidly evolving technology innovation.

Table 3-7 Results of difference-in-difference models: COVID-19 pandemic

Panel A Comparison of political uncertainty exposure change before and after events

(1)	(2)	(3)	(3)
Events	Groups	Number of Observations	Differences of Political Uncertainty Change before and after Events
COVID-19	Higher	6,361	0.001*
	Lower	6,330	

Panel B Result of difference-in-difference model

	(1)
Variables	*FRETech*
Concentration	-0.001
	(0.004)
*Concentration *COVIDPost*	-0.017***
	(0.007)
COVIDPost	-0.021
Controls	YES
Year FE	YES
Industry FE	YES
Province FE	YES
Observations	15,764
Pseudo/Adj. R^2	0.453

Panel A in this table shows the value and comparison of changes in political uncertainty between the firms in the treatment group and the control group. Column (1) shows the exogenous shock events, column (2) shows the types of groups, column (3) shows the number of observations in each type of group, and Column (4) shows the differences in political uncertainty change before and after events. Panel B in this table presents the results of DID model regressions. The dependent variables are *FRETech*. The key independent variables are the treatment group, post, and the product of these two variables, the DID indicators. The control variable consists of firm features and macroeconomy variables. Year, industry, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.5.2 SLS regressions and difference model

For the instrumental variable approach, in line with Fisman and Svensson (2017), we use the industry-location average value of $Uncertainty$ (*UncertaintyMean*) as the instrumental variable. The first- and second-stage results of the 2SLS analysis are reported in Columns (1) and (2) of Table 3-8. Column (1) shows that *UncertaintyMean* loads positively at the 1% level, implying a positive and significant correlation between a firm's political uncertainty and the average political uncertainty in the industry location. Column (2) presents the second-stage results using the fitted values of *Uncertainty* computed from the first stage. We find that the coefficient estimate of *Uncertainty* is negative and significant at the 1% level, suggesting that our previous findings are not driven by endogeneity concerns.

We also conduct the difference model following Chiu et al. (2019) to address the endogeneity issue. We regress the model (3-11) using the difference between the current year and the previous year for the dependent, independent, and control variables in the model. Column (3) of Table 3-8 presents the result. The coefficient of the difference of *Uncertainty* ($\Delta Uncertainty$) is negative and significant, further alleviating the potential endogeneity concerns.

Table 3-8 Endogeneity Analysis

Variables	(1)	(2)	(3)
	IV		Difference Model
	First-Stage	Second-Stage	
	Uncertainty	*FRETech*	*FRETech*
UncertaintyMean	1.070***		
	(0.021)		
Uncertainty		-0.084***	
		(0.018)	
$\Delta Uncertainty$			-0.019*
			(0.011)
Controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Province FE	YES	YES	YES
Observations	31,502	31,502	26,181

This table presents the results of the two stages of instrumental variables regression (2SLS) and the result of the difference model. In the 2SLS model, the dependent variables are political uncertainty and firms' RETech innovation. The independent variables are the location-industry political uncertainty and the political uncertainty fitted in the first stage regression. In the difference model, the dependent variable is the *FRETech*. The independent variable is the difference in political uncertainty. The control variable consists of firm features and macroeconomy variables. Year, industry, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.6 Mechanism and heterogeneity

3.6.1 Mechanisms

In this section, we investigate the channels through which political uncertainty could impact the RETech innovation of firms. Following recent studies (Chen et al., 2021; Francis et al., 2021; Lai et al., 2023), we employ the mediating effect tests developed by Baron and Kenny (1986) to examine these mechanisms. Additionally, we implement the Sobel (1982) test to determine statistically significance of the mediation effect.

Firstly, we examine the mediation effect of a firm’s financing constraints. Financial constraints are known to impede investment (Froot et al.,1993; Almeida and Campello, 2007; Jens, 2017), which includes innovation (Weeds, 2002). Financial development has been shown to promote technology innovation (Hsu et al., 2014). Ayyagari et al. (2021) analyzed a vast sample of companies in 47 emerging economies and found that better access to foreign financing is linked to greater innovation. The relaxation of financial constraints has a positive impact on R&D investments (Brown et al., 2012) and innovation output (Moshirian et al., 2021). Moreover, higher political uncertainty is associated with a decline in trade credit (Mello and Toscano, 2020) and increased financial constraints (Duong et al., 2020). Xu (2020) finds that government political uncertainty raises the cost of capital for firms, leading to reduced innovation. Therefore, it is plausible that political uncertainty increases financial constraints, subsequently reducing a firm's rapidly evolving technology innovation.

We examine this channel by testing the mediating mechanism of two financial constraint measures: trade credit (*TradeCredit*), proxied by account payable to debt (Fisman and Love, 2003; Kong et al., 2020), and *WW* index (White and Wu, 2006; Guariglia and Yang, 2016; Buehlmaier and Whited,2018). The results shown in Panel A of Table 3-9 indicate a positive coefficient for TradeCredit in both stages of regression and a negative coefficient for *Uncertainty* in the second stage, all statistically significant. Similarly, the coefficients of *WW* are positive in the first stage and negative in the second stage, while *Uncertainty* remains negative, which is all significant. These findings suggest that political uncertainty is associated with higher financial constraints, leading to decreased firm innovation.

Secondly, we explore the mediation effect of risk tolerance through the mediating Mechanism of the Employee Stock Ownership Plan (*ESOP*). Innovating and developing groundbreaking technology often involve long-term and highly uncertain characteristics

(Holmstrom, 1989). Manso (2011) demonstrates that an optimal incentive scheme for innovation motivates a substantial tolerance to early failure and rewards for long-term successes. Evidence from China indicates that the ESOP can increase the risk tolerance of managers and motivate firm innovation due to their short-term failure tolerance and long-term award features (Tian and Meng, 2018).

The results, presented in Table 3-9, show that the coefficients of *Uncertainty* are all negative and significant in Column (1), which indicates that political uncertainty is negatively associated with the issuing of ESOPs. The coefficient of ESOP in Column (2) is positive and significant. These results indicate that political uncertainty is associated with lower issuing of ESOPs or lower risk tolerance, which in turn reduces the incentive of a firm's rapidly evolving technology innovation.

Overall, our results in Table 3-9 suggest that increased financial constraints and decreased risk tolerance are plausible channels through which political uncertainty exposure reduces a firm's rapidly evolving technology innovation.

Table 3-9 Mechanisms

Panel A Mechanism of financial constraints

	(1)	(2)	(3)	(4)
Variables	*TradeCredit*	*FRETech*	*WW*	*FRETech*
Uncertainty	-0.016**	-0.050***	0.006***	-0.056***
	(0.003)	(0.010)	(0.002)	(0.011)
TradeCredit		0.109***		
		(0.019)		
WW				-0.163***
				(0.037)
Indirect effect	-0.002		0.001	
Sobel test (z-value)	-3.974***		-2.763***	
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Observations	31,407	31,407	26,128	26,128

Pseudo/Adj. R^2	0.301	0.463	0.808	0.473

Panel B Mechanism of risk aversion

	(1)	(2)
Variables	*ESOP*	*FRETech*
Uncertainty	-0.002***	-0.048***
	(0.001)	(0.010)
ESOP		0.368***
		(0.102)
Indirect effect	-0.001	
Sobel test (z-value)	-2.700***	
Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
Province FE	YES	YES
Observations	31,502	31,502
Pseudo/Adj. R^2	0.039	0.470

This table presents the results of mechanism tests of the effect of political uncertainty on the RETech innovation of firms. The dependent variables are *FRETech* and mediating variables. The mediator variables are trade credit, WW index, and ESOP value. The key independent variables are the political uncertainty and mediator variables. The control variable consists of firm features and macroeconomy variables. Year, industry, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.6.2 Heterogeneities

In this section, we explore several dimensions of heterogeneity in relation to firms' political uncertainty exposure and innovation in rapidly evolving technology areas. We aim to enrich our understanding of the causes of these effects and the factors that exacerbate or mitigate them.

Firstly, we examine the difference in the effects of firm political uncertainty on rapidly evolving technology innovation between the state-owned enterprises (SOEs) and the non-SOEs in China. Unlike maximizing shareholder value, government officials exercise control over SOE for objectives related to managerial promotion (Shleifer and Vishny, 1994; Chen et al., 2011; Wu et al., 2012). Evidence suggests that managers in

SOEs may be less sensitive to the potential impact of political uncertainty.

Moreover, compared to non-SOEs, SOEs often have better access to funds (Faccio, 2010; Johansson et al., 2015). Non-SOEs tend to exhibit worse stock performance (Zhou, 2017) and lower investment (Li et al.,2020; Chaudhry and Veld, 2023) under high political uncertainty environments, indicating their greater vulnerability and sensitivity to such an environment.

We divide the observations into two subsamples based on SOEs and non-SOEs and re-estimate the regression of Model (3-11). The results in Columns (1) and (2) of Table 3-10 show that political uncertainty in the SOE subgroup exerts no significant effect on the RETech innovation of firms, while it exerts a negative and significant impact on the RETech innovation of firms in the non-SOEs subgroup. These results suggest that political uncertainty only influences the innovation of non-SOEs, which is consistent with our conjecture.

Secondly, we examine the difference in the effects of political uncertainty on a firm's rapidly evolving technological areas innovation across firms under different intensities of business competition. Financial constraint is positively associated with product market competition (Bolton and Scharfstein, 1990; Fresard and Valta, 2016). Haushalter et al. (2007) demonstrate that firms facing fiercer competition are more exposed to predation risk and may reserve cash more conservatively. Therefore, firms within higher competition-intensity environments may make innovation decisions more cautiously.

Our proxy for market competition intensity is the Herfindahl-Hirschman Index (*HHI*), which is a widely used proxy for product market competition (Hoberg and

Philips, 2010; Valta, 2012). We separate the observations into two groups: the firms in the industry with HHI higher than the median into the “higher group” and those lower than the median into the “lower group.” The insignificant coefficient in Column (3) and the negative and significant one in Column (4) indicate that the effect between political uncertainty and RETech innovation is more pronounced for firms in more intensively competing environments, consistent with our conjecture.

Thirdly, we examine the effect of political uncertainty on a firm’s innovation in rapidly evolving technological areas under different levels of investment irreversibility. The literature emphasizes that if investment in a project is irreversible, uncertainty can increase the incentive of the firm to delay the investment until part of the uncertainty is resolved because the presence of uncertainty raises the value of the option to wait (Bernanke, 1983; Rodrik, 1991; Bloom et al., 2007). Gulen and Ion (2016) provide further evidence that the negative association between political uncertainty and capital investment is more pronounced for firms with a higher degree of investment irreversibility. Therefore, under political uncertainty, firms with more irreversible investments and innovation projects are more likely to conduct less rapidly evolving technology innovation.

Following Gulen and Ion (2016), we use the ratio of fixed to total assets (*FixAsset*) as a proxy for irreversibility. Observations are divided into two groups: the firms in the industry with a fixed asset value higher than the median value into the "higher group" and vice versa. The results are presented in Table 3-10, Column (5), and (6) in Table 3-8. Consisting to our conjecture, the coefficient of the higher irreversibility group is negative and significant, while the coefficient of the lower group is not significant, and the difference between these coefficients is -0.067 and significant. These results suggest that firms with higher irreversibility investments tend to conduct a more conservative innovation strategy than peers with lower irreversibility.

Table 3-10 Heterogeneity

	SOE/non-SOE		HHI		FixAsset	
	SOE	non-SOE	High	Low	High	Low
	FRETech					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty	-0.006	-0.046***	-0.010	-0.050***	-0.064***	0.003
	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Observations	10,103	16,937	13,321	13,747	13,304	13,909
Pseudo/Adj. R^2	0.308	0.226	0.310	0.305	0.258	0.318
Difference in Coefficient	0.040*		0.040*		-0.067***	
Statistic (p-value)	0.064		0.068		0.006	

This table presents regressions that estimate the relation between political uncertainty and RETech innovation under the subgroups of SOEs and non-SOEs, high HHI and low HHI, and high and low fixed investment ratios. The dependent variable is the *FRETech*. The key independent variable is the firm-year level textual-based political uncertainty exposure. The control variable consists of firm features and macroeconomy variables. Year, industry, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 are given in the table. The inter-group differences of coefficients and significance values are given. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

3.7 Conclusion

In this study, we investigate how political uncertainty exposure of individual firms impacts the choice of innovation, to conduct an aggressive innovation strategy and work on innovation in rapidly evolving technological areas, or to adopt a conservative strategy for complementary innovation. To do so, we first measure the positioning of given patents and firms within technology cycles by using the textual analysis method and text data of the patent. We also construct alternative measures for validation and robustness checks. Then, we develop a text-based political uncertainty exposure for each firm in each year.

In the empirical studies, we regress the political uncertainty proxy on the measure of a firm’s innovation in rapidly evolving technological areas. The results show that political uncertainty exposure is negatively associated with rapidly evolving technological areas' innovation. This result consists of control variables, including the R&D expenditure and the number of patent applications, and is robust in robustness check and endogeneity analysis. The results of the mechanism examination indicate that the aggravation of financing constraints and the increase of executives' risk aversion are the channels of the effect. Heterogeneity tests show that the effect is more pronounced for non-SOEs, firms in more intensive competing industries, and firms with more irreversible investments. The evidence demonstrates that political uncertainty impedes the firm's innovation in rapidly evolving technological areas.

Our research offers some insights into the relationship between governance, policymaking and firms’ innovative strategies. Firstly, in developing countries like China, frequent economic reforms and a complex international landscape often create significant uncertainties for businesses. These uncertainties arise from both political instability and frequent, unpredictable policy shifts. To foster greater engagement in rapidly evolving technological innovation, policymakers should aim for greater coherence and consistency in their polices. This would provide firms with a more stable and predictable environment, encouraging long-term investment in cutting-edge technologies. Additionally, firms facing high levels of political uncertainties must recognize the importance of maintaining a focus on breakthrough innovations in emerging fields. Such innovations are more likely to drive technological advancements, enhance competitiveness, and equip firms with better market adaptability and survival capabilities amid uncertain conditions.

While our research demonstrate that firms tend to adopt more conservative innovation strategies in the face of political uncertainty, there are still limitations that future studies should address. One key limitation is the degree to which our text-analysis-based variables, “rapidly evolving technology innovation” and “firm’s political uncertainty” accurately reflect textual analysis the cutting-edge nature of innovation and the firms’ actual exposure to political risks. Without an authoritative measure of technological frontier, our proxy for rapidly evolving innovation is only an indirect measure. Ideally, experts in relevant technology fields would assess the value of patents to determine technological breakthroughs. However, this method is impractical for large-scale analysis, given the millions of patents across diverse domains.

In the future, more advanced tools for large-scale patent analysis could provide more precise measure of technological innovation. Moreover, there is the potential issue of “cheap talk” in firms’ reports, where companies may exaggerate or underplay political uncertainties in their annual disclosures to gain economic advantages, thereby skewing our measurement of political uncertainty. When future research can access direct judgments from top executives regarding the political uncertainties their firms face, it will allow for more accurate and reliable conclusions.

Reference

Abernathy, W.J. and Utterback, J.M., 1978. Patterns of industrial innovation. *Technology Review*, 80(7), pp.40-47.

Aghion, P., Bloom, N., Blundell, R., Griffith, R. and Howitt, P., 2005. Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics*,

120(2), pp.701-728.
Aghion, P. and Tirole, J., 1994. The management of innovation. *The Quarterly Journal of Economics*, 109(4), pp.1185-1209.
Aghion, P., Van Reenen, J. and Zingales, L., 2013. Innovation and institutional ownership. *American Economic Review*, 103(1), pp.277-304.
Almeida, H. and Campello, M., 2007. Financial constraints, asset tangibility, and corporate investment. *The Review of Financial Studies*, 20(5), pp.1429-1460.
Atanassov, J., 2016. Arm's length financing and innovation: Evidence from publicly traded firms. *Management Science*, 62(1), pp.128-155.
Ayyagari, M., Demirgüç-Kunt, A. and Maksimovic, V., 2011. Firm innovation in emerging markets: The role of finance, governance, and competition. *Journal of Financial and Quantitative Analysis*, 46(6), pp.1545-1580.
Baghdadi, G.A., Safiullah, M. and Heyden, M.L., 2023. Do gender diverse boards enhance managerial ability?. *Journal of Corporate Finance*, 79, p.102364.
Baker, S.R., Bloom, N. and Davis, S.J., 2016. Measuring economic political uncertainty. *The Quarterly Journal of Economics*, 131(4), pp.1593-1636.
Balsmeier, B., Fleming, L. and Manso, G., 2017. Independent boards and innovation. *Journal of Financial Economics*, 123(3), pp.536-557.
Baron, R.M. and Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), p.1173.
Bellstam, G., Bhagat, S. and Cookson, J.A., 2021. A text-based analysis of corporate innovation. Management Science, 67(7), pp.4004-4031.
Benguria, F., Choi, J., Swenson, D.L. and Xu, M.J., 2022. Anxiety or pain? The impact of tariffs and uncertainty on Chinese firms in the trade war. *Journal of International Economics*, 137, p.103608.
Bernanke, B.S., 1983. Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, 98(1), pp.85-106.
Bhattacharya, U., Hsu, P.H., Tian, X. and Xu, Y., 2017. What affects innovation more: policy or political uncertainty?. *Journal of Financial and Quantitative Analysis*, 52(5), pp.1869-1901.
Bloom, N., 2007. Uncertainty and the Dynamics of R&D. *American Economic Review*, 97(2), pp.250-255.
Bloom, N., Bond, S. and Van Reenen, J., 2007. Uncertainty and investment dynamics. *The Review of Economic Studies*, 74(2), pp.391-415.
Bloom, N., Draca, M. and Van Reenen, J., 2016. Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *The Review of Economic Studies*, 83(1), pp.87-117.
Bolton, P. and Scharfstein, D.S., 1990. A theory of predation based on agency problems in financial contracting. *American Economic Review*, pp.93-106.
Bowen III, D.E., Fresard, L. and Hoberg, G., 2023. Rapidly evolving technologies and startup exits. *Management Science*, 69(2), pp.940-967.
Brogaard, J., Dai, L., Ngo, P.T. and Zhang, B., 2020. Global political uncertainty and asset prices. *The Review of Financial Studies*, 33(4), pp.1737-1780.
Brogaard, J. and Detzel, A., 2015. The asset-pricing implications of government economic political uncertainty. *Management Science*, 61(1), pp.3-18.

Brown, J.R., Martinsson, G. and Petersen, B.C., 2012. Do financing constraints matter for R&D?. *European Economic Review*, 56(8), pp.1512-1529.
Buehlmaier, M.M. and Whited, T.M., 2018. Are financial constraints priced? Evidence from textual analysis. *The Review of Financial Studies*, 31(7), pp.2693-2728.
Byun, S.K., Oh, J.M. and Xia, H., 2021. Incremental vs. breakthrough innovation: The role of technology spillovers. *Management Science*, 67(3), pp.1779-1802.
Caldara, D. and Iacoviello, M., 2022. Measuring geopolitical risk. *American Economic Review*, 112(4), pp.1194-1225.
Callander, S., 2011. Searching and learning by trial and error. *American Economic Review*, 101(6), pp.2277-2308.
Callen, J.L., Fang, X. and Zhang, W., 2020. Protection of proprietary information and financial reporting opacity: Evidence from a natural experiment. *Journal of Corporate Finance*, 64, p.101641.
Cao, C., Li, X. and Liu, G., 2019. Political uncertainty and cross-border acquisitions. *Review of Finance*, 23(2), pp.439-470.
Chang, X., Chen, Y., Wang, S.Q., Zhang, K. and Zhang, W., 2019. Credit default swaps and corporate innovation. *Journal of Financial Economics*, 134(2), pp.474-500.
Change, E.T., 1990. Endogenous Technological Change. *Journal of Political Economy*, 98(5), p.2.
Chaudhry, N. and Veld, C., 2023. Political uncertainty and investments by private and state-owned enterprises. *International Review of Finance*.
Chemmanur, T.J., Loutskina, E. and Tian, X., 2014. Corporate venture capital, value creation, and innovation. *The Review of Financial Studies*, 27(8), pp.2434-2473.
Chen, J., Chen, X., Hou, Q. and Hu, M., 2021. Haste doesn't bring success: Top-down amplification of economic growth targets and enterprise overcapacity. *Journal of Corporate Finance*, 70, p.102059.
Chen, S., Sun, Z., Tang, S. and Wu, D., 2011. Government intervention and investment efficiency: Evidence from China. *Journal of Corporate Finance*, 17(2), pp.259-271.
Cheng, S., Hua, X. and Wang, Q., 2023. Corporate culture and firm resilience in China: Evidence from the Sino-US trade war. *Pacific-Basin Finance Journal*, p.102039.
Cong, L.W. and Howell, S.T., 2021. Political uncertainty and innovation: Evidence from initial public offering interventions in China. *Management Science*, 67(11), pp.7238-7261.
D'Mello, R. and Toscano, F., 2020. Economic political uncertainty and short-term financing: The case of trade credit. *Journal of Corporate Finance*, 64, p.101686.
Duong, H.N., Nguyen, J.H., Nguyen, M. and Rhee, S.G., 2020. Navigating through economic political uncertainty: The role of corporate cash holdings. *Journal of Corporate Finance*, 62, p.101607.
Faccio, M., 2010. Differences between politically connected and nonconnected firms: A cross-country analysis. *Financial Management*, 39(3), pp.905-928.
Ferreira, D., Manso, G. and Silva, A.C., 2014. Incentives to innovate and the decision to go public or private. *The Review of Financial Studies*, 27(1), pp.256-300.
Fisman, R. and Love, I., 2003. Trade credit, financial intermediary development, and industry growth. *The Journal of Finance*, 58(1), pp.353-374.
Fisman, R. and Svensson, J., 2007. Are corruption and taxation really harmful to growth?

Firm level evidence. *Journal of Development Economics*, 83(1), pp.63-75.
Francis, B., Hasan, I., Liu, L., Wu, Q. and Zhao, Y., 2021. Financial analysts' career concerns and the cost of private debt. *Journal of Corporate Finance*, 67, p.101868.
Frésard, L. and Valta, P., 2016. How does corporate investment respond to increased entry threat?. *The Review of Corporate Finance Studies*, 5(1), pp.1-35.
Froot, K.A., Scharfstein, D.S. and Stein, J.C., 1993. Risk management: Coordinating corporate investment and financing policies. *The Journal of Finance*, 48(5), pp.1629-1658.
Fulghieri, P. and Sevilir, M., 2009. Organization and financing of innovation, and the choice between corporate and independent venture capital. *Journal of Financial and Quantitative Analysis*, 44(6), pp.1291-1321.
Funk, R.J. and Owen-Smith, J., 2017. A dynamic network measure of technological change. *Management Science*, 63(3), pp.791-817.
Gao, H., Hsu, P.H. and Li, K., 2018. Innovation strategy of private firms. *Journal of Financial and Quantitative Analysis*, 53(1), pp.1-32.
Garcia-Vega, M., 2006. Does technological diversification promote innovation?: An empirical analysis for European firms. *Research Policy*, 35(2), pp.230-246.
Gomes, J. and Livdan, D., 2004. Optimal diversification: Reconciling theory and evidence. *The Journal of Finance*, 59(2), pp.507-535.
Griliches, Z., 1990. Patent statistics as economic indicators: A survey part I. NBER.
Guariglia, A. and Yang, J., 2016. A balancing act: managing financial constraints and agency costs to minimize investment inefficiency in the Chinese market. *Journal of Corporate Finance*, 36, pp.111-130.
Gulen, H. and Ion, M., 2016. Political uncertainty and corporate investment. *The Review of Financial Studies*, 29(3), pp.523-564.
Hall, B.H., Jaffe, A. and Trajtenberg, M., 2005. Market value and patent citations. *RAND Journal of Economics*, pp.16-38.
Handley, K. and Limão, N., 2017. Political uncertainty, trade, and welfare: Theory and evidence for China and the United States. *American Economic Review*, 107(9), pp.2731-2783.
Hassan, T.A., Hollander, S., Van Lent, L., Schwedeler, M. and Tahoun, A., 2023. Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1. *The Review of Financial Studies*, 36(12), pp.4919-4964.
Hassan, T.A., Hollander, S., Van Lent, L. and Tahoun, A., 2019. Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4), pp.2135-2202.
Hassan, T.A., Hollander, S., Van Lent, L. and Tahoun, A., 2024. The global impact of Brexit uncertainty. *The Journal of Finance*, *79*(1), pp.413-458.
Haushalter, D., Klasa, S. and Maxwell, W.F., 2007. The influence of product market dynamics on a firm's cash holdings and hedging behavior. *Journal of Financial Economics*, 84(3), pp.797-825.
Hoberg, G. and Phillips, G., 2010. Real and financial industry booms and busts. *The Journal of Finance*, 65(1), pp.45-86.
Holmstrom, B., 1989. Agency costs and innovation. *Journal of Economic Behavior & Organization*, 12(3), pp.305-327.
Hsu, P.H., Tian, X. and Xu, Y., 2014. Financial development and innovation: Cross-

country evidence. *Journal of Financial Economics*, 112(1), pp.116-135.
Jens, C.E., 2017. Political uncertainty and investment: Causal evidence from US gubernatorial elections. *Journal of Financial Economics*, 124(3), pp.563-579.
Jeong, B., 2002. Political uncertainty and long-run investment and output across countries. *International Economic Review*, pp.363-392.
Johansson, A.C. and Feng, X., 2016. The state advances, the private sector retreats? Firm effects of China's great stimulus programme. *Cambridge Journal of Economics*, 40(6), pp.1635-1668.
Julio, B. and Yook, Y., 2012. Political uncertainty and corporate investment cycles. *The Journal of Finance*, 67(1), pp.45-83.
Kelly, B., Papanikolaou, D., Seru, A. and Taddy, M., 2021. Measuring technological innovation over the long run. *American Economic Review: Insights*, 3(3), pp.303-320.
Klepper, S., 1996. Entry, exit, growth, and innovation over the product life cycle. *The American Economic Review*, pp.562-583.
Koellinger, P., 2008. The relationship between technology, innovation, and firm performance—Empirical evidence from e-business in Europe. *Research Policy*, 37(8), pp.1317-1328.
Kong, D., Pan, Y., Tian, G.G. and Zhang, P., 2020. CEOs' hometown connections and access to trade credit: Evidence from China. *Journal of Corporate Finance*, 62, p.101574.
Lai, K.M., Khedmati, M., Gul, F.A. and Mount, M.P., 2023. Making honest men of them: Institutional investors, financial reporting, and the appointment of female directors to all-male boards. *Journal of Corporate Finance*, 78, p.102334.
Lee, N., Sameen, H. and Cowling, M., 2015. Access to finance for innovative SMEs since the financial crisis. *Research Policy*, 44(2), pp.370-380.
Lemley, M.A. and Shapiro, C., 2005. Probabilistic patents. *Journal of Economic Perspectives*, 19(2), pp.75-98.
Liu, G. and Zhang, C., 2020. Economic policy uncertainty and firms' investment and financing decisions in China. *China Economic Review*, 63, p.101279.
Li, Q., Lin, C. and Xu, L., 2020. Political investment cycles of state-owned enterprises. *The Review of Financial Studies*, 33(7), pp.3088-3129.
Liu, Q. and Ma, H., 2020. Trade political uncertainty and innovation: Firm level evidence from China's WTO accession. *Journal of International Economics*, 127, p.103387.
Manso, G., 2011. Motivating innovation. *The Journal of Finance*, 66(5), pp.1823-1860.
Martinsson, G., 2010. Equity financing and innovation: Is Europe different from the United States?. *Journal of Banking & Finance*, 34(6), pp.1215-1224.
Mokyr, J., 1990. Punctuated equilibria and technological progress. *The American Economic Review*, 80(2), pp.350-354.
Moshirian, F., Tian, X., Zhang, B. and Zhang, W., 2021. Stock market liberalization and innovation. *Journal of Financial Economics*, 139(3), pp.985-1014.
Nelson, R.R., 1959. The simple economics of basic scientific research. *Journal of Political Economy*, 67(3), pp.297-306.
Phan, D.H.B., Iyke, B.N., Sharma, S.S. and Affandi, Y., 2021. Economic policy uncertainty and financial stability–Is there a relation?. *Economic Modelling*, 94,

pp.1018-1029.
Rodrik, D., 1991. Political uncertainty and private investment in developing countries. *Journal of Development Economics*, 36(2), pp.229-242.
Scherer, F.M. and Harhoff, D., 2000. Technology policy for a world of skew-distributed outcomes. *Research Policy*, 29(4-5), pp.559-566.
Shleifer, A. and Vishny, R.W., 1994. Politicians and firms. *The Quarterly Journal of Economics*, 109(4), pp.995-1025.
Solow, R.M., 1957. Technical change and the aggregate production function. *The review of Economics and Statistics*, pp.312-320.
Tadesse, S., 2006. Innovation, information, and financial architecture. *Journal of Financial and Quantitative Analysis*, 41(4), pp.753-786.
Tian, X. and Meng, Q., 2018. Do stock incentive schemes spur corporate innovation. *Nankai Business Review*, 120, pp.176-190.
Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. *The Rand Journal of Economics*, pp.172-187.
Tushman, M.L. and Anderson, P., 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly*, pp.439-465.
Tushman, M.L. and Anderson, P., 2018. Technological discontinuities and organizational environments. *In Organizational Innovation*, pp.345-372. Routledge.
Valta, P., 2012. Competition and the cost of debt. *Journal of Financial Economics*, 105(3), pp.661-682.
Van Vo, L. and Le, H.T.T., 2017. Strategic growth option, uncertainty, and R&D investment. *International Review of Financial Analysis*, 51, pp.16-24.
Wadho, W. and Chaudhry, A., 2018. Innovation and firm performance in developing countries: The case of Pakistani textile and apparel manufacturers. *Research Policy*, 47(7), pp.1283-1294.
Weeds, H., 2002. Strategic delay in a real options model of R&D competition. *The Review of Economic Studies*, 69(3), pp.729-747.
Whited, T.M. and Wu, G., 2006. Financial constraints risk. *The Review of Financial Studies*, 19(2), pp.531-559.
Wu, W., Wu, C., Zhou, C. and Wu, J., 2012. Political connections, tax benefits and firm performance: Evidence from China. *Journal of Accounting and Public Policy*, 31(3), pp.277-300.
Xiong, J., Ouyang, C., Tong, J.Y. and Zhang, F.F., 2021. Fraud commitment in a smaller world: Evidence from a natural experiment. *Journal of Corporate Finance*, 70, p.102090.
Xu, Z., 2020. Economic policy uncertainty, cost of capital, and corporate innovation. *Journal of Banking and Finance*, 111, p.105698.
Zhou, Z., 2017. Government ownership and exposure to political uncertainty: Evidence from China. *Journal of Banking and Finance*, 84, pp.152-165.

Appendix

Appendix 3-1. Political Dictionary and Uncertainty Dictionary

Political Terms		Uncertain Terms			
政策	Policy	风险	Risk	难料	Unpredictable

政府	Government	不确定	Uncertain	难以估计	Unpredictable
政治	Politics	可能性	Possibility	难以预计	Unpredictable
监管	Supervision	有可能	Possible	难以预测	Unpredictable
有关部门	Relevant Departments	不可控	Uncontrollable	难以预料	Unpredictable
相关部门	Relevant Departments	不可预期	Unpredictable	无法估计	Unpredictable
国家机构	National Institutions	难以预期	Unpredictable	无法预料	Unpredictable
国家部门	State Sector	未知	Unknown	无法预测	Unpredictable
央行	Central Bank	难以预料	Unpredictable	无法预计	Unpredictable
调控	Regulation	不明朗	Unclear	波动	Fluctuation
财政政策	Fiscal Policy	不明晰	Unclear	徘徊	Wander
货币政策	Monetary Policy	不明确	Unclear	不稳	Unstable
证监会	Securities Supervision Commission	复杂性	Complexity	不稳定	Unstable
银监会	China Banking Regulatory Commission	复杂因素	Complex Factors	不寻常	Unusual
保监会	China Insurance Regulatory Commission	不定因素	Uncertain Factor	错综复杂	Intricacy
财政部	Ministry of Finance	变数	Variable	非常复杂	Very Complex
外经贸部	Ministry of Foreign Trade and Economic Cooperation	潜在	Potential	纷繁复杂	Complex
商务部	Ministry of Commerce	不稳定	Instability	纷纭复杂	Complex
人民银行	People's Bank of China	变化	Change	十分复杂	Very Complex
发改委	National Development and Reform Commission	调整	Adjust		
国务院	the State Council	改变	Change		
改革	Reform	不确定	Uncertain		
法规	Laws and Regulations	不明确	Unclear		
国债	National Debt	不明朗	Unpredictable		
政府债务	Government Debt	未知	Unknown		
政府赤字	Government Deficit	未明	Unclear		

Appendix 3-2. Variables definitions

Variables	Definition
FRETech	The averaged patents' RETech of firm.
Uncertainty	The text-based firm-level political uncertainty exposure.
ROA	Return on asset.
Firmsize	Natural logarithm of total asset of firm.
Lev	Leverage of firm, Debt divided by Asset.
TobinQ	Tobins' Q of firm.
GDP	GDP growth rate.
PatNum	Natural logarithm of number of patent application.
R&D	Research and development expenditure.

Chapter 4. Masculinity, Femininity, and ESG Performance: Evidence from Artificial Intelligence Models

ABSTRACT

In this paper, we investigate the relationship between a firm's ESG performance and the masculinity-femininity cultural value of the chairman and CEO by drawing on Hofstede's theories. First, we utilized artificial intelligence models, including the word-embedding model, ERINE Bot, and ChatGPT, to capture the regional masculinity-femininity culture for provincial regions in Mainland China, dominated more by masculinity or femininity. We identified the cultural value of each chairman and CEO based on their birthplaces and examined how these cultural orientations influence their firm's ESG performance. Our findings align with theoretical expectations regarding ESG performance and masculinity-femininity culture: firms led by chairmen and CEOs from masculine regions tend to have poorer ESG performance, while those from feminine regions tend to perform better in ESG metrics. These results remain robust across different culture measures, ESG performance variables, and estimation methods. We addressed potential endogeneity concerns by using the abnormal turnover of the chairman or CEO as a quasi-natural experiment, and our main results remained consistent. We identified two primary mechanisms driving these results: more serious financial distress and a higher corporate risk-taking led by executives from masculine regions. Additionally, our findings are more pronounced for firms in regions with poorer business environments and lower levels of social trust and for SOEs. Overall, our study highlights the value of the masculinity-femininity cultural dimension in a firm's ESG decision-making and introduces new artificial intelligence-based cultural analysis.

Keywords: ESG, Regional Culture, Masculinity, Femininity, Artificial Intelligence

4.1 Introduction

The extent to which firms' benefit or harm social welfare has received increasing attention from various stakeholders. Environmental, Social, and Governance (ESG) performance is an important indicator for evaluating a firm's impact on social welfare and sustainable development (Gillan et al., 2021). ESG performance hinges on the strategic decisions made by corporate leaders, especially the chairman and CEO. This article examines how the masculinity-femininity cultural values of the chairman and CEO influence their firm's ESG performance, utilizing artificial intelligence-based cultural measures and evidence from China.

Decision-makers often face trade-offs between the interests of shareholders and ESG activities. ESG initiatives can, in the short term, negatively impact a firm's performance and innovation capability (Bocquet et al., 2015), exacerbate agency problems (Ferrell et al., 2016), and infringe on shareholders' rights and interests (Kruger, 2015). Therefore, strategic decisions about resource allocation to enhance ESG performance are critical. According to the "upper echelons perspective" theory, managerial background characteristics can partially predict strategic choices and performance outcomes (Hambrick et al., 1984; 2007). For example, Borghesi et al. (2014) suggest that the CEO's altruism can improve a firm's CSR performance.

Culture acts as a "mental program" or "software of the mind" and shapes how people think, feel, and potentially act (Hofstede et al., 2005). This cultural influence extends to the personal characteristics of the chairman or CEO, making their response partially predictable based on their cultural background and experiences. Drawing on Hofstede's theories (1980, 2001, 2005), this article argues that the masculinity-femininity cultural value of chairman and CEO can significantly impact their firm's ESG performance. Individuals in masculine societies tend to have strong egos, focus on achieving goals, value financial success, and exhibit more assertiveness. In contrast, individuals in feminine societies prioritize relationships, social harmony, and modesty and focus more on life quality and preservation (Hofstede, 2001). The masculinity-femininity dimension captures the extent to which male assertiveness (e.g., aggression, achievement, confidence) is valued over female nurturance (e.g., modesty, caring for others, focusing on relationships) in a given region (Hofstede et al., 2005; El Ghoul and Zheng, 2016).

On the one hand, the assertive, egocentric, and profit-oriented motivations brought by masculinity traits can drive chairmen or CEOs to prioritize economic interests, potentially at the expense of social responsibilities and without regard for the legal and reputation risks associated with poor ESG performance. On the other hand, individuals from feminine societies are more likely to balance the aggressive pursuit of career success with the desire for harmonious relationships. Pro-social values, altruism, and an emphasis on social connections can motivate CEOs to prioritize ESG activities.

Studies have shown that companies with CEOs who are married (Hegde and Mishra, 2019), have daughters (Cronqvist and Yu, 2017), or operate in environments with higher social capital (Zhu and Wang, 2024) tend to exhibit better corporate social responsibility (CSR) or ESG performance due to the pro-social values nourished by these factors. Therefore, our research proposes that chairmen and CEOs from feminine societies are more likely to gain psychological benefits from altruism and build social connections through their engagement in ESG activities.

Previous studies on the relationship between managers' characteristics and a firm's ESG performance have often overlooked the impact of regional culture. Existing studies on the influence of regional culture on corporate performance have mainly focused on international cultural differences, neglecting the cultural heterogeneity within countries or regions. Our study addresses these gaps by studying the relationship between the masculinity-femininity cultural values of the chairman and CEO and their companies' ESG performance. To achieve this, we utilized artificial intelligence models to identify the regional masculinity-femininity cultural values across provincial regions in Mainland China. These AI models helped us to determine which regions are more dominated by masculinity or femininity. We then measured the cultural value of the chairman and CEO based on their birthplaces. Using regression models, we analyzed how cultural values influence the ESG performance of firms.

Previous literature on cultures and values (Hofstede, 1980; House et al., 2004; Schwartz, 2012) has attempted to identify cultural dimensions and score them across various countries. These studies typically relied on surveys or interviews to obtain cultural scores. However, such methods have drawbacks, including limited coverage of respondents and restricted sample sizes. Additionally, these approaches often lack cultural scoring for regions within a single country, an important consideration given the significant cultural variations that can exist within national borders. To address these shortcomings, we introduce artificial intelligence models to provide new AI-based cultural scorings for regions within Mainland China. This approach allows for a deeper understanding of regional cultural differences and their impact on corporate ESG performance. By incorporating these AI-driven cultural measures, our study offers a novel perspective on how the cultural backgrounds of top executives influence their strategic decision-making and ESG outcomes.

First, we refer to the methods of Garg et al. (2018) and Kozlowski et al. (2019) and use the word-embedding models to identify the masculinity-femininity culture of regions. In these models, each word or term is represented as a 200-dimension vector, with the geometry of these vectors capturing the semantic relationships between words. The word-embedding model is typically trained on large corpora of text that describe regional cultures, so the vectors for cultural words or terms incorporate information about people's perception of regional culture. We reveal the association between region names and terms described as masculine or feminine by computing the averaged embedding distances between the region names and those terms. The regional masculinity-femininity culture score is calculated as the averaged embedding distance between region names and terms of femininity minus the averaged embedding distance between region names and terms of masculinity. A higher score indicates that the region is more dominated by masculinity, while a lower score indicates a dominance of femininity.

Second, we use two Large Language Models (LLMs), ERINE Bot and ChatGPT, to construct alternative measures of regional masculinity-femininity culture for variable validation and robustness checks. Similar to the word-embedding model, LLMs are trained on vast amounts of textual data, thus incorporating people's overall understanding and perspectives on regional cultures. We obtain the culture measures by querying these models for descriptions of masculinity-femininity culture in various regions. To mitigate the impact of randomness in LLMs responses, we repeat this process multiple times and average the resulting scores.

To validate our regional masculinity-femininity culture measures, we regress these measures against regional and firm indicators related to this culture dimension. Results indicate that the culture measure developed using the word-embedding model significantly correlates with those developed using LLMs. Furthermore, regions with higher masculinity scores are positively associated with the ratio of violent crime lawsuits, negatively associated with female enrollment rates in secondary and higher education, and negatively associated with the proportion of female legal representatives among SMEs. The results also suggest that firms with chairmen and CEO from masculine regions tend to have more mergers and acquisitions, financial restatements, and higher trade credit usage. These findings are consistent with existing theories and literature, indicating that our measure of the regional masculinity-femininity culture is valid.

We construct the firm's masculinity-femininity culture score variable based on the averaged masculinity-femininity cultural scores of the chairman and CEO's birthplaces. According to Hofstede et al. (2005), an individual's mental programming is shaped by the social environments in which they grew up and accumulated life experiences. Even if an individual's birthplace differs from their place of upbringing, their parents often reproduce the cultural education they received, allowing the culture to perpetuate itself. Moreover, while cultural practices can change rapidly with technological advancements, core values change more slowly (Hofstede et al., 2005). These arguments address potential concerns regarding differences between the chairman or CEO's birthplace and upbringing location, as well as the potential impact of regional cultural changes over time on the validity of our cultural measures.

Using a sample of 8,654 firm-year observations from the Chinese A-Share stock market over the 2013-2022 period, we find that firms with the chairman and CEO from masculine region tend to have worse ESG performance, while those with chairman and CEO from feminine regions tend to have better ESG performance. These results remain consistent even after including controls for governance indicators, chairman and CEO's characteristics, local masculinity-femininity culture variables, and firm-, year-, and province-fixed-effects. The robustness of our findings is confirmed using alternative measures of culture and ESG performance and through various estimation models. To address endogeneity concerns, we conduct a quasi-natural experiment. Following Schweizer et al. (2019), we examine whether the abnormal turnovers of the chairman or CEO, which result in an increase (or decrease) in the masculinity-femininity culture score, correspondingly decrease (or increase) ESG performance.

Exploring the mechanisms underlying our main findings through mediation effect analysis, we confirm that the dominance of masculinity among chairmen and CEOs weakens ESG performance by suffering a higher level of financial distress and having more risk-taking within the firm. In our heterogeneity analysis, the association between the chairman and CEO's cultural value and ESG performance is more pronounced for firms located in regions with weaker business environments, lower social credit environments, and state-owned firms. We also find that the masculinity-femininity culture impacts both environment, social responsibility, and corporate governance activity intensities.

Our paper contributes to two streams of research. First, it addresses the literature on the determinants of a firm's ESG or CSR performance. Previous studies have discussed the determinants from the perspectives of executives' personal characteristics and the business environment. For instance, McGuinness et al. (2017) found that female board members and foreign equity investors improve the CSR performance of Chinese firms. Borghesi et al. (2014) suggested that altruistic managers might choose to make socially responsible investments even if they are not value-enhancing. Di Giulio and Kostovetsky (2014) found that, compared with Republican founders, Democratic founders lead to better CSR performance. Moreover, He et al. (2024) note that media coverage plays an effective supervisory role in improving corporate ESG performance, while Zhu and Wang (2024) demonstrate that social trust is positively associated with corporate ESG performance. However, these studies have not examined the impact of firm characteristics on ESG performance from the perspective of manager's cultural values. Our research fills this gap by investigating the influence of the chairman and CEO's cultural values on ESG performance, thereby providing new insights into how cultural dimensions shape corporate behavior and sustainability outcomes.

Our paper also contributes to the literature on the masculinity-femininity culture and corporate finance. Research has shown that CEOs with masculine traits tend to engage in more mergers and acquisitions (Kamiya et al., 2018) and are more likely to have financial restatements (Jia, 2014). Labidi et al. (2021) found that masculinity is negatively associated with flows into socially responsible investment. Additionally, Mertzanis and Tebourbi (2023) demonstrated that countries scoring higher in masculinity are associated with lower issuance of green bonds.

The study most closely related to our research is Cai et al. (2016), which examined the influence of national culture on corporate social performance (CSP). They found that CSP ratings are higher in countries with strong civil liberties, political rights, and cultures oriented toward harmony and autonomy. However, this study did not account for cultural heterogeneity within countries. Moreover, the influence of national cultures on local firms may be confounded by factors such as varying environmental protection policies implemented by national governments. Our research addresses these gaps by identifying the masculinity-femininity culture of regions within China and providing new evidence on how managers' cultural value impacts ESG engagement.

The remainder of the paper is organized as follows. Section 2 reviews existing literature and develops hypotheses linking masculinity-femininity culture and ESG performance. Section 3 describes how the main variables are constructed and provides validation for the key variables. Section 4 describes the data. Section 5 presents our main empirical analysis, results of the robustness test, and tests for endogeneity issues. Section 6 reports the results of additional tests, including mechanisms and heterogeneity. Section 7 concludes.

4.2 Literature review and hypothesis development

The essence of ESG lies in the synergistic development of the environment, economy, and society, urging companies to balance their own growth with environmental sustainability while optimizing societal welfare (Chen et al., 2023). A large body of research has explored the economic implications of corporate ESG and the various factors that shape a firm's ESG performance. For example, studies have found that cross-listing (Yu and Luu, 2021), media coverage (He et al., 2024), environmental subsidy disruption (Zhang et al., 2023), and corporate resources (Drempetic et al., 2020) can promote ESG or CSR performance.

While some literature suggests that ESG engagement is motivated by economic benefits, such as attracting investors and maintaining stock performance (Lin et al., 2023), other studies highlight that managers' support for ESG activities can also stem from prosocial, altruistic, and social connection motivations. For example, Wang and Juslin (2009) propose that the Chinese harmonious culture can positively influence firms' ESG or CSR performance. Additionally, better ESG performance is associated with higher levels of local social trust (Zhu and Wang, 2024) and social capital (Jha and Cox, 2015). Companies with CEOs who are married (Hegde and Mishra, 2019) or have daughters (Cronqvist and Yu, 2017) tend to have better ESG performance due to the prosocial motivation of these CEOs. Borghesi et al. (2014) find that altruistic managers personally believe that they and their firm have a moral imperative to invest in CSR activities. Moreover, cooperative norms can lead to denser social networks, promoting chairman or CEO to engage in ESG/CSR activities to enhance their social capital and maintain favorable relationships with political parties (Jha and Cox, 2015; Zhu and Wang, 2024).

Managers balance economic outcomes and sustainable development issues, such as environmental impact, when making investment decisions (Narayanan et al., 2021). Jian and Lee (2015) find a negative association between ESG/CSR performance and CEO pay, indicating that CEOs may be penalized when ESG/CSR investment deviates from the expected levels. However, non-economic motivations such as prosocial, altruistic, and social connections can drive the chairman or CEO to engage in ESG activities when facing such trade-offs. According to the "upper echelons perspective" theory, managerial background characteristics can partially predict strategic choices and performance levels (Hambrick et al., 1984; 2007). Therefore, we conjecture those cultural values, as characteristic of the chairman or CEO, can significantly influence their decision-making regarding ESG investment.

Hofstede (1983) and Hofstede et al. (2005) proposed the theory of masculinity-femininity cultural values, exploring people's behaviors under this dimension. According to these studies, masculinity is associated with assertive, competitive, and confident behaviors, while femininity is linked to nurturance, concern for relationships, and a tender role. Responding to Hofstede's theory, Mertzanis and Tebourbi (2023) found a correlation between countries with higher masculinity scores and lower issuance of green bonds. Literature also suggests that individuals exhibiting masculine traits tend to display characteristics such as aggression, ambition, egocentricity, and risk-seeking (Jia et al., 2014; Amin et al., 2024).

On the one hand, the assertive, egocentric, and profit-oriented motivations associated with masculinity traits drive chairmen or CEOs to pursue economic interests, often at the expense of social responsibilities and potentially ignoring legal and reputation risks arising from poor ESG performance. On the other hand, femininity leads chairmen or CEOs to adopt more prosocial and altruistic values, making them more attentive to the societal impact of their social responsibility activities. Moreover, decision-makers with feminine values tend to care more about their firm's reputation, relationships, and social capital, making them more willing to invest in ESG initiatives for both the benefit of the firms and their own social capital. Therefore, we hypothesize that ceteris paribus, firms with chairmen and CEOs from masculine regions are more likely to exhibit poorer ESG performance, whereas firms with chairmen and CEOs from feminine regions are more likely to demonstrate better ESG performance.

H1. All else being equal, firms with chairmen and CEOs from masculine regions are more likely to have worse ESG performance, whereas firms with chairmen and CEOs from feminine regions are more likely to have better ESG performance.

Improving ESG performance for a firm requires resources, which may conflict with economic interests (Narayanan et al., 2021). Relaxing financing distress, for example, leads to higher CSR (Attig, 2023). Conversely, when enterprises face greater financial constraints or pressures, they tend to reduce their focus on social responsibility, decrease investments in areas such as the environment, employee welfare, and community contributions, or take fewer preventive measures in terms of product safety and corporate governance, prioritizing the allocation of limited resources towards their core business needs (Sun and Gunia, 2018). Leong and Yang (2021) also discovered that financially constrained enterprises exhibit significantly lower overall CSR performance than their non-financially constrained counterparts through the PSM model, with notable impacts observed across all CSR dimensions except human rights. Furthermore, Wu et al. (2016) found that companies with fewer financial constraints are more likely to invest in CSR to meet the expectations of their communities. When enterprises are compelled to invest in CSR, those under significant financial pressure may be forced to reduce their expenditures on Research and Development (R&D) and capital expenditures (Dang et al., 2022). Consequently, it is reasonable to argue that while ESG or CSR initiatives by enterprises can influence their financing capabilities, enterprises confronted with financing constraints or financial pressures are also prone to reallocate resources, giving precedence to their core businesses over social responsibility activities.

According to the Sino-Security firm's ESG evaluation system, enhancing ESG performance involves improving employee welfare, health, and safety, enhancing product quality and supply chain relationships, and increasing social contributions through inclusive activities. All these activities necessitate substantial financial and other resources. Therefore, greater financial distress weakens a firm's ability to enhance its social responsibility activities, while less financial distress can enhance the firm's ESG performance.

A firm's degree of financial distress is influenced not only by its operating status but also by soft institutions such as culture. Studies have found that a strong corporate culture can improve a firm's operational efficiency and related financial indicators (Li et al., 2021a, b), alleviate financing distress, and enhance financial conditions (Cheng et al., 2023). Regarding regional culture, Zheng et al. (2012) and El Ghoul and Zheng (2016) conjecture that borrowers in higher-masculinity countries engage in high-risk overinvestment at the expense of their lenders, leading lenders to extend shorter maturity loans to mitigate borrower opportunism. On the contrary, femininity, characterized by relatively lower speculation and stronger social connections, tends to make companies exhibit more stability, responsibility, and ease of communication. Companies with chairmen and CEOs who have feminine cultural values are more likely to gain the trust of financing institutions and obtain the necessary resources to improve their financial situation.

Consequently, we propose that firms with chairmen and CEOs from masculine regions tend to experience greater financial distress, which limits their ability to invest in social responsibility initiatives and ultimately results in poorer ESG performance.

H2. Firms with chairmen and CEOs from masculine regions tend to experience greater financial distress, which in turn weakens their ESG performance. Conversely, firms with chairmen and CEOs from feminine regions tend to experience less financial distress, thereby enhancing their ESG performance.

One of the critical decision-making elements for a chairman or a CEO is the level of risk-taking within the firm. When a firm takes on a higher level of risk, it faces a greater chance of encountering operational or financial difficulties, yet it may also achieve higher returns (Coles et al., 2006). Some managers bring high risks to the firm in pursuit of potentially high returns. Existing literature has found that the personal characteristics of corporate executives influence managers' willingness to take risks when making decisions, as well as the level of risk undertaken by the firm, such as age, experience, gender, and social capital (Ferris et al., 2017; Farag and Mallin, 2018). We propose that cultural values can affect the chairman or CEO's choice of risk-taking levels within the firm. According to Hofstede (2005) and El Ghoul and Zheng (2016), individuals from masculine regions tend to be more ambitious, confident, and speculative, making them more likely to take on more risks for more benefits. For example, research shows that overconfident individuals may underestimate the risks of investment due to excessive optimism, or they may overestimate their ability to manage these risks (Pikulina et al., 2017) and are more inclined to invest at a higher level of risk (Malmendier and Tate, 2005). Conversely, individuals from feminine regions tend to show nurturance features and modesty, encouraging their firms to take on less risk.

Furthermore, a greater risk appetite stemming from cultural values can lead to neglecting social responsibility risks, reducing a company's ESG activities. Wang and Yan (2023) found that the higher the CEO's risk aversion, the better the company's CSR performance. They demonstrate and verify the risk mitigation hypothesis, which hypothesizes that risk-averse CEOs are more likely to engage in CSR activities to reduce various risks faced by the company, such as providing "insurance-like" protection, improving risk management, facilitating access to financial markets and scarce resources, and ultimately enhancing long-term shareholder value. Other studies have also revealed the role of CSR in mitigating corporate risks, such as risks associated with the COVID-19 pandemic and crash risks (Kim et al., 2014; Bae et al., 2021). These research findings indicate that ESG or CSR activities serve as avenues for mitigating a firm’s risks, and firms’ executives tend to increase their investment in social responsibility activities when they aim to alleviate such risks.

However, when CEOs or other decision-makers take on higher risks due to overconfidence or speculative motives, they may overlook the importance of ESG or CSR in mitigating corporate risks, leading to reduced investment in these areas. For example, Bouslah et al. (2018) document that the CEO’s risk-taking incentives are positively related to socially irresponsible activities. McCarthy et al. (2017) also reveal a negative correlation between CEO confidence or more risk-taking and corporate investment in CSR, indicating that CEOs’ overconfidence may lead to reduced corporate investment in CSR. This could be attributed to the fact that they underestimate the risks associated with corporate social responsibility that the firm faces.

Therefore, overconfident managers with a stronger risk preference or overlook risk can pursue higher compensation at the cost of ESG activity, underestimate the potential negative impacts of socially irresponsible activities, and conduct socially irresponsible business strategies. Therefore, we propose that the chairmen or CEOs from masculine regions are more likely to pursue short-term personal interests and overlook risks in their decision-making, leading to higher risks for the firm and an increased likelihood of socially irresponsible activities, which in turn deteriorates the firm's ESG performance. On the other hand, the chairmen or CEOs from feminine regions are more concerned with the interests of all stakeholders within the firm. They are more likely to avoid overly risky business practices and reduce socially irresponsible activities, leading to better ESG performance.

H3. Ceteris paribus, firms with chairmen and CEOs from masculine regions bring more risk-taking to the firms, which in turn weakens their ESG performance. Conversely, firms with chairmen and CEOs from feminine regions tend to experience less risk-taking, thereby enhancing their ESG performance.

4.3 Measuring masculinity-femininity culture and other key variables

4.3.1 Measuring masculinity-femininity culture

This article introduces a novel method for measuring regional masculinity-femininity culture in China using advanced AI techniques, including the word-embedding model and two LLMs, namely, ERINE Bot and ChatGPT. We then validate our culture measure by regressing the scores against regional and firm indicators and construct the firm's culture variable based on the chairman and CEO's birthplaces. These approaches aim to address the limitations of traditional culture studies.

Culture is a multifaceted phenomenon that defies easy description and can be subjective and superficial to measure (Hofstede, 1983). While cultures lack physical entities, they manifest in various forms, such as symbols, heroes, rituals, and values (Hofstede, 2005). Moreover, an individual's personality is shaped in part by their unique experiences (Hofstede, 2005), which leads to variations in cultural manifestations even among people from the same cultural background. Thus, the challenge of how to effectively measure cultures has long perplexed social scientists.

Comparative research on culture often relies on measuring values, which are considered more stable elements of culture compared to practices (Hofstede, 2005). Previous research primarily employed paper-and-pencil questionnaires and interviews for culture measurement. For example, Hofstede (1983) collected data on employee's attitudes and values during his work as a psychologist at IBM. Similarly, the GLOBE study conducted by House et al. (2004) and Schwartz (2012) employed surveys to define cultural values and score cultures. The international cultural indicators developed by these studies have been widely used in relevant academic research (El Ghoul and Zheng, 2016).

However, existing national-level cultural measurement techniques based on questionnaire surveys may have limitations. Firstly, these methods typically provide generalized cultural values for entire countries, overlooking the heterogeneity of cultures within these nations, particularly in large and diverse countries like China. Secondly, the questionnaire surveys and interviews are constrained by sample size and the scope of sample groups, which may lead to biased conclusions. Thirdly, individuals may not always behave in accordance with their responses on the questionnaire, and it is important to distinguish between desirable values and actual behaviors when interpreting survey results.

To address these challenges, we propose a novel method leveraging artificial intelligence models. Word-embedding models [1] and LLMs are trained based on extensive text data, including diverse sources such as news articles, novels, and online forum discussions. Consequently, they capture perspectives from various regions and industries, educational backgrounds, and cognitive frameworks. These AI models analyze text data containing direct or indirect expressions of cultural perspectives on different regions, enabling a more comprehensive understanding of regional cultures. Furthermore, online statements made anonymously may better reflect individuals' genuine behaviors and opinions compared to their survey responses, which can be influenced by social desirability bias. The advantages of artificial intelligence models trained on big data make our approach more objective and representative. By incorporating diverse perspectives and minimizing biases, our method offers a more feasible and robust approach to measuring regional cultures in our research.

4.3.1.1 Measuring masculinity-femininity culture using word-embedding model

Firstly, we use the word-embedding model to identify masculinity-femininity cultural

[1] The Tencent word2vec model covers a large-scale of news, webpage text, and novels in model training. The model contains 12,287,936 unique words or terms in Chinese and English, each of which has a 200 dimensions vector. The downloading link and the other information about this model are available on: https://ai.tencent.com/ailab/nlp/en/embedding.html

values across different provincial regions in China. The word-embedding model (Mikolov et al., 2013) employs a neural network to generate dense, low-dimensional vector representations that capture the semantic meaning of words or terms. In this model, words are represented as high-dimensional vectors, where semantically similar terms are positioned closer together in the vector space. The underlying principle is that words appearing in similar contexts tend to have similar meanings.

This model is trained using techniques such as CBOW or Skip-Gram, which predict either a target word based on its surrounding contexts (CBOW) or the surrounding context based on a target word (Skip-Gram). Through iterative adjustments, the model minimizes prediction errors and produces semantically meaningful word representations, which are applicable to various NLP tasks.

In our approach, each word or term is assigned to a 200-dimensional vector, allowing us to capture semantic relationships between words. Using this vector space, the model enable us to identify terms that are semantically similar to a given word by calculating the Euclidean distance between their corresponding vectors. This makes the word-embedding model an effective tool for uncovering regional cultural values by analyzing linguistic patterns in large corpora.

The word-embedding model has found widespread applications in diverse academic disciplines in social science (e.g., Li et al., 2021a,b; Cheng et al., 2023). For example, Waller and Anderson (2021) utilized the word-embedding model to quantify online communities positioning along social dimensions, revealing a significant political polarization within social media content. Similarly, Tshitoyan et al. (2019) encoded material science knowledge into dense word embeddings, facilitating the discovery of novel materials for functional applications.

In our research, we adopt the methodology proposed by Garg et al. (2018) and Kozlowski et al. (2019) to identify masculinity-femininity cultural values across Chinese regions using word-embedding models. These studies first trained the word-embedding models on extensive textual datasets, such as news articles and books. They then identified antonym pairs of words and compared the embedding distance between these pairs and target words. For example, Garg et al. (2018) computed average word-embedding distances between words representing women and those representing occupations, subsequently contrasting them with distances between words representing men and the same occupations. Kozlowski et al. (2019) employed this approach to examine the associations between cultural dimensions, such as education and the rich-poor pair of affluence, shedding light on shared understandings of social class.

The underlying principle of this method rests on the notion that word vectors within the word-embedding model encapsulate semantic meanings and societal perceptions. In a word-embedding model, each word is represented as a vector within a shared vector space, where words with similar contextual usage are positioned closer together, and those with dissimilar contexts are situated further apart. A diagrammatic representation of this vector space is provided by Kozlowski et al. (2019), depicted in in Figure 4-1.

Panel A of Figure 4-1 shows the positioning of words associated with affluence within the vector space. Panel B further extends this representation by projecting names of various sports onto the affluence dimension vector space. Notably, words like "boxing" and "campaign" are projected toward the poor side of the dimension, while "golf" and "tennis" are associated with the affluent side, indicating a strong association with social class. Panel C exhibits the vector space incorporating multiple cultural dimensions.

Following this approach, we introduce the word-embedding model provided by Tencent AI-Lab and we ascertain the semantic association between region names and terms representing masculinity or femininity by computing the averaged embedding distances. Specifically, we identify the masculinity-femininity cultural dimension in word-embedding model by averaging the vectors of the words representing masculinity ($\overline{V_M} = [x_{M1}, x_{M2}, \dots, x_{M200}]$) or femininity ($\overline{V_F} = [x_{F1}, x_{F2}, \dots, x_{F200}]$), where the x_{Md} represents the d^{th} element in the averaged masculinity vector and likewise for femininity. We use the terms[2] that are carefully selected according to the description of cultural values in Hofstede (2005) and in related studies (Jia et al., 2014; Kamiya et al., 2019) as the terms that represent masculinity or femininity cultural values.

Next, we calculate the Euclidean distance between each region's name vector ($V_R = [x_{R1}, x_{R2}, \dots, x_{R200}]$) and the averaged vectors of masculinity ($D_{RM} = (\sum_{d=1}^{200}|x_{Rd} - x_{Md}|^2)^{\frac{1}{2}}$) or femininity culture ($D_{RF} = (\sum_{d=1}^{200}|x_{Rd} - x_{Fd}|^2)^{\frac{1}{2}}$). Subsequently, the masculinity-femininity culture score of each region R ($MFCulture_R$) is obtained by subtracting D_{RM} from D_{RF} ($MFCulture_R = D_{RF} - D_{RM}$). This approach yields relative measures of masculinity-femininity culture, mitigating irrelevant influences. For instance, economically developed regions may have lower distances to both masculinity and femininity vectors, introducing bias if D_{RM} or D_{RF} alone were used. The regional masculinity-femininity culture scores are provided in Appendix 4-1.

Based on the masculinity-femininity culture scores we obtained, we matched these

[2] The words or terms we select for masculinity in English are masculinity, competitive, aggressive, over-confidence, rough, male chauvinism, and resolved conflict by a show of strength or by fighting; The words or terms we select for femininity in English are feminine, humanistic, sociable, sensitive, tender, and attention to detail.

scores to the chairmen and CEOs of listed companies in mainland China according to their birthplace. Then, for each firm i in each year t, we averaged the culture scores of the chairman and CEO ($FMFCulture_{it}$), which is:

$$FMFCulture_{it} = \frac{MFCulture_{Chairman,i,t} + MFCulture_{CEO,i,t}}{2} \tag{4-1}$$

One potential concern is that, in some cases, there is a disparity between the chairman or CEO’s birthplace and the place of upbringing. According to Hofstede et al. (2005), one’s mental programming originates from the social environments in which he or she grew up and accumulated life experiences. The influence of their parents or families frequently perpetuates the culture in which they were raised, thus enabling the reproduction of cultural values, even though the chairman or CEO moved away from their hometown at a very young age. Moreover, a potential issue is that the changing world over time, such as the advancement of technology, could undermine our assumption about the continuity of cultural values. However, Hofstede et al. (2005) document that, while cultural change can be fast for practices, the change is slow for culture's value when the world is changing. These arguments validate the appropriation of how we score the masculinity-femininity culture to chairmen and CEOs according to their birthplaces.

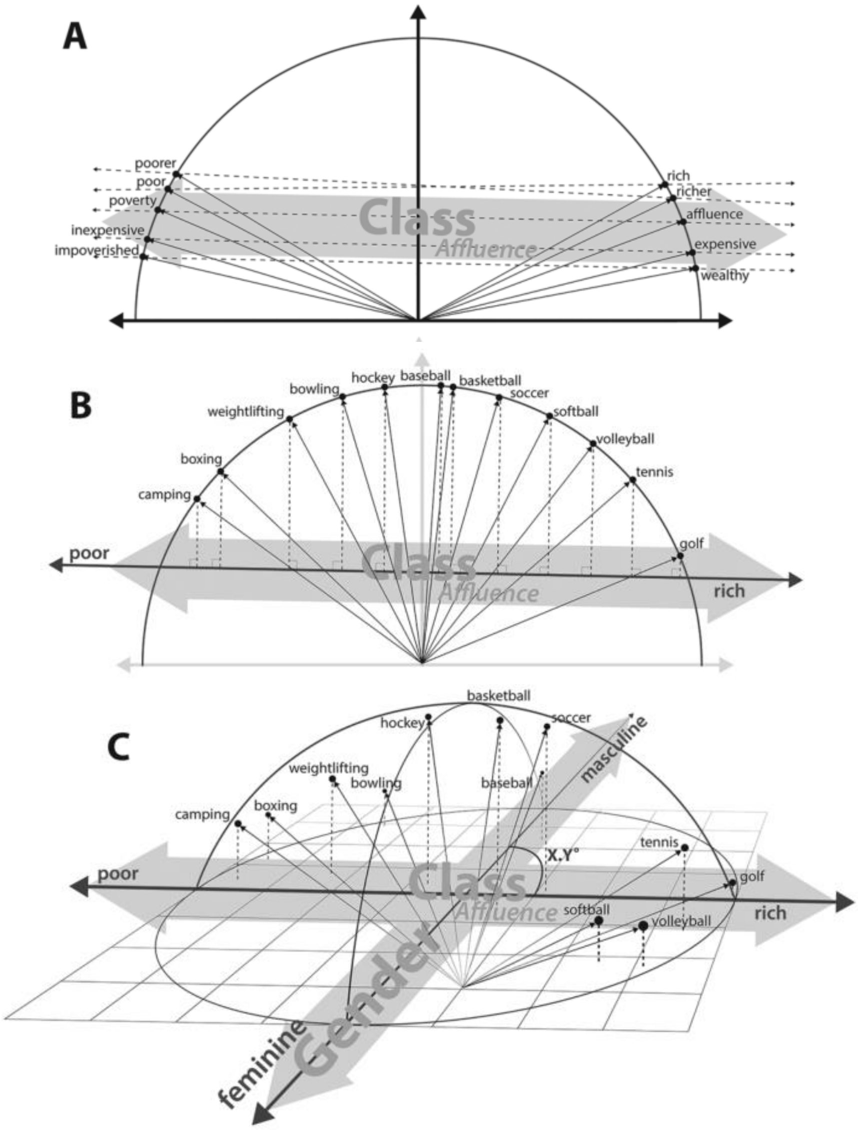


Figure 4-1. Conceptual Diagrams of Vector Spaces (Kozlowski et al., 2019)

4.3.1.2 Measuring masculinity-femininity culture using LLMs

Despite recent advances in textual analysis, extracting complicated information such as culture and values remained challenging until the advent of revolutionary AI tools (Jha et al., 2024). As LLMs, ERINE Bot[3] and ChatGPT set themselves apart from previous LLMs (Large Language Models), such as the ERINE Bot and ChatGPT distinguish

[3] ERNIE Bot, also known as Wenxin-Yiyan, is a large language model developed by Baidu, Inc., a Chinese firm listed in the U.S. and Hong Kong. Similar to ChatGPT, it provides question-answering services based on common-sense knowledge and textual understanding. Wenxin-Yiyan is one of China's most popular large language models. The web address is https://yiyan.baidu.com/

themselves from earlier AI models by handling long, sophisticated questions and providing detailed, expert-level answers. Similar to the training of word-embedding models, LLMs are trained on vast amounts of text data, encompassing the society's overall cognition and understanding of regional cultures. Therefore, these models inherently contain a general perspective on the regional cultures.

In addition to using a word-embedding model, we also used one of the most popular LLMs in China, the ERINE Bot, to measure the masculinity-femininity culture for each provincial region in mainland China. When provided with appropriate prompts, ERINE Bot can articulate perspectives and understandings of the masculinity-femininity culture of different regions in China. Jha et al. (2024) used ERINE Bot to extract information about corporate policy by analyzing conference call transcripts. In our study, since views on regional culture are publicly available and commonsensical, there is no need to supply additional text data to the ERINE Bot. Providing extra text data might introduce biases due to the potentially unrepresentative nature of a small supplemental dataset.

We provided the following prompt to ERINE Bot in Chinese and collected its responses: "*Suppose you are a sociological expert who has a profound understanding of the regional cultural characteristics across China. Please describe the characteristics of a specific province (or municipality) from the six dimensions of power distance, uncertainty avoidance, individualism/collectivism, masculinity/femininity, long-term orientation/short-term orientation, and indulgence versus restraint.*" We found that including all six cultural dimensions proposed by Hofstede (Hofstede, 2001) was necessary to obtain stable and feasible responses. We only used the responses related to masculinity-femininity culture from ERINE Bot in our study.

By manually reviewing the responses, we classified them into three levels based on the descriptions of the dominance of masculinity culture: high, medium, and low, assigning scores of 2, 1, and 0, respectively. Therefore, a higher score indicates a more dominant masculinity culture. To account for the inherent randomness in ERINE Bot's inferences, we repeated this process twenty times, obtaining twenty sets of scores. We then averaged these sets to derive our second set of regional masculinity-femininity culture scores ($MFCultureERINE_R$). These scores are exhibited in the Appendix 4-2.

For the robustness checks, we also obtained a set of scores from ChatGPT, another powerful but less popular LLM in China, resulting in the third set of regional masculinity-femininity culture score ($MFCultureGPT_R$).

Similar to how we construct for the masculinity-femininity culture variable for firm i in year t based on the culture score developed by using the word-embedding model ($FMFCulture_R$), we matched the scores developed by using LLMs to the chairmen and CEOs of listed companies according to their birthplace. For each firm in each year, we averaged the scores of the masculinity-femininity culture score for the chairman and CEO developed by using ERINE Bot ($FMFCultureERINE_{it}$) and by ChatGPT ($FMFCultureGPT_{it}$):

4.3.1.3 Validating our measure of masculinity-femininity culture

Given that our method for scoring masculinity-femininity culture is new, it is essential to validate our measure using relevant indicators. We employ several region- and firm-level indicators to validate the masculinity-femininity culture scores developed using the word-embedding model.

To validate our key measure, we conducted cross-sectional data regression analysis using region-level data. We examined the association between the masculinity-femininity culture score developed using the word-embedding model (*MFCulture*) and the scores generated by ERINE Bot (*MFCultureERINE*) as well as the scores by using ChatGPT (*MFCultureGPT*). Moreover, we selected several indicators reflecting the perspectives on masculinity-femininity culture, as demonstrated in Hofstede et al. (2005). Compared to femininity, masculinity emphasizes gender differences in social and family roles, being more assertive, ambitious, aggressive, and supporting the strong. Therefore, we selected four indicators that reflect these characteristics:

1. The ratio of civil litigation due to violence[4] (*ViolenceCase*) to reflect aggressive, ambitious, and support for the strong.
2. The female enrollment rate in the senior schools[5] (*GenderEdu*) to reflect gender differences in social roles.
3. The proportion of female legal representatives among SMEs [6] (*BusinessRepresentativeRatio*).
4. A gender equality measure developed by (Zhao et al., 2015) (*GenderEqual*).

---

[4] We count the number and proportion of civil disputes related to fighting and assault in judicial documents from various regions according to the data provided by the "China Judgments Online" website. "China Judgments Online" is the official website of Chinese judicial institutions for publishing judicial documents publicly. According to policy requirements of the Supreme People's Court of the People's Republic of China, since 2014, courts at all levels in China have been required to publish case information and verdicts on this website, including information on the cause of the case and the court that accepted it. The website has so far published over 130 million judicial documents. Based on the cause of action information and the address information of the accepting courts published on this website, we count the number and calculate the proportion of civil cases related to fighting and assault in each region out of the total number of cases.

[5] Since 1986, China has implemented a nine-year compulsory education policy, which means that all school-age children must receive nine years of education in primary and junior high schools. Participation in high school and higher education depends on students' academic performance and personal preferences, such as economic conditions and career planning. Therefore, we divide the ratio of female enrollment rates in high school and higher education by the male enrollment rates as the measure of female enrollment rate.

[6] According to the Firm Law of the People's Republic of China, firms registered in China must have a legal representative, who is typically assumed by management personnel such as the chairman or general manager. We obtained information on SMEs disclosed by the State Administration for Industry and Commerce of China. We used the Ngender package in Python to identify the gender of the legal representatives. This tool is an intelligent model built based on a Bayesian algorithm and can provide gender inference based on names and a probability value.

We performed an OLS (Ordinary Least Squares) regression using these indicators as dependent variables, with the masculinity-femininity culture score developed using the word-embedding model as the independent variable. To exclude the influence of other macro-factors, we controlled for the average GDP per capita (*GDPPer*), the degree of population aging (*OldRatio*), the gender ratio of the population (*SexRatio*), and the average local temperature (*Temperature*) in our regression models.

Appendix 4-3 presents the results of these validation tests. Columns (1) and (2) show that the culture score variable developed by using the word-embedding model is positively and significantly associated with the culture score variables based on ERINE Bot and ChatGPT. This indicates that the results produced by the three artificial intelligence models on masculinity-femininity culture are consistent and mutually validating. In column (3), the culture score is positively and significantly associated with the ratio of civil litigation due to violence, suggesting that people in regions dominated by masculinity culture tend to resolve disputes through violence, leading to more violent civil cases. Columns (4), (5), and (6) show that the culture score is negatively and significantly associated with the female enrollment rate in senior schools, the proportion of female legal representatives among SMEs, and the gender equality measure. This demonstrates that people in the regions dominated by masculinity tend to emphasize gender differences in social roles.

Next, we use the firm's panel data to validate our key culture measure. Kamiya et al. (2018) pointed out that more masculine CEOs are more acquisitive regarding the frequency of deals and the dollar amounts spent on acquisitions. We used the ratio of acquisition payment to total assets (*Acquisition*) to test the association between the masculinity-femininity culture and firm engagement in mergers and acquisitions. Jia et al. (2014) demonstrate that CEOs' facial masculinity is positively associated with financial misreporting. We validated our culture measure by regressing it with the financial report restatement (*Restatement*) variable. Moreover, El Ghoul and Zheng (2016) provided evidence of a positive association between trade credit usage and masculinity culture among countries. Therefore, we also introduce trade credit usage (*TradeCredit*) to examine the validity of our culture measure. Columns (1), (2), and (3) in Appendix 4-4 indicate that our culture measure variable is positively associated with the number of acquisitions, financial report restatement, and trade credit usage. These results suggest that if the chairman and CEO are from the masculinity regions masculinity, the firm tends to have more acquisition, misreporting, and trade credit usage, corresponding to previous studies findings. In summary, the validation tests in Appendix 4-3 and 4-4 reassure us that our masculinity-femininity culture measure has performed as expected.

4.3.2 Explanations of the construction of other variables

4.3.2.1 The ESG variables

The primary measure for firm ESG engagement (ESG) in our study is derived from the ESG rating developed by Sino-Securities Index Information Service (Shanghai) Co. Ltd., which covers most listed firms in China. This ESG index has been used in a recent study on the ESG engagement of firms in China (Lin et al., 2021). The ESG data is collected from the WIND database and ranges from one to nine, with higher scores indicating greater levels of ESG engagement. In addition, we obtained scores for the Sino-Securities ESG Index in three specific dimensions: environment, society, and governance[7]. To ensure robustness, we also use alternative variables based on the SynTao Green ESG[8] rating and Hexun CSR[9] rating, following the methodologies of Wang et al. (2023) and He et al. (2022).

4.3.2.2 The proxy for firm's environment, social responsibility, and corporate governance activity intensity based on news data

To explore the heterogeneity of masculinity-femininity culture's impact on firm practices of ESG, we use news data[10] to measure the firm's engagement intensity of the environment, social responsibility, and corporate governance individually by following the method of Caldara and Iacoviello (2022). These ESG activities are multidimensional. For example, the social responsibility activity encompasses aspects such as employee care, social contributions, supply chain relationships, and product quality. News data is particularly valuable as it covers these dimensions and offers two major advantages. Firstly, news data includes extensive information about a firm's environment, social responsibility, and corporate governance activities. Secondly, as news reports are produced by third parties, they tend to be more objective compared to the firm-disclosed texts, which might contain biases or exaggerations for economic benefits or policy compliance (Li et al., 2021).

To quantify a firm's intensity of engagement in the environment, social responsibility, and corporate governance activities individually using news data, we first

[7] The Sino-Securities Index Information Service (Shanghai) Co., Ltd. specializes in comprehensive services for index and index-based investment. The firm has provided ESG ratings for China's listed companies since 2010. The website is https://www.chindices.com/esg-ratings.html.
[8] SynTao Green Finance is a consultancy that provides professional services in green finance and is responsible for investing in China. The website is https://en.syntaogf.com/.
[9] Hexun is the first vertical financial portal website in China. It provides a leading CSR scoring system and is widely used in research on Chinese listed firms' CSR performance (He et al., 2022). The website is https://www.hexun.com/.
[10] Tonglian.com, an alternative data provider, provides the news text data we used. The news data contains over 85 million financial news stories. We screened out news related to listed companies and then counted the news that contained information on corporate social responsibility practices. The website is https://www.datayes.com/.

constructed three dictionaries of words or terms for these engagements. Following Li et al. (2021) and Cheng et al. (2023), we use the trained word-embedding model, develop the expanded and context-specific lexicons, and then manually check the lexicons to construct the dictionaries. We then screen for the words or terms in the news data and count the frequency of news articles containing them, which we classify as environment, social responsibility, or corporate governance activities engagement news. To normalize the data, we divided the frequencies of these screened news by the total amount of news for each firm, resulting in a ratio that measures environment (*EnvNews*), social responsibility (*SRNews*), or corporate governance activities engagement intensity (*GovNews*).

4.4 Data description and regression models

4.4.1 Source of data and the samples

Our empirical study focuses on A shares companies listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). In addition to the variables constructed in Section 3, we collect other relevant data from the CSMAR database. Given the availability of data on the birthplace of the chairmen and CEOs, we retain observations from the 2013–2022 period. We exclude the following firms from the sample: (1) Special Treatment (ST) and Particular Transfer (PT) companies; (2) financial companies (e.g., banks, insurance companies, and securities companies) because they are heavily regulated, and their return-generating processes differ from those of other companies; (3) companies with missing values. The final sample consists of 1,485 listed firms with 8,654 firm-year observations. The missing data is primarily due to the limited availability of birthplace information for the chairmen and CEOs.

4.4.2 Methodology and Summary Statistics

We present our results in a regression framework, controlling for firm characteristics, managers' attributes, and other relevant factors. The formal regression model examining the association between masculinity-femininity culture and ESG performance is given as follows:

$$ESG_{it} = \beta_0 + \beta_1 EMFCulture_{it} + \beta_2 Controls_{it} + Year + Firm + Province + \varepsilon$$

(4-2)

Where the dependent variable ESG_{it} is the logarithm of one plus the ESG score of the firm i in year t. $MFCulture_{it}$ is the averaged masculinity-femininity cultural score of the birthplace of the chairman and CEO of firm i in year t, where a higher value indicates a stronger dominance of masculinity culture, and conversely, a lower value indicates a stronger dominance of femininity culture. $Controls_{it}$ is the control variable set. Based on McGuinness et al. (2017), Cronqvist and Yu (2017), and Hegde and Mishra (2019), we include controls for the operational status of a firm, corporate governance, and personal information of the chairmen and CEOs. These controls include return on assets (*ROA*), firm size (*Firmsize*), leverage ratio (*Lev*), Tobin's Q (*TobinQ*), total asset turnover (*ATO*), and fixed asset ratio (Fixed), the proportion of female executives (*Female*), board size (*Board*), the proportion of independent directors (*Indep*), the dual role of chairman and CEO (*Dual*), audit status with Big-Four accounting firms in China (*Big4*), averaged management team age (*TMTAge*), gender (*Gender_HC*), age (*Age_HC*) and overseas experience (*Oversea_HC*) of the chairman and CEO, state ownership (*SOE*), length of years since the firm's listing (*ListAge*), and shareholding ratio of the top-10 shareholders (*Top10*) in our analysis. Additionally, to control the potential influence of the local masculinity-femininity culture of the firm on its ESG, we include the masculinity-femininity cultural score for the firm headquarters' location (*LocalMFCulture*) as a control variable. The model controls for year-fixed effects ($Year$), firm-fixed effects ($Firm$), and province-fixed effects (*Province*) to capture time-invariant characteristics at the yearly, firm, and provincial levels.

4.4.2 Summary statistics

Table 4-1 shows the summary statistics of the main variables. The high average level of corporate ESG performance (ESG) coupled with a relatively low standard deviation indicates that a significant number of firms perform well in ESG metrics, while a subset of firms exhibit unsatisfactory ESG performance.

The cultural score variable (*MFCulture*) shows an even distribution, suggesting that the masculinity-femininity culture of the birthplaces of chairmen or CEOs is balanced, without a strong concentration on either the masculinity or femininity side. This balance is also reflected in the local masculinity-femininity culture score of the regions where firms are headquartered (*LocalMFCulture*). Despite the uneven geographical distribution of firms, the value in *LocalMFCulture* is distributed evenly, suggesting a wide variety of cultural backgrounds across different regions.

Table 4-1 Summary statistics

Variable	N	Mean	SD	Min	Max
ESG	8,654	2.025	0.170	0.693	2.303
FMFCulture	8,654	-0.013	0.012	-0.034	0.011
ROA	8,654	0.040	0.074	-1.561	0.880
Firmsize	8,654	22.662	1.439	17.823	28.636
Lev	8,654	0.450	0.225	0.008	8.612

TobinQ	8,654	2.057	1.615	0.641	31.400
ATO	8,654	0.653	0.513	0.002	8.514
FIXED	8,654	0.216	0.165	0.000	0.905
Female	8,654	18.361	11.017	0.000	66.670
Board	8,654	2.145	0.202	1.386	2.890
Indep	8,654	37.480	5.654	16.670	80.000
Dual	8,654	0.214	0.410	0.000	1.000
Big4	8,654	0.077	0.266	0.000	1.000
TMTAge	8,654	49.813	3.127	37.790	62.880
LocalMFCulture	8,609	-0.014	0.012	-0.034	0.011
Gender_HC	8,607	0.950	0.177	0.000	1.000
Age_HC	8,607	53.261	5.967	28.000	81.000
Oversea_HC	8,607	2.868	0.411	1.000	3.000
SOE	8,654	0.393	0.488	0.000	1.000
ListAge	8,654	2.364	0.679	0.000	3.401
Top10	8,654	58.260	15.380	1.310	101.160

This table reports the number of observations, mean, standard deviation, minimum, and maximum for the variables used in this paper. The main sample consists of 8,654 firm-year observations over 2013–2022.

4.5 Main results

4.5.1 Baseline regression results

Table 4-2 presents the regression results of the firm's masculinity-femininity culture on ESG performance. Column (1) shows the result of the regression model without control variables, while Column (2) includes controls for firm operational status. In both columns, the coefficients of the key independent variable *FMFCulture* are negative and significant at a 1% significance level, indicating a robust relationship between masculinity-femininity culture and ESG performance.

To account for the potential confounding factors such as corporate governance and personal characteristics of the chairmen and CEOs, as well as the local masculinity-femininity culture, we introduce additional control variables in Column (3). Despite these controls, the main findings persist, reinforcing the negative association between masculinity-femininity culture and ESG performance.

Moreover, recognizing that the dependent variable (*ESG*) is a multivariate ordinal categorical data, we employ multivariate ordinal logistic regression analysis for robustness in column (4). Remarkably, the main result remains consistent across different regression specifications.

The results in Table 4-2 suggest that firms with chairmen and CEOs from masculine regions tend to exhibit worse ESG performance, all else being equal. For instance, based on the results in column (3), a one-standard-deviation increase in *FMFCulture* corresponds to about an 8.3% decrease in *ESG* performance, underscoring the economic significance of the regression results.

Table 4-2 Baseline results

		ESG		Multivariate Ordinal Logistic Regression
Variable	(1)	(2)	(3)	(4)
FMFCulture	-1.269***	-1.247***	-1.175***	-27.396**
	(0.411)	(0.413)	(0.397)	(10.954)
ROA		0.144***	0.126***	3.036***
		(0.044)	(0.044)	(0.821)
Firmsize		0.039***	0.039***	0.599***
		(0.006)	(0.007)	(0.149)
Lev		-0.081***	-0.063***	-1.108**
		(0.023)	(0.024)	(0.501)
TobinQ		0.005**	0.006***	0.100**
		(0.002)	(0.002)	(0.045)
ATO		0.007	0.006	-0.168
		(0.011)	(0.011)	(0.250)
Fixed		-0.047	-0.040	-1.059*
		(0.029)	(0.029)	(0.638)
Female			-0.000	-0.004
			(0.000)	(0.008)
Board			0.006	-0.146
			(0.020)	(0.544)
Indep			0.000	-0.001
			(0.001)	(0.014)
Dual			-0.006	-0.070
			(0.008)	(0.168)

Big4			-0.002	-0.225
			(0.015)	(0.451)
TMTAge			-0.000	-0.014
			(0.001)	(0.030)
LocalMFScore			-6.980***	-554.540***
			(1.085)	(200.068)
Gender_HC			0.005	-0.180
			(0.024)	(0.489)
Age_HC			0.000	0.004
			(0.001)	(0.014)
Oversea_HC			-0.000	0.035
			(0.008)	(0.200)
SOE			-0.012	0.206
			(0.017)	(0.373)
ListAge			-0.033*	-0.790**
			(0.017)	(0.343)
Top10			0.001	0.011
			(0.000)	(0.007)
Year fixed effects	No	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Number of observations	8,654	8,654	8,562	8,562
Adjusted r^2	0.005	0.041	0.045	0.460

This table presents the regression estimates of ESG performance on the variable of chairman and CEO's averaged masculinity-femininity culture scores. The sample is a yearly panel of listed firms of the A-Share market in China from 2013 to 2022. The control variable consists of firm features and the managers' characteristics. Year, firm, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

4.5.1 Robustness checks

In this section, we conduct several robustness checks on our main findings. First, using the word-embedding model, we replace the baseline regression masculinity-femininity culture score variable (*FMFCulture*) with variables based on LLMs (*FMFCulture_Ernie* and *FMFCulture_GPT*). Column (1) and (2) in Table 4-3 shows that both ERINE Bot and ChatGPT-based culture score variables are negatively and significantly associated with ESG performance, with ERINE Bot showing significance at the 5% level and ChatGPT at the 10% level. These results affirm the main findings' robustness when different artificial intelligence models measure regional masculinity-femininity culture. The varying significance levels may stem from the different treatments when measuring regional culture using ERINE Bot and ChatGPT. While we average ERINE Bot responses twenty times to address LLM's responses' randomness, we do not employ the same approach for ChatGPT. This underscores the impact of the randomness of LLM on cultural measurement accuracy and the efficacy of repeatedly querying for robust results.

Second, we replace the ESG performance variable based on the Sino-Securities firm's rating (*ESG*) with variables based on the SynTao Green ESG rating (*SynTao*) and Hexun CSR rating (*Hexun*). Columns (3) and (4) of Table 4-3 show that the coefficients of culture score variables remain negative and significant at a 5% level, indicating that the main results hold even with alternative ESG or CSR performance measures.

Third, we alter the definition of the firm's masculinity-femininity culture score and the fixed effect. Instead of using the average masculinity-femininity culture scores of both the chairmen and CEOs' birthplaces, we construct the cultural index of the firm (*FMFCultureHead*) using only the chairmen's birthplace culture score. The chairman and CEO play pivotal roles in shaping a firm's strategic direction. However, existing literature suggests that in the context of China, the chairman often wields the greatest influence over strategic decisions compared to the CEO (Wang et al., 2021). Consequently, it is plausible to infer that the cultural background of the chairmen's birthplace might exert a more pronounced impact on corporate decisions. Therefore, in the robustness check, we only use the masculinity-femininity culture score of the chairmen's birthplace. Column (5) demonstrates that the main result persists even with this change. Moreover, inspired by (Li et al., 2021a, b), we change the firm-fixed effects to the industry-fixed effects in the regression model, which also yields consistent results, as shown in column (6).

Table 4-3 Robustness checks of the baseline result

	ESG		*Hexun*	*SynTao*	*ESG*	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
FMFCultureERNIE	-0.019**					
	(0.009)					
FMFCultureGPT		-0.017*				
		(0.010)				
FMFCulture			-4.850**	-15.913**		-0.739**
			(2.183)	(8.011)		(0.288)
FMFCultureHead					-1.251***	
					(0.454)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	No
Industry fixed effects	No	No	No	No	No	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	8,654	8,654	8,137	1,260	7,756	8,654
Adjusted r^2	0.034	0.050	0.251	0.241	0.043	0.044

This table presents the robustness checks for our baseline results. In columns (1), (2), (5), and (6), the dependent variable is the ESG variable used in our baseline regressions. In contrast, in columns (3) and (4), the dependent variables are the ESG or CST performance developed by SynTao Inc. or Hexun.com. In columns (3), (4), and (6), the independent variable is the masculinity-femininity culture variable used in our baseline regressions. In columns (1), (2), and (6), the independent variables are the alternative masculinity-femininity culture variable developed by ERINE Bot or by ChatGPT or constructed by the chairman's cultural value. The control variable consists of firm features and the managers' characteristics. Year, firm, and province fixed effects are included in the columns from (1) to (5), while the firm fixed effects are replaced with industry fixed effects in column (6). Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

4.5.2 Endogeneity issue

The departure of a chairman or CEO from their position due to health issues, sudden death, or other reasons can create a unique scenario for examining the relationship between their cultural values and a firm's ESG performance. This setting can serve as a quasi-natural experiment, helping to mitigate potential endogenous issues and reverse causality problems.

On the one hand, the cultural values of the departing chairmen or CEOs might influence their career decisions based on the firm's ESG performance, leading to reverse causality concerns. On the other hand, factors like business performance or government policies could influence both firms' ESG performance and the selection of new leadership, leading to a "spurious correlation" between dependent and independent variables.

By following Schweizer et al. (2019), we conduct difference-in-difference regressions to assess whether changes in the masculinity-femininity culture score following abnormal turnovers of chairmen or CEOs impact ESG performance. Since these turnovers are unrelated to financial status, governance, or business environment, they provide an exogenous quasi-natural experiment to address endogeneity. The terms *Treat* and *Post* are omitted in the model due to multicollinearity.

Columns (1) and (3) in Panel A of Table 4-4 display results indicating that when masculinity (femininity) becomes more dominant in the cultural values of the new leadership post-turnover, the firm tends to have worse (better) ESG performance, and vice versa. To validate these findings further, we first conduct robustness checks by restricting observations to the two years surrounding the turnover. Columns (2) and (4) present these results, corroborating the initial findings.

Second, there is a concern that systematic differences between firms with a chairman and CEO from stronger masculinity culture regions and the firms with a chairman and CEO from stronger femininity culture regions may directly or indirectly affect both the choice of chairman and CEO of the firms and the ESG performance., we employ Propensity Score Matching (PSM) to address these issues. We follow the approach outlined by recent literature (e.g., Al Guindy, 2021; Chen and Hu, 2024) and employ a matching approach to compare firms with chairmen and CEOs from regions characterized by stronger masculinity cultural norms against those from regions with stronger femininity cultural norms while ensuring comparable firm characteristics. This enables us to isolate the effects of cultural values, controlling for the propensity of firms.

We estimate the propensity scores for the control and treated companies[11]. We also provide diagnostic tests to ensure the post-match sample is comparable. Appendix 4-5 reports the differences in means of firm characteristic variables between the treatment and control groups. The results indicate that after matching, there are no significant differences between the treatment and the control groups in the firm-specific characteristics under consideration. This confirms the effectiveness of PSM matching. We re-estimate the stagger difference-in-difference model based on the PSM-matched sample and report the results in Panel B in Table 4-4. We see that the coefficients of *Treat*Post* are negative and significant when masculinity is more dominant after turnover, while it is positive and significant when masculinity is less dominant, indicating that the results in the tests with raw data reported in Panel A in Table 4-4 still

[11] We construct the propensity score matched sample by following the methodology developed by Resenbaum and Rubin (1983). Specifically, we first set the treatment group include the samples that the masculinity-femininity culture value becomes more dominate after the abnormal turnover, and samples that the masculinity-femininity culture value does not become more dominate constitute the control group. Then, we estimate the propensity scores for the control and treated companies, using the Logit model that includes various potential determinants of the choice of successor in the turnover, including basic enterprise characteristics, financial status, corporate governance, local regional cultural values, etc. We finally match treated and control companies with the closest propensity scores, using the one-to-four nearest neighbor PSM method. We repeat this process by setting the treatment group including the samples that the masculinity-femininity culture value becomes less dominate after the abnormal turnover and setting as control group otherwise.

holds, demonstrating the robustness of our findings.

Table 4-4 Endogeneity problem: a quasi-natural experiment

Panel A Stagger difference-in-difference model

	Masculinity is more dominant after turnover	Masculinity is more dominant after turnover (two years surrounding the turnover)	Masculinity is less dominant after turnover	Masculinity is less dominant after turnover (two years surrounding the turnover)
	ESG			
Variable	(1)	(2)	(3)	(4)
*Treat*Post*	-0.021**	-0.020*	0.046**	0.049**
	(0.022)	(0.012)	(0.022)	(0.021)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Number of observations	8,696	2,010	8,654	2,010
Adjusted r^2	0.034	0.049	0.038	0.065

Panel B Stagger difference-in-difference model (propensity score matched samples)

	Masculinity is more dominant after turnover	Masculinity is more dominant after turnover (two years surrounding the turnover)	Masculinity is less dominant after turnover	Masculinity is less dominant after turnover (two years surrounding the turnover)
	ESG			
	(1)	(2)	(3)	(4)
*Treat*Post*	-0.030**	-0.038**	0.087***	0.089*
	(0.013)	(0.019)	(0.028)	(0.046)
Controls	Yes	Yes	Yes	Yes

Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Number of observations	2,718	876	1,203	388
Adjusted r^2	0.039	0.024	0.010	0.001

This table presents the regression estimates of ESG performance on the variable of chairman and CEO's averaged masculinity-femininity culture scores, limited to the propensity score matched samples. Panel A shows the results of the raw sample, and Panel B shows the results of the propensity score-matched sample. Column (1) shows the coefficient result of the DID in each panel when masculinity is more dominant after turnover, while column (3) shows the result when masculinity is less dominant. Columns (2) and (4) show the results when we keep observations for two years surrounding the turnover. The sample is a yearly panel of listed firms in the Chinese A-Share market from 2013 to 2022. The control variable consists of firm features and the managers' characteristics. Year, firm, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

4.6 Further discussions

4.6.1 Mechanisms

4.6.1.1 The channel of financial distress

In this section, we investigate the underlying mechanism through which masculinity-femininity culture affects ESG performance, focusing on financial distress. We employ mediation analysis following the approach proposed by Baron and Kenny (1986), decomposing the correlation between the dependent and independent variables in the baseline regression model (3-2) into direct or indirect paths that include mediating variables.

We investigate the mediating mechanism of financial distress using the Z-Score (*ZScore*) developed by Altman (1968), which is well used in recent studies (e.g. Hou et al., 2020). A higher Z-Score indicates a lower level of financial distress. Table 4-5 (columns 1-3) reveal a negative association between the culture score and economic distress (column 1), suggesting that dominance of masculinity culture among chairmen and CEOs leads to higher financial distress levels. Furthermore, a positive association between Z-Score and ESG performance (column 6) indicates a negative correlation between financial distress and ESG performance. The significant statistics of the Sobel tests indicate the indirect effect of this channel.

For the robustness of our result, we examine the mediating mechanism of the financial constraint measures using the WW index (WW) developed by White and Wu (2006), which is also well used in recent studies (e.g., Ding et al., 2022). A higher WW index indicates greater financial constraints. The results in Table 4-5 (columns 4-6) confirm the negative and significant association between the culture variable and the ESG performance, consistent with baseline results. Additionally, we find a positive association between the culture variable and financial distress (column 5), indicating that a stronger masculinity culture correlates positively with financial distress. Moreover, financial constraints negatively affect ESG performance (column 6), implying that higher financial constraints are linked to poorer ESG performance.

These findings support our hypothesis that financial distress is an important channel through which masculinity-femininity culture impacts ESG performance. When the cultural values of chairmen and CEOs are dominated by masculinity, firms are more likely to experience worse ESG performance due to greater financing constraints and financial distress, and vice versa.

Table 4-5 Mechanisms: financial distress

	ESG	*ZScore*	*ESG*	*ESG*	*WW*	*ESG*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
FMFCulture	-0.848***	-16.974**	-0.817***	-1.123***	0.189**	-1.072**

	(0.310)	(6.683)	(0.310)	(0.438)	(0.092)	(0.437)
ZScore			0.002***			
			(0.001)			
WW						-0.268***
						(0.061)
Indirect effect		-0.031*			-0.051*	
Sobel test (z-value)		-1.957			-1.859	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	7,488	7,488	7,488	7,492	7,492	7,492
Adjusted r^2	0.703	0.823	0.703	0.617	0.861	0.619

This table presents the results of mechanism tests of the effect of chairman and CEO's masculinity-femininity cultural value on ESG performance. The dependent variables are the chairman and CEO's averaged masculinity-femininity culture scores and mediating variables. The mediator variables are the Z-Score and WW index values. The key independent variables are the chairman and CEO's masculinity-femininity culture score variable. The control variable consists of firm features and the managers' characteristics. Year, firm, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

4.6.1.2 The channel of corporate risk-taking

In the hypothesis development section, we proposed that firms with a chairman and CEO from masculine regions bring higher risk to the firms, weakening their ESG performance and vice versa. In this section, we empirically examine this channel through which masculinity-femininity culture affects ESG performance.

First, by following Boubakri et al. (2013), we use two measurement indexes for corporate risk-taking to gauge the level of risk-taking of a firm. The first risk-taking measure (*Risk1*) is the volatility of a firm's earnings over periods around the year of observation. The second risk-taking measure (*Risk2*) is the maximum minus the minimum ROA over periods around the year of observation. The higher the value of these measures, the higher the firm's risk-taking.

Table 4-6 presents the results of the regressions examining the mediation effects with the risk-taking variables as the mediating variables. In Table 4-6 (columns 2 and 4), the coefficients of *FMFCulture* are all positive and significant, indicating that the stronger masculine culture value of the chairman and CEO is positively associated with higher corporate risk-taking. The negative coefficients in Table 4-6 (columns 3 and 6) suggest that higher corporate risk-taking is negatively associated with a firm's ESG performance. The significant statistics of the Sobel tests indicate the indirect effect of this channel.

These findings support our hypothesis that corporate risk-taking is an important channel through which masculinity-femininity culture impacts ESG performance. When the cultural values of chairmen and CEOs are dominated by masculinity, firms are more likely to experience worse ESG performance due to greater corporate risk-taking, and vice versa.

Table 6 Mechanisms: firm risk-taking

	ESG	*Risk1*	*ESG*	*ESG*	*Risk2*	*ESG*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
FMFCulture	-1.052***	20.135***	-0.964***	-1.052***	38.482**	-0.963***
	(0.283)	(6.814)	(0.282)	(0.283)	(12.868)	(0.282)
Risk1			-0.004***			
			(0.001)			
Risk2						-0.002***
						(0.001)
Indirect effect		-0.088***			-0.089***	

Sobel test (z-value)		-2.799			-2.831	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	8,385	8,385	8,385	8,385	8,385	8,385
Adjusted r^2	0.708	0.435	0.711	0.708	0.435	0.711

This table presents the results of mechanism tests of the effect of chairman and CEO's masculinity-femininity cultural value on ESG performance. The dependent variables are the chairman and CEO's averaged masculinity-femininity culture scores and mediating variables. The mediator variables are the two firms' risk-taking proxies. The key independent variables are the chairman and CEO's masculinity-femininity culture score variable. The control variable consists of firm features and the managers' characteristics. Year, firm, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

4.6.2 Heterogeneities

In this section, we explore several heterogeneities of the association between a firm's masculinity-femininity culture and ESG performance. We aim to deepen our comprehension of the underlying causes and factors that may exacerbate or mitigate these effects.

Firstly, we explore the heterogeneities in informal institutions, particularly examining differences between better and worse business environments and higher and lower levels of social trust. Informal institutions, such as cultural norms and social trust, influence corporate ESG activities. For instance, studies have shown that Confucian culture (Wang and Juslin, 2009) or higher levels of social trust (Zhu and wang, 2024) encourage firms to actively embrace social responsibility and enhance ESG performance. We propose that under varying informal institutional settings, the impact of chairmen and CEOs' masculinity-femininity cultural values on corporate ESG performance will exhibit heterogeneity.

The business environment has been defined as "*the totality of physical and social factors that are taken directly into consideration in the decision-making behavior of individuals in the organization*" (Duncan, 1972). In a weaker business environment, contract enforcement may be lax, corporate financing more constrained, and informal contracts more prevalent (Demirguc-Kunt et al., 2006). Wu et al. (2014) demonstrate that regions with lower social trust may exhibit weaker social capital, making corporate financing more challenging and investment more cautious. In such contexts, the pro-social, altruistic, and relationship-oriented attributes associated with femininity may significantly motivate companies to engage in ESG activities, thereby bolstering their ESG performance. Hence, we propose that in a weaker business environment or regions with lower social trust, the dominance of femininity in the chairmen and CEOs' cultural values can more markedly enhance the firm's ESG performance.

By following Zhang et al. (2024) and Wu et al. (2014), we introduce the business environment index and social trust index, dividing our samples into subgroups based on the level of business environment or social trust at the location of firms' headquarters. We then repeat the baseline regression for these subgroups. The results in Table 4-7 (columns 3 and 4) reveal that the coefficients are only negative and significant in regressions with samples from regions characterized by weaker business environments or lower levels of social trust. These findings support our hypothesis that the impact of masculinity-femininity culture on ESG performance is more pronounced in firms operating in regions with weaker business environments or lower social trust.

Secondly, we examine heterogeneity in our main finding between state-owned firms (SOEs) and non-SOEs. While both types of firms may be motivated to enhance ESG performance, they require adequate resources and financial stability to support these endeavors. In China, SOEs typically outperform non-SOEs in terms of market performance and have better access to financing channels (Faccio, 2010). As a result, SOEs possess more resources to support their chairmen and CEOs in promoting ESG. Therefore, we conjecture that the impact of masculinity-femininity culture on ESG performance is more pronounced for SOEs. To test this conjecture, we divide our samples according to the nature of firm ownership into SOEs and non-SOEs subgroups. The results confirm that our main funding is more pronounced in SOEs.

Table 4-7 Heterogeneities

	Business Environment		Social Trust		SOE or Non-SOE	
	Weaker	Stronger	Lower	Higher	SOE	Non-SOE
	ESG					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
FMFCulture	-1.322**	-0.870	-1.819***	-0.423	-0.902**	-1.227
	(0.552)	(0.536)	(0.585)	(0.532)	(0.405)	(0.783)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4,404	4,326	3,893	4,837	3,443	5,287
Adjusted r^2	0.050	0.058	0.035	0.069	0.043	0.081

This table presents the regression estimates of ESG performance on the variable of chairman and CEO's averaged masculinity-femininity culture scores under the observations for the firms in weaker or stronger business environments, lower or higher social trust environments, and for the SOEs or non-SOEs. The control variable consists of firm features and the managers' characteristics. Year, firm, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

4.6.3 Which dimensions of ESG activity are more affected?

We further explore the heterogeneity of masculinity-femininity culture's impact on firm practices of the environment, social responsibility, and corporate governance, the sub-items of ESG. Due to the lack of reliable sub-items data in the Sino-Securities ESG Index, we use the ESG sub-items practice indicators developed in Section 3.3 by using news text data as dependent variables for regression in this section. As we introduced earlier, news text data is a more objective third-party information source with high firm coverage when measuring the intensity of firm practices in each ESG sub-item.

Table 4-8 shows the results that all coefficients in this table are negative and significant, suggesting that the firm with a chairman and CEO from masculine regions is negatively associated with the firm's environment, social responsibility, and corporate governance practice intensity, and the firm with those from feminine regions is positively associated to these ESG practice intensity. Although these coefficients vary, the magnitude of the coefficients does not necessarily indicate the degree of masculinity-femininity culture's impact on these activities. This is because news media have different levels of attention towards different types of corporate ESG activities. Overall, these results indicate that masculinity-femininity culture's impact on a firm's ESG practices is comprehensive rather than being confined to a specific type of ESG activity.

Table 4-8 The dimensions of ESG activity affected by masculinity-femininity cultural value

	EnvNews	*SRNews*	*GovNews*

Variable	(1)	(2)	(3)
FMFCulture	-0.521**	-0.116**	-0.759**
	(0.240)	(0.059)	(0.370)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Number of observations	8,560	8,560	8,560
Adjusted r^2	0.090	0.032	0.068

This table presents the regression estimates of the practice of environment, social responsibility, and corporate governance on the variable of the chairman and CEO's averaged masculinity-femininity culture scores. The sample is a yearly panel of listed firms of the Chinese A-Share market from 2013 to 2022. The control variable consists of firm features and the managers' characteristics. Year, firm, and province fixed effects are included. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

4.6.4 Gender vs. Masculinity and Femininity

Hofstede et al. (2005) distinguish between biological gender (male and female) and culturally determined gender roles (masculinity and femininity). The culturally predetermined roles are relative, as a man can exhibit feminine traits and a woman to behave in a masculine manner. Consequently, a question arises: When biological gender differs from culturally determined gender roles, does it impact a firm's ESG performance?

Existing research finds that the firm's manager with androgynous features tends to receive greater support and be more communal. According to Stoker et al. (2012), while managers are generally perceived to embody masculine qualities, both male and female leaders who exhibit "feminine leadership styles" may be more popular, with their caring for others aligning better with contemporary societal expectations of leaders. Based on the Role Congruity Theory, Eagly and Karau (2002) argue that female leaders with masculine traits may face bias, but leaders with androgynous traits tend to perform better. Hence, we aim to explore how corporate leaders' attitudes towards ESG differ when their biological gender aligns or misaligns with their culturally determined gender roles.

To this end, we investigate a firm's ESG performance under different combinations of biological gender and culturally determined gender roles. First, we establish gender dummy variables, marking enterprise-year samples with "all-male chairman and CEO" as 1 and 0 otherwise. Additionally, we categorize samples based on the masculinity-femininity cultural values variable (*FMFCulture*) median, assigning 1 to those above the median and 0 otherwise. By combining these two dummy variables, we generate four dummy variables for different combinations of biological gender and culturally determined gender roles[12], which serve as independent variables in the repeated regression tests of Model (4-2). The results are presented in Table 4-9.

These results indicate that when a firm's chairman and CEO are male and embody masculinity, the company's ESG performance is significantly worse. Conversely, the company's ESG performance is significantly better when both are male but exhibit femininity. When women occupy these positions, masculinity (femininity) leads to slightly worse (better) ESG performance, but these effects are not significant. This reveals two phenomena: First, when male leaders possess feminine traits, their contributions to ESG activities are positive, suggesting that feminine cultural values can

[12] We assign a value of 1 to the *Male_Masculinity* variable when both the chairman and CEO are male and their masculinity values are more dominant, otherwise 0; we assign a value of 1 to the *Male_Femininity* variable when both the chairman and CEO are male and their femininity values are more dominant, otherwise 0; we assign a value of 1 to the *Female_Masculinity* variable when there is at least one female among the chairman and CEO and their masculinity values are more dominant, otherwise 0; we assign a value of 1 to the *Female_Femininity* variable when there is at least one female among the chairman and CEO and their femininity values are more dominant, otherwise 0.

modify innate male traits like overconfidence. Secondly, although masculine cultural values influence the ESG performance of female-led companies, this effect is weaker than for males, indicating that having both feminine and masculine traits mitigates the impact of masculinity. These findings reaffirm the influence of masculinity-femininity cultural values and underscore the positive role of androgyny for top managers.

Table 4-9 Gender vs. Masculinity and Femininity

	ESG			
Variable	(1)	(2)	(3)	(4)
Male_Masculinity	-0.018**			
	(0.009)			
Male_Femininity		0.021**		
		(0.009)		
Female_Masculinity			-0.058	
			(0.038)	
Female_Femininity				0.011
				(0.049)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Number of observations	8,562	8,562	8,562	8,562
Adjusted r^2	0.017	0.017	0.017	0.017

This table presents the regression estimates of ESG performance on the biological gender and culturally determined gender role of the chairman and CEO. The independent variables are four biological gender and culturally determined gender role indicators. The control variable consists of firm features and the managers' characteristics. Year, firm, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

4.7 Conclusion

In this paper, we draw on Hofstede's cultural dimensions to investigate the intricate relationship between a firm's ESG performance and the masculinity-femininity cultural values their chairmen and CEOs embody.

Existing research underscores that managers' pro-social values or social capital influence the impetus for ESG activities. While masculine traits like assertive, egocentric, and profit-oriented motives may lead masculine-oriented leaders to prioritize financial gains over social responsibilities, feminine traits such as nurturing and relational focus can inspire leaders dominated by femininity to engage in ESG strategies. Hence, we embark on an empirical investigation using Chinese data to elucidate the link between the cultural values of chairmen and CEOs and a firm's ESG performance.

To overcome traditional methods' limitations, such as small sample sizes and potential biases, we employ artificial intelligence models, including word-embedding models, ERNIE Bot, and ChatGPT, to quantify masculinity-femininity cultural values across Chinese provincial regions. This approach allows us to capture the varying regional cultures more comprehensively. Subsequently, we validate our culture measures through regression analyses against regional and firm indicators.

Our empirical findings reveal a clear pattern: firms with chairmen and CEOs dominated by masculinity tend to exhibit poorer ESG performance, whereas those dominated by femininity demonstrate better ESG outcomes. These results persist even after we account for firm characteristics, managerial attributes, and fixed effects and are corroborated through robustness checks and quasi-natural experiments to address endogeneity concerns. Furthermore, we discern that the impact of masculinity-femininity cultural values predominantly affects the social responsibility dimension of ESG.

Through mediation analysis, we uncover mechanisms underlying these relationships. Specifically, we find that the dominance of masculinity values weakens ESG performance by exacerbating financial distress and taking more risks to the firm. Additionally, our study reveals that these effects are more pronounced in regions with weaker business environments and lower levels of social trust, as well as among SOEs. We also find that the masculinity-femininity culture impacts both environment, social responsibility, and corporate governance activity intensities.

Our research contributes valuable insights by introducing a novel method for measuring regional cultural values and offering empirical evidence that enriches the literature on culture, executive characteristics, and firms' ESG performance. These findings are relevant for policymakers, executives, and stakeholders seeking to foster sustainable business practices within diverse cultural contexts.

On the one hand, while culture subtly influences people's perception of the importance of sustainable development, firms often overlook its influence due to the challenge of quantifying cultural impact. Therefore, when deciding ESG strategies, goals, and policies, boards of directors and managers should consider the cultural values of senior executives, such as chairpersons or CEOs, to mitigate the potential effects of cultural differences on the rational formulation of ESG policies. On the other hand, regulatory bodies like securities commissions and environmental protection agencies need to consider how regional cultural values, such as masculinity and femininity, affect the ESG activities and performance of listed companies. This awareness can guide the creation of tailored regulatory policies and enforcement measures that align with the cultural characteristics of corporate leadership.

Using artificial intelligence, our method of assessing masculinity-femininity cultural values across Chinese provinces addresses common issues in survey methodologies, such as sample selection bias and limited sample coverage. By utilizing AI trained on vast datasets, we can capture a broad societal perception of regional cultures, and our validation for these measures supports their reliability. However, limitations remain. A key limitation is that our method cannot capture individual-level cultural values. Even within the same region, an individual's cultural values may vary significantly due to differences in life experiences. Consequently, our approach measures the values of the chairperson and executives at a macro level without accounting for individual differences.

Although it is currently impractical to interview the chairmen and CEOs of every listed company to understand their cultural values, future research could benefit from more precise data. Suppose scholars or regulatory bodies like the China Securities Regulatory Commission can gather detailed cultural insights from corporate leaders. In that case, it will enable a more accurate assessment of how cultural values influence ESG decision-making and performance.

Reference

Al Guindy, M., 2021. Corporate Twitter use and cost of equity capital. *Journal of Corporate Finance*, 68, p.101926.

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), pp.589-609.

Amin, K., Feng, C., Guo, P. and You, H., 2024. CEO Facial masculinity and accounting conservatism. *Accounting and Business Research*, 54(2), pp.224-254.

Attig, N., 2024. Relaxed financing constraints and corporate social responsibility. *Journal of Business Ethics*, 189(1), pp.111-131.

Baron, R.M. and Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), p.1173.

Bocquet, R., Le Bas, C., Mothe, C. and Poussing, N., 2017. CSR, innovation, and firm performance in sluggish growth contexts: A firm-level empirical analysis. *Journal of Business Ethics*, 146, pp.241-254.

Borghesi, R., Houston, J.F. and Naranjo, A., 2014. Corporate socially responsible investments: CEO altruism, reputation, and shareholder interests. *Journal of Corporate Finance*, 26, pp.164-181.

Boubakri, N., Cosset, J.C. and Saffar, W., 2013. The role of state and foreign owners in corporate risk-taking: Evidence from privatization. *Journal of Financial Economics*, 108(3), pp.641-658.

Bouslah, K., Liñares-Zegarra, J., M'Zali, B. and Scholtens, B., 2018. CEO risk-taking incentives and socially irresponsible activities. *The British Accounting Review*, 50(1), pp.76-92.

Cai, Y., Pan, C.H. and Statman, M., 2016. Why do countries matter so much in corporate social performance?. *Journal of Corporate Finance*, 41, pp.591-609.

Caldara, D. and Iacoviello, M., 2022. Measuring geopolitical risk. *American Economic Review*, 112(4), pp.1194-1225.

Chen, H.K. and Hu, S.Y., 2024. Insider pledging: Its information content and forced sale. *Journal of Corporate Finance*, p.102655.

Chen, Y., Li, T., Zeng, Q. and Zhu, B., 2023. Effect of ESG performance on the cost of equity capital: Evidence from China. *International Review of Economics & Finance*, 83, pp.348-364.

Cheng, S., Hua, X. and Wang, Q., 2023. Corporate culture and firm resilience in China: Evidence from the Sino-US trade war. *Pacific-Basin Finance Journal*, 79, p.102039.

Coles, J.L., Daniel, N.D. and Naveen, L., 2006. Managerial incentives and risk-taking. *Journal of Financial Economics*, 79(2), pp.431-468.

Cronqvist, H. and Yu, F., 2017. Shaped by their daughters: Executives, female socialization, and corporate social responsibility. *Journal of Financial Economics*, 126(3), pp.543-562.

Demirguc-Kunt, A., Love, I. and Maksimovic, V., 2006. Business environment and the incorporation decision. *Journal of Banking & Finance*, 30(11), pp.2967-2993.

Di Giuli, A. and Kostovetsky, L., 2014. Are red or blue companies more likely to go green? Politics and corporate social responsibility. *Journal of Financial Economics*, 111(1), pp.158-180.

Ding, N., Gu, L. and Peng, Y., 2022. Fintech, financial constraints and innovation: Evidence from China. *Journal of Corporate Finance*, 73, p.102194.

Drempetic, S., Klein, C. and Zwergel, B., 2020. The influence of firm size on the ESG score: Corporate sustainability ratings under review. *Journal of Business Ethics*, 167(2), pp.333-360.

Duncan, R.B., 1972. Characteristics of organizational environments and perceived environmental uncertainty. *Administrative Science Quarterly*, pp.313-327.

Eagly, A. H., & Karau, S. J. (2002). "Role congruity theory of prejudice toward female leaders." *Psychological Review*, 109(3), 573-598.

El Ghoul, S. and Zheng, X., 2016. Trade credit provision and national culture. *Journal of Corporate Finance*, 41, pp.475-501.
Ferrell, A., Liang, H. and Renneboog, L., 2016. Socially responsible firms. *Journal of Financial Economics*, 122(3), pp.585-606.
Ferris, S.P., Javakhadze, D. and Rajkovic, T., 2017. CEO social capital, risk-taking and corporate policies. *Journal of Corporate Finance*, 47, pp.46-71.
Farag, H. and Mallin, C., 2018. The influence of CEO demographic characteristics on corporate risk-taking: evidence from Chinese IPOs. *The European Journal of Finance*, 24(16), pp.1528-1551.
Garg, N., Schiebinger, L., Jurafsky, D. and Zou, J., 2018. Word-embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, 115(16), pp.E3635-E3644.
Geert, H., 1980. Culture's Consequences: International differences in work-related values. Beverly Hills: Sage.
Hambrick, D.C. and Mason, P.A., 1984. Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, 9(2), pp.193-206.
Hambrick, D.C. Upper echelons theory: An update. *Academy of Management Review*, 2007, 32(2): 334-343.
He, F., Guo, X. and Yue, P., 2024. Media coverage and corporate ESG performance: Evidence from China. *International Review of Financial Analysis*, 91, p.103003.
He, Z., Guo, B., Shi, Y. and Zhao, Y., 2022. Natural disasters and CSR: Evidence from China. *Pacific-Basin Finance Journal*, 73, p.101777.
Hegde, S.P. and Mishra, D.R., 2019. Married CEOs and corporate social responsibility. *Journal of Corporate Finance*, 58, pp.226-246.
Hoftstede, G., 1980. Culture’s consequences: International differences in work-related values. Beverly Hills, Cal., and London: Sage, p.77.
Hofstede, G., 1983. The cultural relativity of organizational practices and theories. *Journal of International Business Studies*, 14, pp.75-89.
Hofstede, G., 1984. Culture's consequences: International differences in work-related values (Vol. 5). sage.
Hofstede, G., 2001. Culture's consequences: Comparing values, behaviors, institutions and organizations across nations. Sage publications.
Hofstede, G., Hofstede, G.J. and Minkov, M., 2005. Cultures and organizations: Software of the mind (Vol. 2). New York: McGraw-Hill.
Hou, K., Xue, C. and Zhang, L., 2020. Replicating anomalies. *The Review of Financial Studies*, 33(5), pp.2019-2133.
House, R.J., Hanges, P.J., Javidan, M., Dorfman, P.W. and Gupta, V. eds., 2004. Culture, leadership, and organizations: The GLOBE study of 62 societies. Sage publications.
Jha, A. and Cox, J., 2015. Corporate social responsibility and social capital. *Journal of Banking & Finance*, 60, pp.252-270.
Jha, M., Qian, J., Weber, M. and Yang, B., 2024. ChatGPT and corporate policies (No. w32161). National Bureau of Economic Research.
Jia, Y., LENT, L.V. and Zeng, Y., 2014. Masculinity, testosterone, and financial misreporting. *Journal of Accounting Research*, 52(5), pp.1195-1246.
Kamiya, S., Kim, Y.H. and Park, S., 2019. The face of risk: CEO facial masculinity and

firm risk. *European Financial Management*, 25(2), pp.239-270.
Kozlowski, A.C., Taddy, M. and Evans, J.A., 2019. The geometry of culture: Analyzing the meanings of class through word-embeddings. *American Sociological Review*, 84(5), pp.905-949.
Krüger, P., 2015. Corporate goodness and shareholder wealth. *Journal of Financial Economics*, 115(2), pp.304-329.
Labidi, C., Laribi, D. and Ureche-Rangau, L., 2021. National culture and socially responsible fund flows. *Emerging Markets Review*, 46, p.100751.
Li, K., Liu, X., Mai, F. and Zhang, T., 2021a. The role of corporate culture in bad times: Evidence from the COVID-19 pandemic. *Journal of Financial and Quantitative Analysis*, 56(7), pp.2545-2583.
Li, K., Mai, F., Shen, R. and Yan, X., 2021b. Measuring corporate culture using machine learning. *The Review of Financial Studies*, 34(7), pp.3265-3315.
Lin, X., Zhu, H. and Meng, Y., 2023. ESG greenwashing and equity mispricing: Evidence from China. *Finance Research Letters*, 58, p.104606.
Lin, Y., Fu, X. and Fu, X., 2021. Varieties in state capitalism and corporate innovation: Evidence from an emerging economy. *Journal of Corporate Finance*, 67, p.101919.
McGuinness, P.B., Vieito, J.P. and Wang, M., 2017. The role of board gender and foreign ownership in the CSR performance of Chinese listed firms. *Journal of Corporate Finance*, 42, pp.75-99.
Mertzanis, C. and Tebourbi, I., 2024. National culture and green bond issuance around the world. *European Financial Management*, 30(2), pp.879-934.
Mikolov, T., Sutskever, I., Chen, K., Corrado, G.S. and Dean, J., 2013. Distributed representations of words and phrases and their compositionality. *Advances in Neural Information Processing Systems*, 26.
Narayanan, V., Baird, K. and Tay, R., 2021. Investment decisions: The trade-off between economic and environmental objectives. *The British Accounting Review*, 53(3), p.100969.
Rosenbaum, P.R. and Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), pp.41-55.
Schwartz, S.H., 2012. An overview of the Schwartz theory of basic values. *Online Readings in Psychology and Culture*, 2(1), p.11.
Stoker, J.I., Van der Velde, M. and Lammers, J., 2012. Factors relating to managerial stereotypes: The role of gender of the employee and the manager and management gender ratio. *Journal of Business and Psychology*, 27, pp.31-42.
Waller, I. and Anderson, A., 2021. Quantifying social organization and political polarization in online platforms. *Nature*, 600(7888), pp.264-268.
Wang, B.Y., Duan, M. and Liu, G., 2021. Does the power gap between a chairman and CEO matter? Evidence from corporate debt financing in China. *Pacific-Basin Finance Journal*, 65, p.101495.
Wang, J., Ma, M., Dong, T. and Zhang, Z., 2023. Do ESG ratings promote corporate green innovation? A quasi-natural experiment based on SynTao Green Finance's ESG ratings. *International Review of Financial Analysis*, 87, p.102623.
Wang, L. and Juslin, H., 2009. The impact of Chinese culture on corporate social responsibility: The harmony approach. *Journal of Business Ethics*, 88, pp.433-451.

Whited, T.M. and Wu, G., 2006. Financial constraints risk. *The Review of Financial Studies*, 19(2), pp.531-559.
Yu, E.P.Y. and Van Luu, B., 2021. International variations in ESG disclosure–do cross-listed companies care more?. *International Review of Financial Analysis*, 75, p.101731.
Zhang, D., Meng, L. and Zhang, J., 2023. Environmental subsidy disruption, skill premiums and ESG performance. *International Review of Financial Analysis*, 90, p.102862.
Zhang, F., Zhang, J., Gao, Y. and Wang, Z., 2024. How does optimizing the business environment affect the capital flows between northern and southern China? From the perspective of enterprises' location choice for out-of-town investment. *International Review of Financial Analysis*, 94, p.103295.
Zhao, X., Li, H. and Sun, C., 2015. The regional cultural map in China: is it "the great unification" or "the diversification". *Management World*, 2, pp.101-119.
Zheng, X., El Ghoul, S., Guedhami, O. and Kwok, C.C., 2012. National culture and corporate debt maturity. *Journal of Banking & Finance*, 36(2), pp.468-488.
Zhu, B. and Wang, Y., 2024. Does social trust affect firms' ESG performance?. *International Review of Financial Analysis*, 93, p.103153.

Appendix

Appendix 4-1 The regional masculinity-femininity culture scores developed by using the word-embedding model

Region	*MFCulture*	Region	*MFCulture*
Heilongjiang	-0.024	Guangdong	-0.014
Hainan	-0.014	Anhui	-0.013
Fujian	-0.019	Hebei	-0.007
Henan	0.006	Guizhou	-0.021
Shanghai	-0.034	Beijing	-0.013
Jiangxi	-0.008	Guangxi	-0.013
Shandong	0.011	Hubei	-0.010
Ningxia	-0.012	Jiangsu	-0.025
Gansu	0.006	Jilin	-0.015
Shanxi	0.006	Shaanxi	0.008
Yunnan	-0.017	Tianjin	-0.016
Liaoning	-0.014	Hunan	-0.016
Zhejiang	-0.027	Tibet	0.007
Inner Mongoria	-0.019	Qinghai	-0.001
Xinjiang	-0.024	Chongqing	-0.012
Sichuan	-0.006		

Appendix 4-2 The regional masculinity-femininity culture scores developed by using the ERINE Bot

Region	*MFCultureERINE*	Region	*MFCultureERINE*
Shanghai	0.368	Hebei	1.895

Yunnan	0.947	Henan	1.737
Inner Mongoria	1.579	Zhejiang	0.474
Beijing	1.105	Hainan	0.632
Jilin	1.368	Hubei	0.895
Sichuan	0.211	Hunan	1.278
Tianjin	1.316	Gansu	1.737
Ningxia	1.789	Fujian	0.947
Anhui	1.789	Tibet	1.579
Shandong	1.947	Guizhou	1.368
Shanxi	1.789	Liaoning	1.579
Guangdong	1.105	Chongqing	0.421
Guangxi	1.158	Shanxi	2.000
Xinjiang	1.632	Qinghai	1.889
Jiangsu	0.368	Heilongjiang	1.526
Jiangxi	1.579		

Appendix 4-3 Validations of masculinity-femininity culture measure: region data

	ERNIE	*ChatGPT*	*Violence Case*	*Gender Edu*	*Business Representative Ratio*	*Gender Equal*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
MFCulture_Local	24.263***	20.981**	0.045***	-2.651*	-0.981*	-0.758*
	(6.786)	(9.463)	(0.014)	(1.374)	(0.557)	(0.428)
GDPPer	0.120	-0.188	-0.001	0.008	0.024	-0.006
	(0.182)	(0.285)	(0.000)	(0.041)	(0.015)	(0.012)
OldRatio	-6.627	8.131	0.005	0.188	0.672	-0.692**
	(5.333)	(7.390)	(0.011)	(1.362)	(0.447)	(0.297)
Temperature	-0.599**	-0.702	0.000	-0.126*	-0.004	0.020*
	(0.220)	(0.289)	(0.000)	(0.064)	(0.018)	(0.011)
SexRatio	0.039	0.070	0.000	-0.016	0.010	-0.003
	(0.039)	(0.059)	(0.000)	(0.012)	(0.007)	(0.002)
Number of observations	31	31	31	31	31	31
Adjusted r^2	0.536	0.385	0.487	0.458	0.460	0.269

This table presents the cross-sectional regression estimates of regional indicators on the variable of regional masculinity-femininity culture scores. The control variable consists of regional features. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 4-4 Validations of masculinity-femininity culture measure: Firm Data

	Acquisition	*Restatement*	*TradeCredit*
Variable	(1)	(2)	(3)
MFCulture	1.742**	1.343**	0.570**
	(0.836)	(0.683)	(0.284)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Number of observations	9,447	9,787	10,684
Adjusted r^2	0.099	0.026	0.075

This table presents the regression estimates of firm indicators on the variable of chairman and CEO's averaged masculinity-femininity culture scores. The sample is a yearly panel of listed firms of the A-Share market in China from 2013 to 2022. The control variable consists of firm features. Year, firm, and province fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 4-4 Validations of masculinity-femininity culture measure: Firm Data

	Pre- or post-matching	Mean		%Reduct	t-test	
Variable	U or M	Treatment group	Control group	%Bias	T-statistics	P-value
ROA	U	0.034	0.041	-9.333	-1.52	0.129
	M	0.034	0.034	0.000	-0.02	0.985
Firmsize	U	23.305	22.635	1.458	7.50	0.000
	M	23.305	23.33	-0.054	-0.18	0.853
Lev	U	0.517	0.448	7.150	4.94	0.000
	M	0.517	0.512	0.486	0.27	0.789
TobinQ	U	1.842	2.065	-5.708	-2.21	0.027
	M	1.842	1.807	0.959	0.27	0.788
Fixed	U	0.228	0.216	2.703	1.20	0.23
	M	0.228	0.221	1.559	0.46	0.649
Female	U	17.257	18.432	-3.292	-1.71	0.088
	M	17.257	16.953	0.889	0.33	0.741
Indep	U	37.756	37.47	0.380	0.81	0.417
	M	37.756	37.658	0.130	0.18	0.858

Dual	U	0.143	0.215	-20.112	-2.81	0.005
	M	0.143	0.137	2.143	0.22	0.827
TMTAge	U	50.995	49.766	1.220	6.31	0.000
	M	50.995	51.008	-0.013	-0.04	0.964
Gender_HC	U	0.976	0.949	1.403	2.49	0.013
	M	0.976	0.975	0.051	0.10	0.917
Age_HC	U	53.604	53.251	0.330	0.95	0.342
	M	53.604	53.945	-0.317	-0.67	0.501
Oversea_HC	U	2.896	2.867	0.503	1.12	0.264
	M	2.896	2.892	0.069	0.13	0.895
SOE	U	0.657	0.385	26.104	8.96	0.000
	M	0.657	0.667	-0.755	-0.25	0.801
ListAge	U	2.681	2.350	6.579	7.84	0.000
	M	2.681	2.680	0.019	0.03	0.978

This table reports the balance test results for matched samples, based on propensity score matching (PSM). “U” refers to the pre-PSM matched sample, while “M” refers to the post-PSM matched sample.

Chapter 5. Conclusion

All three studies in my thesis employed big data, textual analysis, and artificial intelligence models to explore three significant topics: corporate culture and the resilience of enterprises during the Sino-US trade war, political uncertainty exposure of firms and their rapidly evolving technological innovation, and the masculinity-femininity cultural values of the chairman and CEO and their firm's ESG performance. These studies can provide rich theoretical and empirical implications, but traditional structured data and analysis methods are insufficient for these studies. New data and methods have made these studies possible.

In my three studies, we are motivated by observed phenomena and combine existing literature theories to find research gaps and formulate our own search topics and theoretical hypotheses. We use textual analysis or artificial intelligence models to extract information from vast amounts of text data to construct variables to verify these hypotheses. After validating these variables, we use them in regression models to study associations between variables and develop causality through exogenous shock events. By effectively combining new methodologies and traditional research paradigms, we verify our proposed research hypotheses in all three studies of my thesis.

In the first study, we examine whether enterprises exposed to the Sino-US trade war exhibit poorer stock market performance during the trade war and whether a strong corporate culture could provide resilience for these exposed enterprises. Through textual analysis and artificial intelligence algorithms, we measure the Sino-U.S. trade war exposure for listed firms in China based on analyst report data. Additionally, we identified the most recognized corporate cultural values from the official websites of listed companies. We used annual report text data to create a corporate culture dictionary and measure corporate culture's strength. The empirical studies' results indicate that the Sino-U.S. trade war leads to poorer stock market performance for firms exposed to this event. Furthermore, we found that corporate culture, encompassing Integrity and Honesty, Innovation and Technology, Hardworking and Performance, Product and Service Quality, and Teamwork and Cooperation, can mitigate the negative impact of the Sino-US trade war. This resilience is primarily achieved by enhancing operating performance and relieving financing constraints. This research offers two insights. First, the Sino-U.S. trade war has a negative impact on Chinese listed companies, and enterprises exposed to the trade war need to focus on risk management and corporate governance to address its effects. Second, a strong corporate culture can provide resilience for Chinese enterprises in crisis, emphasizing the importance of corporate culture in achieving better business performance in a perilous environment.

In the second study, we investigate whether the political uncertainty exposure of firms depresses their rapidly evolving technological innovation. We define the position of patents in the technology cycle and identify the firms that choose to pursue rapidly evolving technological innovation. Additionally, we assess each company's political uncertainty exposure level through textual analysis of their annual reports. The empirical results suggest that companies facing higher political uncertainty are less likely to pursue rapidly evolving technological innovation. The causality of this association is further validated by examining exogenous shock events such as the Sino-U.S. trade war and the COVID-19 pandemic. Mechanism studies reveal that higher political uncertainty leads to increased financing constraints and greater risk aversion among executives, ultimately reducing rapidly evolving technological innovation. These findings offer two insights. First, policymakers should minimize the uncertainty associated with their policies to increase companies' willingness to pursue rapidly evolving technological innovation. Second, companies should not only focus on the quantity of innovative outcomes but also their quality, particularly rapidly evolving technological innovation.

In the third study, we examine the impact of the chairman and CEOs' masculinity-femininity cultural values on their companies' ESG performance. Due to the limitations of traditional measurement methods through questionnaires or interviews, we implement three AI models, including the word-embedding model, ERNIE Bot, and ChatGPT, to measure masculinity-femininity cultural values in various provincial regions in mainland China. Our empirical study revealed that when the chairman and CEO come from masculine regions, their companies tend to have worse ESG performance, while those from feminine regions exhibit better ESG performance. Mechanism studies indicate that the masculinity-femininity cultural values of the chairman and CEO influence a firm's financial distress and risk-taking, thereby affecting ESG engagement and performance. We find the causality by examining abnormal turnover among the chairman or CEO. This study offers two insights. First, firms should focus on the impact of culture on corporate decision-making, especially in terms of ESG or social responsibility engagement. Second, artificial intelligence models and big data perform well in measuring cultural values.

We have investigated three important topics using new methods and data and made contributions in these three areas in terms of theory, methodology, and empirical evidence. Although there may be some oversights in our three studies, I hope that the research in my thesis can inspire future studies and that, in the future, we can make new contributions to research in related fields based on our existing achievements.