Corporate Finance in the Digital Age

Zhonghao Jiang

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Adam Smith Business School, College of Social Sciences

University of Glasgow

Supervised by
Dr. Yukun Shi; Dr. Lu Xing

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Abstract

This thesis, structured into three chapters, delves into novel and significant research questions in corporate finance within the digital age, employing advanced quantitative methodologies: 1. Social Connectedness and Cross-Border Mergers and Acquisitions; 2. Remote or Face-to-Face: CEO Interviews and Investor Disagreement; 3. Climate Change Exposure and Mutual Fund Ownership. Chapter 1 investigates the role of social connectedness in cross-border mergers and acquisitions (M&As). Using Facebook's Social Connectedness Index, the chapter shows that social connectedness induces higher stock returns to acquirers' M&A announcements. Social connectedness works through an information dissemination channel, which reduces target premiums, increases the completion rate, and facilitates long-run success. Chapter 2 examines the financial implications of CEOs' information disclosure modalities. Using CEOs' televised media interviews on CNBC, the chapter finds that, compared to face-to-face interviews, remote interviews are associated with larger investor disagreement around the interview date. The lack of medium richness in remote interviews can lead to increased dispersion in information interpretation among investors, resulting in larger investor disagreement. Chapter 3 documents a negative implication of firms' climate change exposure on their mutual fund ownership, using Sauter et al. (2023)'s climate change exposure index. This thesis provides insights into the evolving corporate finance in the digital age, by employing diverse and dynamic data sources and analytical tools, such as textual analysis and bridging sociological concepts, CEO behaviors, and environmental concerns with corporate finance.

Keywords: Digital Age; Cross-Border M&As; Social Connectedness; CEO Interview; Investor Disagreement; Climate Change Exposure; Mutual Fund Ownership

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Author’s Declaration

“I declare that, except where explicit reference is made to the contribution of others, this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.”

Printed Name: __ZHONGHAO JIANG_

Signature: ________________________

Introduction

The digital age refers to the period in human history characterized by the shift from traditional industry to an economy based on information technology. This era is marked by the widespread use of digital technologies, such as computers, the internet, mobile devices, and digital communication tools, which have transformed the way people live, work, communicate, and access information. Corporate finance in the digital age refers to the integration of advanced digital technologies and data-driven approaches into a company's financial activities, such as investment decisions. Emerging digital innovations, including mobile banking, online financial management products, peer-to-peer (P2P) lending, automated portfolio managers (robo-advisors), and advanced trading platforms, combine technology, regulation, user behavior, and global market dynamics (Yang *et al*. 2023). These developments are significantly shaping the digital economy. For example, based on the China Academy of Information and Communications Technology (CAICT), the value of the digital economy reaches 7.1 trillion U.S. dollars in China in 2021.

The digital age brings both opportunities and challenges for the finance industry and academic research. One significant opportunity is that it creates a large amount of data which continues to grow (Goldstein *et al*., 2021). The data sources expand from traditional data to texts, pictures, and videos. Obaid *et al*. (2022) investigate a large sample of news photos and introduce a daily market-level investor sentiment index. The index can predict market return reversals and trading volume. In addition, Facebook constructs an index that measures social connections between countries, harnessing their global data. This provides scholars with opportunities to explore how social ties can influence international business, a concept previously examined primarily through language similarities or flight patterns (Zhang *et al*., 2021).

Additionally, the digital age creates techniques to assist the investigation of research questions, including machine learning, deep learning, textual analysis, and artificial intelligence. Machine learning in finance refers to the application of advanced algorithms and statistical models to analyze data, identify patterns, and make predictions or decisions without being explicitly programmed for each task. It is widely applied to algorithmic trading, risk assessment, fraud detection, portfolio management, sentiment analysis, etc. For example, Li *et al.* (2021b) tackle the challenge of quantifying corporate culture by using natural language processing to analyze earnings call transcripts. The research uses a machine-learning approach to decompose corporate culture into five dimensions: innovation, integrity, quality, respect, and teamwork. The study finds that corporate culture, as measured by these dimensions, has significant implications for firm behavior, especially in the context of mergers and acquisitions. Textual analysis in finance refers to the use of computational techniques to analyze and extract meaningful information from large volumes of text-based data, such as news articles, earnings reports, social media posts, and financial statements. This approach leverages natural language processing (NLP), machine learning, and other data science methods to quantify and interpret qualitative information that can influence financial markets. According to a survey about textual analysis by Loughran and McDonald (2016), various methodologies used in textual analysis, including sentiment analysis, bag-of-words approaches, and more advanced techniques like machine learning and topic modeling. They emphasize the importance of context when interpreting textual data, as the meaning of words can vary significantly depending on the domain and the document structure. Textual analysis has been used to extract sentiment from corporate disclosures, predict stock returns, assess the tone of earnings calls, and even identify signals of financial distress. The survey highlights seminal studies that have demonstrated the correlation between textual sentiment and market outcomes, showing that textual information can be a valuable complement to traditional quantitative data. However, the survey also points out the imprecision inherent in textual analysis compared to traditional quantitative methods. It discusses issues such as the need for careful parsing of documents, the potential for systematic errors, and the difficulty of replicating results.

Mover, there are emerging financial innovations in the industry, such as mobile banking, peer-to-peer lending, cryptocurrency, and automated portfolio management, etc. Mobile banking refers to the use of smartphones and other mobile devices to access banking services. This innovation allows users to perform a wide range of financial transactions from their mobile devices, including checking account balances, transferring money, paying bills, and even depositing checks. Mobile banking has transformed the banking industry by offering greater convenience, enabling flexible access to financial services, and reducing the need for physical branch visits. Mobile banking has an impact on financial activities. Wang and Wu (2024) illustrate the important role of mobile banking in small business lending after banks close branches. Mobile banking preserves the existing customer-bank relationship though it cannot reduce information asymmetry. Peer-to-peer lending is a financial innovation that connects borrowers directly with individual investors through online platforms, bypassing traditional financial institutions like banks. P2P lending platforms assess the creditworthiness of borrowers, set interest rates accordingly, and facilitate the loan process. Maskara *et al*. (2021) document that P2P lending enhances the financial inclusion of those lacking traditional banking institutions in rural communities and provides a choice to those with fewer fringe banks in urban communities. Cryptocurrency is a digital or virtual form of currency that uses cryptography for security. Unlike traditional currencies issued by governments (like the US dollar or Euro), cryptocurrencies operate on decentralized networks based on blockchain technology, which is a distributed ledger enforced by a network of computers. The most well-known cryptocurrency is Bitcoin, which was introduced in 2009, but there are thousands of other cryptocurrencies, each with unique features and use cases. Wide research has investigated cryptocurrencies. Howell *et al*. (2020) illustrate that initial coin offerings have become a new way of raising capital for early-stage ventures, which is an alternative to traditional sources, such as venture capital and angel finance. Initial coin offerings effectively offer security, liquidity, and transparency than traditional financing instruments.

The digital age has raised new challenges and questions. An emerging debate is the effectiveness of remote work mode compared to face-to-face work mode. For example, shareholders of Mitsubishi Motors complained that they felt muted when the shareholder meetings were virtually conducted in 2020 (Wall Street Journal, 2020).[1] The board has less time to respond to their questions and the shareholders have less opportunity to communicate with each other. The outbreak of the COVID-19 pandemic has accelerated the adoption of remote communication technologies. The shift to work-from-home policies, remote auditing, and the prevalence of virtual meetings have become popular in business. This transformation has prompted scholars to investigate the financial implications of these changes in work and communication practices, such as Brochet *et al*. (2023) and Cai *et al.* (2023). Another issue is data privacy and security. The proliferation of digital financial transactions and the increased use of big data analytics in finance have raised serious concerns about data privacy and security. Financial institutions handle large amounts of sensitive personal and financial data, making them prime targets for cyberattacks. Florackis *et al*. (2023) suggest that cybersecurity risk disclosure is increasingly important, which is intensified by an ever-growing number of data breaches raising serious concerns about corporate cybersecurity. This thesis aims to dissect these facets, providing fresh insights into how digital technologies are being employed in financial practices and analyzing how these digital age developments impact financial ecosystems. By doing so, it seeks to contribute valuable perspectives to the evolving landscape of corporate finance in the digital age.

This thesis aims to investigate the opportunities and challenges in the area of corporate finance. Specifically, it explores the application of big data, the implication of remote communication techniques, and the application of textual analysis. The three chapters of this thesis primarily focus on three important elements of corporate finance through three distinct but interconnected chapters: mergers and acquisitions, CEOs, and mutual fund investors, respectively. In the ever-evolving landscape of global finance, the influential roles of mergers and acquisitions (M&As), Chief Executive Officers (CEOs), and institutional

[1] Available at: https://www.wsj.com/articles/shareholders-feel-muted-as-companies-switch-to-virtual-annual-meetings-11598187600

investors constitute traditional important elements that drive corporate strategies and market performance. Each chapter employs comprehensive statistical methodologies and novel data. Also, the research interweaves traditional financial questions with theories from social science, notably incorporating Social Capital Theory and Organizational Communication Theory to provide a multidimensional perspective.

The first chapter "Social Connectedness and Cross-Border Mergers and Acquisitions" leverages Facebook's Social Connectedness Index (SCI) to measure between-countries' social connectedness and explores how it impacts cross-border M&As. By utilizing the SCI, which aggregates data on interpersonal relationships across geographic boundaries as indicated by Facebook connections, this chapter offers a novel approach to understanding the role of social networks in facilitating or hindering international business transactions. This analysis underscores the growing importance of digital data platforms in corporate finance, particularly in the context of the digital age where traditional data sources are increasingly supplemented or even replaced by digital and social media data. The second chapter "Remote or Face-to-Face: CEO Interviews and Investor Disagreement" investigates how CEOs' communication modalities—specifically, remote versus face-to-face media disclosures—produce differing outcomes in the financial markets. This chapter addresses the significant challenges that have arisen with the rapid development and adoption of remote communication technologies. This chapter is a response to the growing shift towards remote communication, a trend that has been dramatically accelerated by global events like the COVID-19 pandemic. As businesses may move their operations online, how information is disseminated to investors, analysts, and other stakeholders has also transformed. The research examines whether remote communication is perceived differently compared to face-to-face interactions, which could lead to positive market reactions. The third chapter "Climate Change Exposure and Mutual Fund Ownership" investigates the relationship between firms' climate change exposure and mutual fund ownership, providing an examination of how climate change is increasingly influencing investment decisions in the financial markets. A central focus of this chapter is the innovative application of a climate change exposure index estimated by textual analysis and machine learning techniques (Sautner *et al*., 2023). By analyzing vast amounts of unstructured textual data from earnings calls, the research quantifies the extent to which firms are exposed to climate change. This approach represents a cutting-edge methodology in financial analysis, leveraging advanced digital tools to extract meaningful insights from large datasets that traditional analysis methods might overlook.

In Chapter 1 Social Connectedness and Cross-Border Mergers and Acquisitions, the focus is laid on an important financial activity cross-border M&As. It illustrates how big data is seamlessly integrated into financial activities. Scholars have explored the various determinants of cross-border M&As, such as cultural proximity, language similarity, political relations, etc. However, the role of regional social connections in international business, a critical aspect, has not been extensively examined. This gap in research primarily stems from the challenges associated with accurately measuring these social connections. Facebook's between-countries' Social Connectedness Index (SCI) is a proxy for social connectedness between pair regions. The available SCI is constructed by using aggregated and anonymized information from the universe of friendship links between Facebook users. Using Facebook's SCI and a sample of cross-border M&As from 2009 to 2018 at the deal level, this segment of the thesis attempts to unravel to what extent social connections at the country level impact the outcomes of cross-border M&As. The results suggest that social connectedness is positively associated with acquirers' abnormal announcement stock performance. It operates through an information dissemination channel, assisting acquirers to reduce target premiums, increase the deal completion rate, and achieve long-run success. Social connectedness plays a similar role within the U.S. domestic M&As, and it increases the number and dollar value of cross-border M&As between countries. This effect is amplified when the acquirer and target countries have more severe information asymmetry and greater bilateral trust.

The chapter contributes to extending the literature on cross-border M&As by presenting first evidence of the role of social connectedness in determining acquirer value creation. Also, it contributes to the merging of social finance literature on the informational role of social connectedness and its financial and economic consequences. In summary, the study on Facebook's Social Connectedness Index and cross-border M&A significantly enriches the discussion of corporate finance in the digital age by providing empirical evidence on the relevance of digital social networks in financial strategies. It illustrates how digital platforms and the data they generate can be crucial tools for modern financial analysis, decision-making, and strategy, thus helping firms navigate the complexities of the global digital economy.

Chapter 2 Remote or Face-to-Face: CEO Interviews and Investor Disagreement shifts the narrative to the financial consequences of CEOs' information disclosure modalities. This research is motivated by the increasing prevalence of remote communications, which have become a critical component of both personal and professional interactions. The widespread adoption of digital technologies and the internet has fundamentally transformed the way individuals and organizations communicate, enabling efficient and effective interactions across geographic boundaries. This trend has been significantly accelerated by global events such as the COVID-19 pandemic, which compelled businesses and individuals to adapt rapidly to remote work and virtual collaboration. As remote communication continues to integrate into various facets of life, it is reshaping organizational structures, operational processes, and the dynamics of global markets. This research aims to examine the broader implications of this shift, particularly in how it affects corporate strategies in a digitally connected world. In the business world, work-from-home and virtual meetings are growing. Emerging scholars investigate to what extent this transformation impacts financial outcomes, such as shareholding meetings (Brochet *et al*., 2021) and board meetings (Cai *et al*., 2022). Central to this chapter is the exploration of whether and how remote interviews lead to superior investor disagreement, compared to face-to-face ones. Utilizing a sample of televised media interviews with public firm CEOs in the U.S. on CNBC, this part of the thesis finds that remote interview is associated with larger investor disagreement around the interview date. The lack of medium richness, specifically non-verbal cues in remote interviews, can lead to increased dispersion in information interpretation among investors, resulting in larger investor disagreement. Traditional studies primarily focus on the impact of verbal content conveyed by CEOs. Emerging studies highlight the significance of CEOs' non-verbal cues, such as vocal cues (Mayew and Venkatachalam, 2012) and facial cues (He *et al*., 2018; Hsieh *et al*., 2020; Flam *et al*., 2020). The implications of the research conducted in this chapter extend to CEO disclosure and its financial implications, highlighting the importance of an unexplored factor: CEOs' communication modalities. The chapter also has an impact on reality by highlighting the differences between remote and face-to-face communications, a new debate about which has become popular after the outbreak of COVID-19.

Finally, Chapter 3 Climate Change Exposure and Mutual Fund Ownership explores the increasingly pertinent and globally recognized environmental issues. This chapter applies a climate change exposure index estimated by textual analysis and machine learning. It provides valuable insights into how digital tools can be used to address firms' emerging exposure to climate change. This chapter explores the nuanced relationship between climate change and financial markets, specifically focusing on how the exposure of firms to climate change impacts their attractiveness to mutual fund investors. We currently have little evidence of the impact of climate change on mutual fund investors' investment decisions. A majority of previous studies focus on a specific climate change issue, such as temperature exposure (Pankratz *et al.*, 2023), or focus on regional climate change exposure (Painter, 2020; Li *et al*., 2023). However, climate change has a complex impact on firms. Sautner *et al*. (2023) employ textual analysis to construct a measure of climate change exposure at the firm level, which provides an efficient proxy for firms' overall exposure to climate change. Using Sautner *et al*. (2023)'s climate change exposure measure, this chapter provides evidence that firms' climate change exposure is negatively associated with the net growth of mutual fund ownership. The impact is pronounced in high carbon-emitting and innovative sectors. This aversion stems from mutual funds' concern over heightened transition risks associated with climate change, which introduce substantial uncertainties in investment performance. The chapter adds to the literature by answering whether and how mutual fund investors incorporate climate change. Also, it enriches our understanding of the financial implications of climate change.

In sum, the thesis integrates sophisticated analytical tools and novel data, this thesis makes a substantial contribution to corporate finance in a digital age, offering fresh insights and opening avenues for the innovative application of technology and data in financial studies. The chapters contribute to the literature on the determinants of cross-border M&As, social finance, CEO behaviors, sources of investor disagreement, climate change in finance, and mutual fund investors' investment decisions. In addition to the substantial contributions to specific aspects of the literature and diverse theoretical frameworks, these chapters are not just a collection of three individual studies; rather, the thesis is a cohesive body of work to present a holistic view of key questions in corporate finance.

This thesis is organized into several key sections, beginning with an Introduction, a Literature Review, and culminating in a comprehensive Conclusion. The body of the work is divided into three main chapters, each following a systematic and coherent structure to facilitate in-depth understanding and analysis. Each chapter commences with its own focused Introduction, presenting the specific topic and its relevance within the broader scope of the thesis. This is followed by a thorough Literature Review and Hypothesis Development, where existing research is examined, and the theoretical framework for the study is established. In the Empirical Results section, the findings of the research are presented and discussed in detail. The final section of the thesis synthesizes the findings from each chapter, drawing overarching conclusions and discussing the implications of the research.

Literature Review

We draw on different strands of literature to introduce the current research on emerging topics in the digital age, including big data, advanced analytical techniques, and financial innovations. Big data is traditionally defined as data encompassing volume, velocity, and variety (Goldstein *et al*., 2021). However, this definition is more related to engineering or computer science. Goldstein *et al*. (2021) define big data in finance as large size, high dimension, and complex structure. Large size means that data are large in an absolute or relative sense. Using a larger dataset helps to overcome the sample selection bias compared to a smaller dataset. High dimension refers to that the data have many variables relative to the sample size. This characteristic facilitates the application of machine learning, which is increasingly popular in finance research. The complex structure is comparable to the traditional row-column format data. Texts, pictures, and videos are data with complex structure. They can capture economic activities that traditional structured data cannot. Emerging literature fits into one or more of these characteristics. For example, according to Goldstein *et al.* (2021), research by Anand *et al*. (2021) investigate the agency conflicts between brokers and customers using the Order Audit Trail System (OATS) established by the Financial Industry Regulatory Authority (FINRA). This dataset contains publicly unavailable broker identities. Compared to traditionally used self-reported data, this dataset has fewer concerns about attrition and selection bias. The complex unstructured data draws increasing researchers' attention, such as voices, pictures, and videos. Mayew and Venkatachalam (2012) explore the role of vocal expressions in conveying information about a firm's future performance. The research collects voice samples from earnings calls. Obaid *et al*. (2022) investigate a large sample of news photos and introduce a daily market-level investor sentiment index. The index can predict market return reversals and trading volume. Cade *et al.* (2020) explore the impact of nonverbal cues displayed by CEOs during video disclosures on investor perceptions and judgments. The study emphasizes how visual and vocal nonverbal cues, including facial expressions, body language, and tone of voice, can significantly influence investors' reactions to forward-looking information. As the characteristic high dimension usually serves the machine learning analytical tool, we review the literature on this characteristic in the following section.

Advanced analytics, particularly through machine learning, have significantly transformed finance research. These technologies enable financial studies to analyze large volumes of data, make predictions, automate processes, and gain insights that were previously unattainable. Machine learning has been widely used in research, especially for analyzing big data. Choudhury *et al.* (2019) explore CEOs' non-verbal cues, the study employing a convolutional neural network (CNN)-based machine learning algorithm to code facial expressions from video interviews of CEOs. The algorithm categorizes facial expressions into eight distinct emotions: anger, contempt, disgust, fear, happiness, neutral, sadness, and surprise. This approach allows the researchers to quantify the intensity and frequency of these emotions as they appear on the CEO's face during the interviews. The study identifies five distinct communication styles based on the analysis of both verbal and non-verbal cues: Excitable, Stern, Dramatic, Rambling, and Melancholy. One of the key findings is that CEOs with a "Dramatic" communication style, characterized by a wide range of facial emotions and fluctuating verbal sentiment, are less likely to pursue major acquisitions. Giglio *et al*. (2021) develop a rigorous framework that uses a combination of machine learning techniques and statistical methods to control the false discovery rate (FDR) in multiple hypothesis testing scenarios. The dataset for this research is distinctive for its high dimensionality. The methodology is applied to hedge fund performance evaluation using the Lipper TASS database. The findings show that their procedure can successfully identify a subset of hedge funds that consistently outperform benchmarks, even when controlling FDR below 5%.

The introduction of financial innovations has influenced industry and academic research. This process is also a part of the FinTech revolution. According to Goldstein *et al*. (2019), the scope of the activities started from mobile payments, money transfers, peer-to-peer loans, and crowdfunding to the emerging blockchain, cryptocurrencies, and robo-investing. Accordingly, literature started to explore related topics. When bank branches close, small businesses far away from the lending branches suffer from higher lending costs. Wang and Wu (2024) suggest that mobile banking helps preserve the existing customer-bank relationship but cannot reduce information asymmetry. Maskara *et al*. (2021) document that P2P lending enhances the financial inclusion of those lacking traditional banking institutions in rural communities and provides a choice to those with fewer fringe banks in urban communities. Buttice *et al.* (2020) explore the impact of equity crowdfunding on the ability of firms to attract venture capital financing post-campaign. The study finds that successfully raising funds through equity crowdfunding can serve as a positive signal to venture capitalists, thereby increasing the likelihood of receiving follow-on VC financing. This effect is stronger when the equity crowdfunding campaign uses a nominee shareholder structure rather than a direct structure. Howell *et al*. (2020) illustrate that initial coin offerings have become a new way of raising capital for early-stage ventures, which is an alternative to traditional sources, such as venture capital and angel finance. Initial coin offerings effectively offer security, liquidity, and transparency than traditional financing instruments.

This thesis contributes to these streams of literature by investigating big data and the application of textual analysis.

1. Social Connectedness and Cross-Border Mergers and Acquisitions

Abstract

We investigate the role of social connectedness in cross-border mergers and acquisitions (M&As). Using Facebook's between-country social connectedness index, we show that social connectedness induces higher stock returns to acquirers' M&A announcements. The impact of social connectedness on cross-border M&As operates through an information dissemination channel, assisting acquirers to reduce target premiums, increase the deal completion rate, and achieve long-run success. We also find a similar role of social connectedness within the U.S. domestic M&As. Furthermore, social connectedness increases the number and dollar value of cross-border M&As between countries. This effect is amplified when the acquirer and target countries have more severe information asymmetry and greater bilateral trust. Finally, we demonstrate that social connectedness plays a similar beneficial role in domestic M&As within the U.S.

Keywords: cross-border M&As, social connectedness, information dissemination

1.1 Introduction

Cross-border M&As are significant capital events in international markets. Worldwide, cross-border M&A volume represented 23.5% of total M&A volume in 2022, with a total value of $775 billion.[2] In light of the substantial role of cross-border M&As in global markets, understanding the source of value creation in cross-border M&As is of great importance for companies and regulators. Recent studies have investigated how bilateral country-level distinctions and connections, such as geographical distance, cultural distance, societal affinity, political events, and institutional differences, influence the success of cross-border M&As (Rossi and Volpin, 2004; Erel *et al*., 2012; Ahern *et al*., 2015; Lim et al., 2016; Aleksanyan *et al*., 2021; Siganos and Tabner, 2020). Building upon the prior literature, our paper examines how the degree of social connectedness between countries affects stock market reactions to cross-border M&A announcements.

The socioeconomic literature suggests that social connectedness facilitates information dissemination and attenuates information asymmetry via social learning and word-of-mouth effects (Bailey *et al*., 2018a; Kuchler and Stroebel, 2021). The social capital theory defines social capital as the information, trust, and norms of reciprocity inherent in social networks (Woolcock, 1998). Information shared via social networks can help market participants better understand market dynamics and respond to uncertainties (e.g. Hong *et al.*, 2004; Chaudhry *et al*., 2022). Cross-border M&As are a type of complex, irreversible investment in the global market. These transactions frequently involve significant challenges related to information asymmetry between acquiring firms and targets, particularly during the stages of target searching, due diligence, and negotiation (e.g. Bruner and Perella, 2004). In the international market, this information asymmetry is particularly pronounced due to the significant differences in regulatory environments, cultural norms, and market conditions

[2] Deloitte. (2023). Mergers and acquisitions and opportunities. Available at: https://www.deloitte.com/global/en/issues/resilience/gx-charting-new-horizons.html.

across countries. Consequently, M&A participants must rely on a variety of sources of information (Erel *et al*., 2012; Lim *et al*., 2016; Zhang *et al*., 2021). Social connectedness is instrumental in reducing information asymmetry, which in turn improves acquirers' ability to identify foreign acquisition opportunities, make accurate valuations of foreign targets in socially connected countries, and deter competition (Bruner and Perella, 2004; Capron and Shen, 2007; Cai and Sevilir, 2012; Erel *et al*., 2012; Li and Tong, 2018). Moreover, reduced information asymmetry can also help acquirers achieve long-term success after the merger (Cai and Sevilir, 2012). Therefore, we expect that stock investors tend to react favorably to announcements of cross-border M&As between socially connected countries.

We measure social connectedness between two countries using the Facebook Social Connectedness Index (SCI) constructed by Bailey *et al*. (2018a) based on Facebook friendship link data. This index provides a snapshot of the intensity of country-pair social interactions. In our paper, social connectedness refers to the degree of real-world social connections between two countries, including but not limited to online communications on Facebook. Two reasons supporting SCI as an effective proxy for real-world social connections (Bailey *et al*., 2018b). First, Facebook runs on a large scale and has great coverage (Allen *et al*., 2018).[3] Facebook's user base is very representative of the general population (Bailey *et al*., 2018b; Allen *et al*., 2018). Facebook is frequently used by people to engage with friends and acquaintances (Bailey *et al*., 2018b; Kuchler *et al*., 2022). Second, the friendship links require both users' approval and are formed on actual familiarity or friendship (Kuchler *et al*., 2022). Other social networking platforms, such as Twitter, allow their users to follow one another without seeking permission, resulting in a large number of unidirectional links to strangers (Kuchler *et al*., 2022).

[3] Facebook has become one of the largest online social networking platforms in the world. By the end of 2019, there were 2.4 billion monthly active users in the world, of which 243 million were based in North America, 384 million in Europe, 981 million in the Asia-Pacific region, and 758 million in the rest of the world (Bailey *et al*., 2021).

We collect a sample of 6,136 cross-border M&A deals between 42 acquirer countries and 44 target countries during the period from 2009 to 2018. By evaluating the social connectedness between the acquirer and target countries, we show that social connectedness has a positive and significant effect on stock returns to acquirers' cross-border M&A announcements, after controlling for a wide array of acquirer-level, deal-level, and country-level characteristics. To alleviate endogeneity concerns, we adopt a two-stage least squares (2SLS) approach. According to the social homophily principle (McPherson *et al*. 2001), people are likely to establish social networks with those of a similar age owing to similar interests and perspectives, which facilitate mutual understanding and stronger interpersonal connections. Bailey *et al*. (2020) provide empirical evidence that country pairs with similar population median ages have greater social connectedness. Nonetheless, it is unlikely that the age similarity between the acquirer and target countries would affect acquirers' announcement returns. Therefore, we use the absolute difference in the population's median age between the acquirer and target countries as an instrumental variable for social connectedness. Our 2SLS results show that the instrumented measure of social connectedness significantly enhances acquirers' stock returns around cross-border M&A announcements. As additional robustness tests, we adjust our sample. First, we exclude the cross-border M&As involving U.S. acquirers or targets to ensure that the results are not driven by U.S. firms, which represent a large fraction of the sample. Second, we remove country pairs with less than ten cross-border M&A deals. This approach minimizes the impact of outliers by focusing on country pairs with a sufficient number of deals. Third, we delete the deals where both the acquirer and the target are from the top 'Anglosphere' countries (i.e., the U.S., the U.K., Australia, and Canada). These countries, accounting for a large share of deals, share similar languages, cultures, and social norms. Removing them can minimize the impact of these proximities. Our baseline results are unchanged when we employ these adjusted samples. Next, we employ alternative measures or fixed effects. First, we employ different dependent variables. One is the cumulative market-adjusted return over the three days centered around the announcement date. The other is the cumulative abnormal return over the five days centered around the announcement date. Second, we employ granular fixed effect *Year* × *Industry* to control for industry-level time-varying characteristics. The results remain consistent with our baseline findings.

We test the potential mechanism through which social connectedness influences acquirers' M&A announcement returns. If social connectedness facilitates information transmission and alleviates information asymmetry embedded in cross-border M&As, the effect of social connectedness should be more pronounced in the M&As with greater information asymmetry. Literature suggests that several proxies can be used for the severity of information asymmetry in cross-border M&As. First, if acquires have board directors or institutional investors from the target country, they can gain valuable insights into the local business environment of the target country and better assess the target firm's risks and performance (Marra *et al*., 2024). On the other hand, acquirers without any board members or institutional investors from the target country are associated with higher information asymmetry. Second, private targets have less public information available to outsiders, and their information is less transparent (Erel *et al*., 2012). Foreign acquisitions involving private targets are associated with greater information asymmetry. Lastly, targets from a country that adopts lower-quality accounting disclosure standards pose challenges for acquirers to analyze the target's financial information (Rossi and Volpin, 2004; Erel *et al*., 2012). Our empirical results show that social connectedness has a stronger positive effect on acquirers' announcement returns when there is greater information asymmetry between the acquirer and target firms, as indicated by increased use of non-cash payments, low representation of the target country's board directors or institutional investors in the acquirer firm, the target firm's private status, and distance in the quality of accounting disclosure standards implemented between the acquirer and target country.

Why do investors positively perceive the cross-border M&As between socially connected countries? We propose that the informational role of social connectedness offers several advantages to acquirers. First, they can value targets more accurately and avoid overpayment. Second, reduced information asymmetry facilitates a smoother negotiation process and increases the likelihood of successful deal completion. Third, informed acquirers are likely to experience improved long-term performance following the merger. Finally, informed acquirers could rely less on financial advisors, resulting in reduced transaction fees (Cai and Sevilir, 2012). We find empirical evidence in support of the first three channels that cross-border M&As between socially connected countries are associated with lower target premiums, higher deal completion rates, and better long-term post-merger performance. However, we find no empirical support for the transaction fee argument.

Moving away from the market reaction analysis, we examine the aggregate volume of cross-border M&As between country pairs. Previous research suggests that diminished market frictions in the form of information costs encourage cross-border M&A activities (Rossi and Volpin, 2004; Erel *et al*., 2012). Social connectedness facilitates acquirers' familiarity with target countries and enables them to discern potential investment opportunities more effectively. As such, acquirers are more willing to invest in socially connected countries. To test this proposition, we aggregate cross-border M&A data at the country-pair and year level and show that social connectedness increases both the quantity and dollar value of cross-border M&As between countries.

We investigate how social connectedness is intertwined with other country-level characteristics to affect cross-border M&A volume. First, when the acquirer and target countries participate in the same customs union (i.e. European Union Customs Union (EUCU), Southern Common Market (MERCOSUR)), they adhere to common trade and competition policies (Aleksanyan *et al*., 2021). We find that enhanced information exchange due to the establishment of customs unions reduces the demand for information obtained from social interactions and mitigates the effect of social connectedness on cross-border M&A volume. Second, political disagreement between countries increases political uncertainties and impedes information exchange (Bertrand *et al.*, 2016). We use the United Nations General Assembly voting outcomes to measure political disagreement and find that social connectedness has a larger positive effect on cross-border M&A volume in pairs of countries where information exchange is severely hampered by their political disagreement. Third, countries with a large time zone difference are geographically distant and have fewer overlapped working hours, which reduces the efficiency of information communications (Bacidore and Sofianos, 2002; Stein and Daude, 2007). We document a stronger positive impact of social connectedness on cross-border M&A volume for country pairs with a larger time zone difference. Fourth, bilateral trust promotes international trade and investment. A higher level of bilateral trust between countries fosters social connectedness. We show that the effect of social connectedness on cross-border M&A volume is more salient for pairs of countries with greater bilateral trust.

The U.S. has the most vibrant and active M&A market in the world. We exploit the level of social connectedness between U.S. cities and examine its influence on cross-city M&A deals within the U.S. from 2009 to 2018. This sub-country analysis helps us address the concern that our main findings based on a cross-country setting may be unduly influenced by interregional differences in country-specific characteristics such as culture, institutions, and language. These factors, prominent in cross-country research designs, could potentially confound our main findings. We find empirical evidence showing that acquirers' M&A announcement returns are positively and significantly associated with the degree of social connectedness between acquirer and target cities within the U.S. Furthermore, our results show that the influence of social connectedness on announcement returns is reduced when the target firm is situated in a "financial hub" city, where information flows more easily.

Our paper makes several contributions. First, we advance the cross-border M&A literature by presenting the first evidence on the role of social connectedness in value creation for acquirers in a global context. Our research introduces social connectedness as a critical bilateral determinant that significantly influences both market perceptions and the volume of cross-border M&As, primarily through enhanced information dissemination.

Previous studies have identified various country-level determinants of cross-border M&As, including geographical distance (Erel *et al*., 2012), cultural distance (Ahern *et al*., 2015; Lim *et al*., 2016), societal affinity (Siganos and Tabner, 2020), political visits (Aleksanyan *et al*., 2021), and differences in accounting standards, institutional qualities, exchange rates, and tax policies (Rossi and Volpin, 2004; Erel *et al*., 2012). Despite these well-documented factors, our study demonstrates that social connectedness has a unique impact on cross-border M&As even after controlling for these correlated socioeconomic forces in the empirical models.

In particular, our research on social connectedness distinguishes from Ahern *et al*.'s (2015) study on the role of cultural proximity in cross-border M&As. Cultural proximity refers to the extent to which two countries share a common cultural heritage, including the mutual values, beliefs, and traditions derived from a shared cultural background. This concept emphasizes the deep-rooted cultural similarities that exist between countries. Ahern *et al.* (2015) find that culturally proximate countries have a higher volume of cross-border M&As, and that reduced cultural distance in dimensions of trust and individualism leads to higher combined announcement returns. In contrast, social connectedness is regarding the relationships and interactions that individuals develop within their social networks. These connections are formed through direct interactions, shared experiences, and personal relationships with friends, family members, coworkers, and acquaintances. Social connectedness emphasizes the dynamic and relational aspects of social ties that individuals establish and maintain in their daily lives. Our findings highlight the importance of social connectedness in mitigating information asymmetry in cross-border M&As, presenting a functional mechanism distinct from cultural proximity. According to Ahern *et al*. (2015), cultural similarity facilitates better teamwork among employees following the merger, thereby reducing the integration costs in cross-border M&As. Another closely related factor is societal affinity, which represents the preferential relationship, affection, and sympathy between countries, indicating an emotional and psychological bond between different societies. Siganos and Tabner (2020) measure societal affinity using voting bias in the

Eurovision Song Contest. They observe that voting populations tend to favor poor-quality songs from a country with which they share affinity over high-quality songs from a country with which they share antipathy. Their study shows that greater societal affinity between two countries results in a higher number of cross-border M&As. Societal affinity, which facilitates trusting committed relationships, acts as a moderator of distance between countries (Siganos and Tabner, 2020). In contrast, social connectedness captures the tangible and observable connections individuals develop in their social networks, without directly reflecting the emotional or psychological sentiments in these relationships. Regarding impact, social connectedness enhances acquirers' announcement returns, whereas this effect is not observed for societal affinity.

The effect of social connectedness also applies to a culturally and institutionally homogeneous single country setting. Using a sample of U.S. domestic M&As, we find that social connectedness between U.S. cities has a positive impact on acquirers' announcement returns. This confirms the pervasive influence of social connectedness, not only across national borders but also within them, disregarding the diverse cultural, institutional, and linguistic contexts across countries. Furthermore, this analysis reinforces the informational channel of social connectedness by showing that the effect is stronger when the target city is a financial hub, where information flows more smoothly.

Finally, our paper contributes to the growing body of literature examining the implications of social connectedness for finance and economics. Previous research suggests that social connectedness functions as a crucial informational resource, influencing a broad spectrum of decision-making processes, such as individuals' housing investment (Bailey *et al.*, 2018b), mortgage leverage choices (Bailey *et al.*, 2019), peer-to-peer lending (Allen *et al.*, 2018), retail investors' trading activity (Bali *et al.*, 2021), institutional investment (Kuchler *et al.*, 2022; Au *et al.*2023), venture capital allocation (Nguyen *et al.*, 2023), and international trade (Bailey *et al.*, 2021). Our study adds to this strand of literature by demonstrating the significant impact of social connectedness on cross-border M&A activities, which constitute major irreversible capital investments in the global economy.

The rest of the chapter is organized as follows. Section 1.2 introduces related studies and our hypothesis development. Section 1.3 presents our variables and summary statistics. Section 1.4 reports the results of baseline regressions and robustness tests. In Section 1.5, we examine the mechanism. Section 1.6 presents additional analyses. Section 1.7 concludes the paper.

1.2 Literature Review and Hypothesis Development

According to psychological research, individuals seek to fulfill their needs for belongingness through social interactions and engagement, which promotes the development of cognitive representations that define the "self-in-relation-to-other" (Lee and Robbins, 1998). This concept emphasizes the importance of social relationships in shaping cognitive and emotional processes. An individual's understanding and expression of self are determined by their social connections and interactions with others. Social networks, which encompass a range of interpersonal relationships from close familial ties to broader societal connections, are crucial in this context. These social experiences over time cultivate a strong sense of belonging and connectedness.

Early studies inferred individuals' social networks from their regions (Hwang and Kim, 2009; Kong *et al*., 2020), work experience (Hwang and Kim, 2009; Luong *et al.*, 2021), and educational background (Cohen *et al*., 2008). Recently, friendship links on social networking platforms, such as Facebook, have emerged as an efficient tool to measure the extent of social interactions between geographic regions. The Social Connectedness Index developed by Bailey *et al*. (2018a) calculates the ratio of Facebook friendship links between two regions to the product of the number of Facebook users in each region. This index is widely recognized for its ability to represent real-world social interactions, primarily due to the vast and diverse user base of Facebook (Kuchler *et al*., 2022). Furthermore, Facebook requires users' mutual consent to establish friendship links, indicating a genuine bilateral relationship between them (Kuchler *et al*., 2022). The dimension of social connectedness also extends to the international arena and captures how countries develop relationships and connections with one another through their social structures and historical ties. As discussed by Bailey *et al*. (2018a) and Bailey *et al.* (2020), social connectedness is determined by various factors, including geographical proximity, historical bonds, linguistic similarity, and demographic compositions such as race, religion, and age. While individuals tend to interact with those who share similar characteristics, previous studies suggest that the influence of social connectedness transcends those correlated socioeconomic factors and has a distinct influence on economic outcomes (Bailey *et al*., 2018a; Bailey *et al.*, 2020).

Research has shown that social connectedness shapes various financial and economic decisions. Bailey *et al*. (2018b) and Bailey *et al*. (2019) find that individuals' investment decisions, particularly in the housing market, are influenced by friends' experiences within their social networks. The information flow within social networks plays an important role in shaping perceptions of the attractiveness of property investments. Allen *et al*. (2018) examine the effect of social connectedness on peer-to-peer lending decisions. Social connectedness facilitates information dissemination, which lowers information acquisition costs and information asymmetry. As a result, both loan approval rates and loan quality improve between highly connected regions. Bali *et al*. (2021) employ SCI as a measure of the intensity of connections of a local firm. Higher SCI indicates greater social connectedness, increasing investor attention and attraction to local stocks with lottery-like characteristics. The findings highlight the critical role of social connection in driving the demand for lottery stocks. In addition to individual investors, social connectedness can also impact professional investors. Kuchler *et al*. (2022) show that institutional investors are more likely to invest in firms from regions with which they share stronger connectedness, attributing to the enhanced familiarity and improved information access afforded by these social ties. Au *et al*. (2024) explore how social connectedness influenced the trading behavior of active mutual fund managers during the COVID-19 pandemic. The study finds that fund managers located in or socially connected to COVID-19 hotspots sold more stock holdings compared to those who were not connected to these hotspots. The study suggests that social connections can amplify salience bias, leading to panic-driven trading behaviors that negatively affect fund performance, particularly among less skilled managers. Nguyen *et al.* (2023) examine how the geographical structure of social networks influences venture capital investment decisions. Using SCI, the study finds that venture capital firms are more likely to invest in portfolio companies within regions with stronger social connectedness. Social networks facilitate the flow of information, enhancing decision-making efficiency. Moreover, social connectedness shapes international trade. Bailey *et al*. (2021) employ SCI to investigate the impact of countries' social connectedness on international trade, suggesting that two countries trade more when they are more socially connected. This enhanced trade is attributed to the facilitated information flows and the reduction of trade frictions.

The above studies highlight the informational role of social connectedness in financial and economic activities. Individuals from strongly connected countries are likely to have established relationships and connections, facilitating frequent and efficient information exchange. This notion also aligns with the social capital theory, which conceptualizes social capital as the information, trust, and norms of reciprocity embedded in social networks (Woolcock, 1998). Within this framework, the flow of information is a key mechanism through which social capital influences investment decisions. Evidence shows that social capital enhances investment efficiency (Javakhadze *et al.*, 2016) and prompts firms to undertake value-enhancing risky investments (Ferris *et al.*, 2017) by ameliorating market frictions such as information asymmetry.

M&As, as large complex capital investments, can achieve better outcomes when the information asymmetry associated with these transactions is reduced. Cai and Sevilir (2012) find that the presence of shared board directors between the acquiring and target firms improves information exchange. This enhanced communication fosters a deeper understanding of each firm's operations and business environment, yielding higher announcement returns for the acquiring firms. The transparency and visibility of target firms reduce information asymmetry, which impacts targets' valuation and acquiring firms' M&A decisions. For example, Raman *et al*. (2013) examine how target firms' earnings information affects acquiring firms' decisions in M&As. Better earnings quality reduces the need for extensive due diligence and negotiations, lowering transaction costs.

Cross-border M&As typically involve greater degrees of information asymmetry than domestic M&As due to a variety of factors. For example, geographical distance matters in cross-border M&As. Acquirers and targets geographically close to each other reduce combination costs, prompting a high propensity for proximate firms to merge (Erel *et al*., 2012). Cultural distance also plays an important role. Countries with closer cultural ties witness more efficient communication and mutual understanding, leading to synergy benefits in M&As (Ahern *et al.*, 2015; Lim *et al*., 2016). Ahern *et al*. (2015) investigate how distances in three key dimensions of national culture (trust, hierarchy, and individualism) between countries affect merger volume and synergy gains. Larger cultural distances lead to a smaller volume of cross-border M&As and lower combined announcement returns. Cultural distance increases the costs of post-merger coordination and integration. Employees from different cultural backgrounds may have conflicting values, leading to mistrust, misunderstandings, and misaligned goals. Differences in trust and hierarchical structures can cause friction, reducing the effectiveness of teamwork and collaboration. Lim *et al.* (2016) find that cultural distance is asymmetrically perceived by acquirers and targets. The impact of cultural distance on premiums varies on acquirer origin, for instance, when U.S. firms bid for foreign targets and foreign bidders bid for U.S. targets. Cultural familiarity theory explains this. Foreign countries are more familiar with the U.S. compared to the opposite, which plays a moderating role thus leading to the asymmetric relationship between cultural distances and premiums. Moreover, societal affinity between countries also plays an important role. In Signanos and Tabner (2020), societal affinity refers to the sense of preference between the populations of different countries. The paper uses the Eurovision Song Contest voting patterns to measure societal affinity, as voting populations prefer bad songs from a country with which they share an affinity to good songs from a country with which they share antipathy. The findings suggest that higher societal affinity is associated with a greater volume of cross-border M&As. It argues that affinity is an important moderator of distance, without which the trusting committed relationship necessary for sharing information is hard to construct. Countries' political events affect M&A activities. Aleksanyan *et al*. (2021) find a larger number of cross-border M&As post country leaders' visit to another country. These visits facilitate business networking a reduce investment uncertainty and cultural barriers. Countries' governance-related differences, such as accounting standards, institutional qualities, exchange rates, and tax policies, can affect the outcomes of cross-border M&As. Rossi and Volpin (2004) find that better accounting standards and stronger shareholder protection facilitate the volume of M&As. Erel *et al*. (2012) propose that tax and exchange rate considerations influence cross-border M&A decisions. Specifically, acquirer firms tend to originate from countries with higher corporate tax rates compared to those of the target firms' countries. Furthermore, the lack of full integration of international capital markets can result in scenarios where a more valuable acquirer buys a relatively cheaper target, prompted by fluctuations in exchange rates or variations in stock market valuations within the local currency.

In this study, we posit that social connectedness serves as a valuable channel for information dissemination, which in turn facilitates M&As across borders. This improvement in information flow can drive a positive market response by reducing target premiums, increasing deal completion rates, promoting post-merger long-term success, and lowering transaction costs for acquirers. First, reduced information asymmetry enables acquirers to promptly identify acquisition opportunities and accurately evaluate the intrinsic value of the target firm. In the M&A process, acquirers with smaller information asymmetry hold a strong bargain position, enabling them to complete the deal at a bargain value (Li and Tong, 2018). Additionally, lower information asymmetry mitigates the challenges posed by less transparency, visibility, and market price, deterring the competition from potential competitors and resulting in lower offer prices (Capron and Shen, 2007; Cai and Sevilir, 2012). Second, following the announcement of an M&A transaction, acquirers, targets, and other relevant parties remain engaged in ongoing information exchange as the negotiation process unfolds (Dikova *et al*., 2010). Social connectedness smooths the negotiation process by attenuating information asymmetry, thereby augmenting the likelihood of deal completion. Given the complex and costly nature of cross-border M&As, higher completion rates contribute to cost efficiencies and reputation maintenance, inducing a positive market response. Third, the effective information flow fostered by social connectedness helps acquirers gain deeper insights into the local market in the target country and sustain existing relationships with local stakeholders. This will enhance the prospects of successful post-merger operations and contribute to long-term success. Lastly, we conjecture that efficient information exchange between acquirers and targets streamlines negotiations and reduces reliance on advisors, thereby lowering transaction costs (Boeh, 2011). This improved operational efficiency results in a positive market response. Taken together, we expect that social connectedness between acquirers and target countries benefits acquiring firms and creates value for them. Therefore, we formulate the following hypothesis:

Hypothesis: ***Social connectedness positively affects acquirers' cross-border M&A announcement returns.***

1.3 Data

1.3.1 Social Connectedness

In this paper, Facebook's Social Connectedness Index (SCI) (Bailey *et al.*, 2018a) is used as a proxy for social connectedness between pair regions. The available SCI is constructed by using aggregated and anonymized information from the universe of friendship links between Facebook users. Facebook was established by Mark Zuckerberg in 2004, and it has become one of the largest social networking platforms in the world. As of 2016, 69% of adults in the U.S. are Facebook users, and no other major social networking platform comes close in terms of popularity. Facebook users interact with their real-world friends by adding connections on Facebook. The large-scale coverage of Facebook and the representativeness of users make Facebook friendships a reasonable proxy for real-world connections. SCI is a snapshot of the year 2020.

The SCI between two locations i and j is defined as follows.

$$SCI_{i,j} = FB\_Connections_{i,j}/(FB\_Users_i \times FB\_Users_j)$$

Here, FB_Users_i and FB_Users_j are the number of Facebook users in locations i and j, and $FB\_Connections_{i,j}$ is the total number of Facebook friendship connections between individuals in the two locations. The SCI measures the relative probability of a Facebook friendship link between any Facebook user in locations i and j.

Our paper uses the country-pair SCI to measure the degree of social connectedness between countries i and j. The SCI ranges from 206 to 313,120 in our sample. The data is positively skewed with a skewness of 5.16. In our regression, we will take the natural logarithm of SCI. Figure 1-1 Panel A describes the SCI between the United States and other countries in our final sample. The United States has a strong social connectedness with Canada, Australia, Mexico, and European countries, as indicated in the figure.

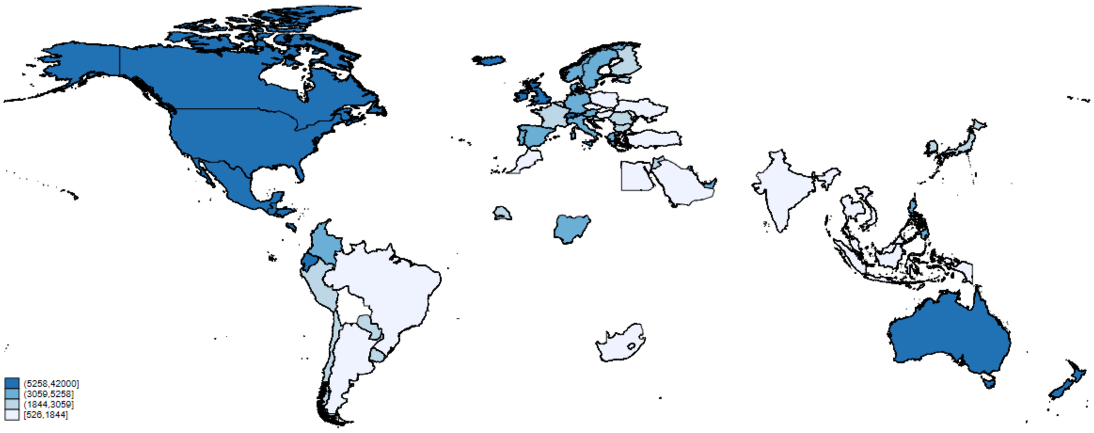
1.3.2 Cross-Border M&A Data

The cross-border M&A deals are collected from the Thomson One Merger and Acquisition Database (Thomson One). The announcement dates in the sample start on January 1st, 2009, and end on December 31st, 2018. We apply the following procedures to clean the M&A data (Rossi and Volpin, 2004; Aleksanya et al., 2021). We keep (1) M&A deals with transaction values larger than one million USD, (2) completed cross-border M&A deals, (3) deals in which the acquirers possess less than 10% of the targets before the deal and more than 50% afterward, and remove (4) all privatizations, leveraged buyouts, reverse takeover, bankruptcy acquisition, and going-private deals, and (5) deals involving countries where Facebook data is unavailable, such as China, Iran, North Korea, Tajikistan, and Turkmenistan. Finally, the sample contains 6,136 deals, 42 acquirer countries, 44 target countries, 613 country pairs, and 3,525 acquirer firms.

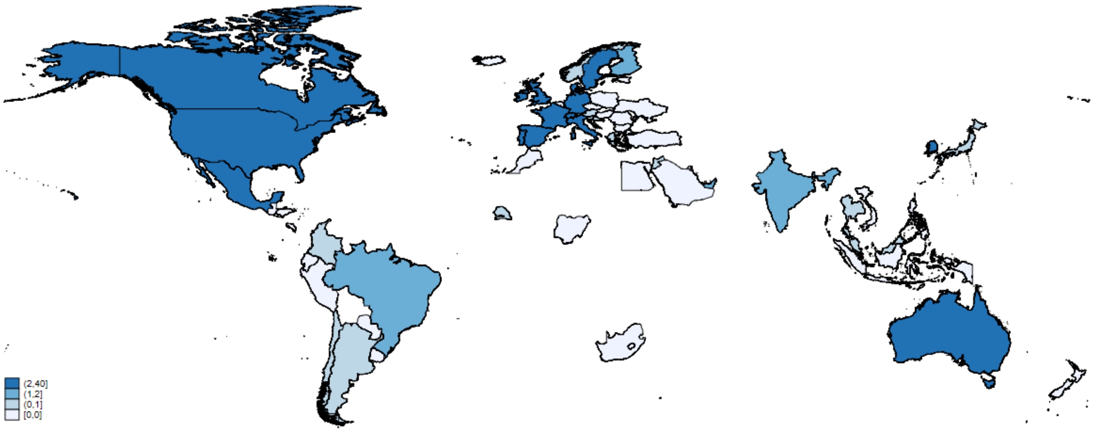
Figure 1-1 Panel B and Panel C show the number and value of cross-border M&As between the United States (as the acquirer) and other nations (as the targets). Acquirers in the United States prefer targets in Canada, Australia, Mexico, and some European countries, as illustrated in Panel B. This pattern is similar to Panel A, implying that social connectedness and cross-border M&A volume are correlated. A similar conclusion can be drawn from Figure 1-1 Panel C.

Figure 1-1 Distribution of social connectedness, cross-border M&A number, and dollar value

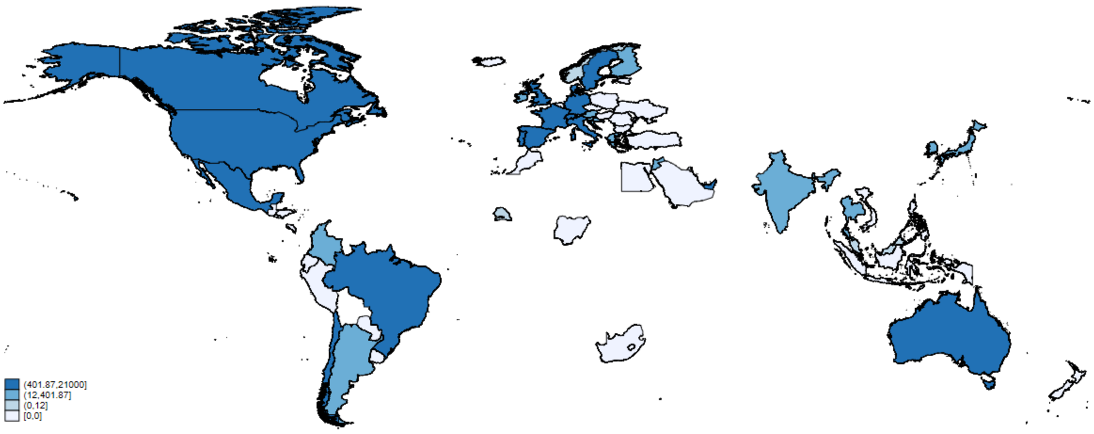
The figures plot the distribution of social connectedness, M&A number, and M&A value between the United States and other countries in our sample. (A) plots the SCI between the United States and other countries. (B) plots the M&A number between the United States (as the acquirer) and other countries (as the target). (C) plots the M&A dollar value between the United States (as the acquirer) and other countries (as the target).



(A) SCI between the United States and other countries



(B) M&A number between the United States and other countries



(C) M&A value between the United States and other countries

1.3.3 Stock Return Performance

We calculate the acquirer's cumulative abnormal return (CAR) in the three days centered around a deal's announcement date. The $CAR_{[-1,+1]}$ is calculated using a market model with parameters estimated over a period beginning 240 trading days and ending 41 trading days prior to the deal announcement date, where the market return is the acquirer country's primary market index return. We also use an alternative measure $ALT\_CAR_{[-1,+1]}$, which changes the estimation window to between 240 and 21 trading days preceding the announcement date. Stock returns are collected from DataStream. We also use other measures for robustness checks: CAR 5-day centered around a deal's announcement date ($CAR_{[-2,+2]}$), and cumulative market-adjusted return in the three days centered around a deal's announcement date ($CMR_{[-1,+1]}$).

1.3.4 Control Variables

We include the following country-pair control variables.

(1) Geographical factors influence the economic costs of international investment and the establishment of social connections (Erel *et al*., 2012; Ahern *et al*., 2015; Bailey *et al*., 2018b). We include the natural logarithm of the geographical distance (in *km*) between pair countries (*Geo Distance*) and a dummy variable indicating whether the two countries share a border (*Share Border*). (2) We include the dummy indicators of whether the countries have the same legal origin (*Same Law*) and same language (*Same Language*). Additionally, we include a common religion index (*Same Religion*) to indicate the pair countries' religious proximity. These factors have been widely documented to influence international investment. (3) According to Guiso *et al*. (2006) and Ahern *et al*. (2015), cultural proximity affects cross-

border M&A outcomes. Following Lim *et al*. (2016) and Hofstede (2001), we calculate the cultural distance between pair countries (*Cultural Distance*) using Hofstede's four-dimension cultural framework.[4] (4) Political discord (*Political Discord*) as reflected by the voting disagreement between pair countries in the U.N. General Assembly (Voeten and Merdzanovic, 2009) is included to capture the countries' political relationships. (5) We include a dummy variable (*Signed Treaty*) denoting whether the countries have signed a bilateral investment treaty, which influences international investment flows (Ahern *et al*., 2015; Lim *et al*., 2016). (6) Bilateral trade flows between the target and acquirer countries (*Trade Flow*) are also included because international trade affects cross-border M&As (Erel *et al*., 2012). (7) The country-pair differences in GDP growth (Δ*GDP Growth*), GDP per capita (Δ*GDP per capita*), GDP (Δ*GDP*), openness (Δ*Openness*), exchange rate growth (Δ*Exchange*), as well as the degree of institutional quality (Δ*Institution Quality*) and the quality of business environment (Δ*Business Env*) both sourced from the Index of Economic Freedom, are also considered (Ahern *et al*., 2015; Aleksanyan *et al*., 2021; Huang *et al*., 2016; Zhu *et al*., 2019). (8) Following Rossi and Volpin (2004) and Erel *et al*. (2012), we control for the difference in the accounting disclosure quality between the acquirer and target countries (Δ*Disclosure Quality*).

Deal-level control variables include the natural logarithm of deal value in million USD (*Deal Value*), whether the deal is a tender offer (*Tender Offer*), whether the acquirer is a financial firm (*Financial Acquirer*), whether the transaction payment method is non-cash (*Non-Cash Deal*), and whether the deal attitude is friendly (*Attitude*). Acquirers' firm-level characteristics include the leverage ratio (*Leverage*), return on assets (*ROA*), and the natural logarithm of total assets (*Size*).

[4] $Cultural\ Distance_{i,j} = \sqrt{\sum_{k=1}^{k=4}(H_{k,i} - H_{k,j})^2/4}$, where $H_{k,i}$ is the acquirer country's cultural score on dimension k, and $H_{k,j}$ is the target country's cultural score on dimension k. The four cultural dimensions are individualism, power distance, masculinity, and uncertainty avoidance.

1.3.5 Descriptive Statistics

Panel A of Table 1-1 reports the sample distribution. There are 42 acquirer countries involved in 6,136 observations at the cross-border M&A deal level. The United States has the largest number of observations (1,345) and acquirer firms (864), initiating 21.92% of the total deals.[5] The mean values of the Social Connectedness Index between acquirer countries and their targets range from 1,561 (Indonesia) to 168,142 (New Zealand).

[5] Due to the large fraction of the sample, consistent with Ahern *et al*. (2015), we will exclude U.S. firms for robustness that our results are not driven by the U.S. firms.

Table 1-1 Descriptive statistics

This table presents the cross-border M&A distribution (Panel A), the summary statistics of the variables (Panel B), the univariate analysis (Panel C), and the correlation matrix (Panel D). Panel A reports the acquirer countries, observations, percentage of the observations, number of acquirer firms, number of target countries, and the mean value of the social connectedness index. Panel B reports the observations, mean, standard deviation, minimum, maximum, 20th percentile, 50th percentile, and 75th percentile values for each variable in our baseline sample. The variables include key dependent and independent variables, and control variables at the country pair level, deal level, and firm level. All variables are defined in Appendix Table A1-1. Panel C reports the observations, mean value, and standard deviation of acquirers' announcement returns, and reports the results for the t-tests. Panel D reports the correlations between the variables in our baseline regression.

Panel A**:** Sample distribution

Acquirer country	N	Percent	#Firms	#Target countries	Mean SCI
United States	1,345	21.92	864	37	6,538
Canada	994	16.20	533	35	11,224
United Kingdom	912	14.86	391	38	12,899
Australia	373	6.08	256	33	45,070
Japan	370	6.03	248	32	3,547
Sweden	286	4.66	130	33	38,097
France	237	3.86	112	30	8,716
Singapore	179	2.92	94	20	51,737
Switzerland	157	2.56	73	23	25,421
Germany	152	2.48	83	27	20,153
Ireland-Rep	137	2.23	38	17	36,366
Netherlands	124	2.02	50	24	15,118
India	88	1.43	62	22	1,688
Spain	86	1.40	45	20	11,283
South Korea	76	1.24	61	20	3,515
Belgium	73	1.19	41	17	41,296
Norway	63	1.03	34	13	54,589
Finland	62	1.01	37	18	13,035
Italy	62	1.01	44	18	23,589
Malaysia	52	0.85	41	9	116,961
South Africa	47	0.77	32	17	4,633
Denmark	46	0.75	32	12	19,399
Mexico	40	0.65	21	14	7,236
Brazil	35	0.57	25	12	4,589
New Zealand	32	0.52	18	5	168,142
Austria	18	0.29	12	11	31,888
Chile	18	0.29	11	7	13,859
Philippines	14	0.23	12	9	13,447
Thailand	13	0.21	9	9	2,925
Argentina	8	0.13	6	5	11,134
Colombia	8	0.13	5	4	19,016
Peru	8	0.13	6	4	24,803
Turkey	5	0.08	5	5	5,737
Greece	4	0.07	3	3	9,872
Egypt	2	0.03	2	2	2,156
Indonesia	2	0.03	2	2	1,561
Portugal	2	0.03	2	1	30,562
Uruguay	2	0.03	2	1	10,387
Jordan	1	0.02	1	1	3,780
Nigeria	1	0.02	1	1	2,656
Pakistan	1	0.02	1	1	12,549
Sri Lanka	1	0.02	1	1	11,291
Total	6,136				

Panel B: Summary statistics of the variables

Key dependent and independent variables	N	Mean	SD	P25	P50	P75	Min	Max
SCI	6136	8.976	1.147	8.296	8.962	9.452	5.328	12.654
$\mathrm{CAR}_{[-1,+1]}$	6136	0.015	0.070	-0.014	0.006	0.032	-0.166	0.423
$\mathrm{ALT\_CAR}_{[-1,+1]}$	6136	0.015	0.069	-0.014	0.006	0.033	-0.168	0.420
$\mathrm{CMR}_{[-1,+1]}$	6136	0.018	0.070	-0.013	0.008	0.035	-0.160	0.424
$\mathrm{CAR}_{[-2,+2]}$	6136	0.018	0.093	-0.019	0.008	0.040	-0.385	1.023
Number	8788	0.427	0.677	0	0	0.693	0	4.852
Value	8788	1.816	2.687	0	0	3.734	0	11.530
Controls at the country pair level	N	Mean	SD	P25	P50	P75	Min	Max
Geo Distance	6136	8.032	1.272	6.541	8.625	8.866	5.153	9.875
Share Border	6136	0.229	0.420	0	0	0	0	1
Same Law	6136	0.543	0.498	0	1	1	0	1
Same Language	6136	0.490	0.500	0	0	1	0	1
Same Religion	6136	0.225	0.183	0.110	0.221	0.291	0.000	0.936
Cultural Distance	6136	9.932	6.495	3.758	7.818	14.940	1.392	28.750
Political Discord	6136	1.069	0.707	0.561	0.976	1.514	0.001	3.994
Signed Treaty	6136	0.098	0.297	0.000	0.000	0.000	0.000	1.000
Trade Flow	6136	16.800	1.763	15.630	16.950	17.840	9.681	19.670
Δ*GDP Growth*	6136	-0.046	2.866	-1.034	-0.041	0.831	-24.060	24.520
Δ*GDP per capita*	6136	-0.070	2.041	-1.854	-0.114	1.765	-4.612	5.724
Δ*GDP*	6136	0.136	0.918	-0.210	0.018	0.289	-3.967	4.041
Δ*Openness*	6136	5.505	80.640	-30.380	4.620	32.800	-348.700	348.700
Δ*Exchange*	6136	-0.003	0.084	-0.043	0.000	0.040	-0.736	0.372
Δ*Institution Quality*	6136	1.863	9.071	-2.900	1.500	5.700	-36.000	36.500
Δ*Business Env*	6136	2.365	13.370	-3.600	1.000	6.300	-61.600	61.300
Δ*Disclosure Quality*	6136	-0.045	0.274	-0.250	0.000	0.170	-1.000	0.920
Controls at the deal and firm levels	N	Mean	SD	P25	P50	P75	Min	Max
Deal Value	6136	0.023	0.151	0	0	0	0	1
Tender Offer	6136	0.056	0.231	0	0	0	0	1
Financial Acquirer	6136	0.291	0.454	0	0	1	0	1
Non-Cash Deal	6136	0.991	0.094	1	1	1	0	1
Attitude	6136	23.880	19.710	7.540	22.190	35.650	0.000	131.000
Leverage	6136	2.286	14.270	1.499	5.117	8.754	-45.510	38.530
ROA	6136	3.880	1.946	2.458	3.773	5.247	0.000	11.530
Size	6136	6.964	2.519	5.470	7.150	8.567	0.020	12.440
US city level	N	Mean	SD	P25	P50	P75	Min	Max
PW_SCI^{CITY}	1,924	9.681	1.663	8.568	9.346	10.389	0.693	15.752
EW_SCI^{CITY}	1,924	9.756	1.650	8.669	9.442	10.463	0.693	15.752
$CAR_{[-1,+1]}$	1,924	0.008	0.060	-0.019	0.004	0.031	-0.249	0.333
$ALT\_CAR_{[-1,+1]}$	1,924	0.008	0.061	-0.019	0.004	0.032	-0.245	0.327

Panel C: Univariate analysis

	High social connectedness			Low social connectedness			T-statistic for differences
	N	Mean	SD	N	Mean	SD	(High minus Low)
$\mathrm{CAR}_{[-1,+1]}$	3,086	0.017	0.073	3,050	0.013	0.065	2.235**
$\mathrm{ALT\_CAR}_{[-1,+1]}$	3,086	0.017	0.073	3,050	0.013	0.066	2.323**
$\mathrm{CMR}_{[-1,+1]}$	3,086	0.020	0.074	3,050	0.015	0.065	2.512**
$\mathrm{CAR}_{[-2,+2]}$	3,086	0.022	0.101	3,050	0.014	0.084	3.266***

(Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses)

Panel D: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	$CAR_{[-1,+1]}$	1.0000													
(2)	*SCI*	0.0318	1.0000												
(3)	*Geo Distance*	-0.0164	-0.5467	1.0000											
(4)	*Share Border*	0.0111	0.4135	-0.7290	1.0000										
(5)	*Same Law*	-0.0034	0.4226	-0.1783	0.3741	1.0000									
(6)	*Same Language*	-0.0088	0.4020	-0.1207	0.3549	0.8397	1.0000								
(7)	*Same Religion*	0.0309	0.2480	-0.3144	0.3428	0.0677	-0.1022	1.0000							
(8)	*Cultural Distance*	-0.0057	-0.3796	0.2263	-0.3657	-0.6581	-0.6674	-0.1954	1.0000						
(9)	*Political Discord*	-0.0174	-0.5154	0.4566	-0.2284	-0.1613	-0.0884	-0.2018	0.3497	1.0000					
(10)	*Signed Treaty*	0.0034	-0.3091	0.1685	-0.1400	-0.1048	-0.1741	-0.0729	0.2569	0.1646	1.0000				
(11)	*Trade Flow*	-0.0275	0.1668	-0.5137	0.5681	0.3138	0.3467	-0.0506	-0.4027	-0.0009	-0.3589	1.0000			
(12)	*ΔGDP Growth*	-0.0073	0.0771	-0.0223	-0.0011	0.0407	0.0600	0.0633	-0.0527	-0.0318	-0.0735	0.0137	1.0000		
(13)	*ΔGDP per capita*	0.0087	-0.1518	0.0686	-0.0843	-0.1559	-0.1552	0.0039	0.1785	0.1277	0.2369	-0.2138	-0.2324	1.0000	
(14)	*ΔGDP*	-0.0368	-0.0875	0.1207	-0.1481	-0.1460	-0.1626	0.0084	0.1534	0.0439	0.0614	-0.2395	-0.1746	0.2463	1.0000
(15)	*ΔOpenness*	0.0090	0.0623	-0.0367	0.0490	0.0820	0.0833	-0.0008	-0.0141	0.0347	0.1009	0.0343	0.2775	0.1404	-0.6146
(16)	*ΔExchange*	0.0061	0.0729	-0.0519	0.0433	0.0929	0.0884	-0.0305	-0.0781	-0.0530	-0.1049	0.1149	-0.0544	-0.2077	-0.1857
(17)	*ΔInstitution Quality*	0.0229	-0.1204	0.0217	-0.0485	-0.1502	-0.1300	0.0191	0.1202	0.0961	0.2071	-0.1830	-0.0165	0.7268	0.0568
(18)	*ΔBusiness Env*	0.0211	-0.1559	0.0517	-0.0766	-0.1557	-0.1470	-0.0315	0.1507	0.1154	0.2475	-0.1808	-0.2067	0.7648	0.1171
(19)	*ΔDisclosure Quality*	-0.0062	0.1052	-0.0544	0.1030	0.2020	0.2070	-0.0659	-0.1558	-0.0683	-0.1463	0.2410	-0.0214	-0.2415	-0.6294
(20)	*Deal Value*	-0.0270	0.0025	0.0049	-0.0045	-0.0252	-0.0175	0.0131	0.0255	0.0020	-0.0362	0.0041	-0.0064	-0.0400	-0.0270
(21)	*Tender Offer*	0.0128	-0.0271	-0.0135	0.0114	-0.0351	-0.0375	0.0029	0.0242	0.0123	-0.0304	0.0389	-0.0205	0.0222	0.0128
(22)	*Financial Acquirer*	0.0314	0.0709	-0.0597	0.0661	0.0254	0.0124	0.0544	-0.0113	-0.0412	0.0115	-0.0393	-0.0300	0.0285	0.0314
(23)	*Non-Cash Deal*	0.0069	0.0054	-0.0186	0.0189	0.0099	0.0206	0.0290	-0.0237	0.0120	-0.0270	0.0248	0.0172	0.0019	0.0069
(24)	*Attitude*	0.0265	0.0286	-0.0998	0.1368	0.0513	0.0288	0.0669	-0.0175	-0.0010	-0.0110	0.0972	0.0023	-0.0003	0.0265
(25)	*Leverage*	-0.1209	-0.0224	0.0331	-0.0947	-0.0581	-0.0813	-0.0386	0.0523	-0.0009	0.0130	-0.0139	0.0218	-0.0739	-0.1209
(26)	*ROA*	-0.0559	-0.1271	0.0625	-0.0474	-0.0912	-0.0855	0.0280	0.0245	0.0980	-0.0701	0.1009	0.0146	-0.0678	-0.0559
(27)	*Size*	-0.1800	-0.1666	0.0949	-0.1063	-0.1392	-0.1562	-0.0105	0.0974	0.0878	0.0217	0.0347	-0.0267	-0.0008	-0.1800

(continued)

		(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(15)	Δ*Openness*	1.0000												
(16)	Δ*Exchange*	0.0020	1.0000											
(17)	Δ*Institution Quality*	0.3103	-0.1992	1.0000										
(18)	Δ*Business Env*	0.1736	-0.1841	0.7434	1.0000									
(19)	Δ*Disclosure Quality*	0.2148	0.1904	-0.3733	-0.2848	1.0000								
(20)	*Deal Value*	-0.0033	0.0089	-0.0570	-0.0424	0.0395	1.0000							
(21)	*Tender Offer*	-0.0232	-0.0248	-0.0200	-0.0005	-0.0282	-0.0097	1.0000						
(22)	*Financial Acquirer*	0.0062	-0.0215	0.0492	0.0258	-0.0072	-0.1577	-0.0112	1.0000					
(23)	*Non-Cash Deal*	-0.0119	0.0000	0.0167	0.0061	-0.0025	-0.1114	0.0158	0.0380	1.0000				
(24)	*Attitude*	0.0385	-0.0044	0.0025	-0.0137	-0.0308	-0.0120	0.0746	-0.0114	-0.0047	1.0000			
(25)	*Leverage*	0.0100	0.0114	-0.0845	-0.0590	0.0322	0.0282	0.0154	-0.0947	-0.0166	-0.0370	1.0000		
(26)	*ROA*	0.0068	0.0087	-0.0935	-0.0949	0.0451	0.1829	0.0466	-0.1706	-0.0605	0.1660	0.2485	1.0000	
(27)	*Size*	-0.0023	-0.0111	-0.0879	-0.0599	0.0178	0.1127	0.0353	-0.1806	-0.0432	0.1763	0.4911	0.6550	1.0000

Panel B of Table 1-1 presents the descriptive statistics of the key variables in our baseline sample. Acquirers' CARs ($CAR_{[-1,+1]}$ and $ALT\_CAR_{[-1,+1]}$) calculated using two different estimation windows have similar statistics. The mean values of them are 0.015 and the standard deviations are about 0.070.[6] The natural logarithm of SCI has a mean value of 8.976 and a standard deviation of 1.147. At the country level, before log transformation, the average number of cross-border M&As between countries is 1.27, and the standard deviation of 4.988. That is, cross-border M&As, as a major capital event, are not frequent. The average dollar value of cross-border M&As between countries is 446.6 million US dollars. The minimum value of 0 indicates that, in some years, the two countries do not have any cross-border M&A.

Panel C of Table 1-1 reports the results of the univariate analysis. We compare the differences in acquirers' mean announcement performance between the groups with high and low social connectedness. We identify an observation as belonging to the high group if the variable *SCI* is higher than the median value of *SCI* for the entire sample. The t-statistics suggest that the high group has significantly higher announcement performance than the low group. The results are consistent with our hypothesis.

Panel D of Table 1-1 reports the Pearson correlation coefficients between our key variables in the baseline sample. The correlation between $CAR_{[-1,+1]}$ and *SCI* is positive, which is consistent with our hypothesis. Consistent with Bailey *et al*. (2018a) and Bailey *et al*. (2021), social connectedness is negatively correlated with geographical distance, cultural distance, and political disagreement, and positively correlated with the same legal origin, language, and religion.

[6] The statistics are similar to Levine *et al*. (2020). The papers investigate cross-border M&As from around 50 countries, which are comparable to this paper.

1.4 Main Results

1.4.1 Effects of Social Connectedness on M&A Announcement Return

We estimate the *Hypothesis* that social connectedness positively affects acquirers' announcement returns using the following equation at the deal level. The dependent variable is the acquirer's 3-day cumulative abnormal return, estimated by the market model with an estimation window from 240 trading days to 41 trading days prior to the announcement date ($CAR_{[-1,+1]}$). We also use an alternative measure, the acquirer's 3-day CAR estimated from 240 trading days to 21 trading days preceding the announcement ($ALT\_CAR_{[-1,+1]}$). The country pair, deal, and firm characteristics are included as control variables. The definition and calculation of the variables are explained in the appendix.

$$CAR_{[-1,+1]_{k,t}} = \beta_0 + \beta_1 SCI_{ij} + \beta_2 PAIR\_CONTROL_{ij,t} + \beta_3 DEAL\_CONTROL_{k,t} + \beta_4 FIRM\_CONTROL_{k,t} + T + I + \varepsilon_{k,ij,t} \qquad (1-1)$$

where the dependent variable is the acquirer firm *k*'s announcement cumulative abnormal return 3 days around the announcement day *t*. The main variable of interest, SCI_{ij}, is the natural logarithm of the Social Connectedness Index between acquirer country *i* and target country *j*. The vector of $PAIR\_CONTROL_{ij,t}$ is an array of country-pair control variables for acquirer country *i* and target country *j* at time *t*. $DEAL\_CONTROL_{k,t}$ are the deal-level control variables for a deal by acquirer firm *k* at time *t*. $FIRM\_CONTROL_{k,t}$ are the firm-level control variables for acquirer firm *k* at time *t*. *T* is the year fixed effect. I is the acquirer industry fixed effect. β_0 is the constant. $\varepsilon_{k,ij,t}$ is the error term.

Table 1-2 reports the regression results. In column (1), the dependent variable is $CAR_{[-1,+1]}$. The coefficient of social connectedness (*SCI*) is positive and significant at the 5% significance level. The positive coefficient suggests that higher social connectedness is associated with a higher acquirer announcement stock return, lending support to the *Hypothesis*. The positive effect is also economically meaningful. A one-unit increase in *SCI*, which is approximately from the degree of social connectedness between the U.S. and Egypt (6.94) to the degree of social connectedness between the U.S. and Belgium (7.94), leads to an increase of 0.2% in $CAR_{[-1,+1]}$. This is equivalent to increasing the CAR by 13.3% from its sample mean. As shown in column (2), the finding is also robust to using $ALT\_CAR_{[-1,+1]}$.

Table 1-2 SCI and acquirer's announcement stock return

This table presents the OLS regressions (1-1) for the sample of 6,136 completed cross-border M&As between 2009 and 2018, estimating the impact of social connectedness on the acquirer's announcement stock returns. $CAR_{[-1,+1]}$ is the acquirer's cumulative abnormal return in the three days centered around the announcement date, estimated from the market model using a [-240, -41] day estimation period. $ALT\_CAR_{[-1,+1]}$ is the acquirer's cumulative abnormal return in the three days centered around the announcement date, estimated from the market model using a [-240, -21] estimation period. The independent variable *SCI* is the logarithm of the Social Connectedness Index between the acquirer and target countries. The remaining country pair controls, deal controls, and acquirer firm controls are explained in Appendix Table A1-1. Year fixed effect and acquirer industry fixed effect are included. *Constant* is the constant term. *N* is the number of observations. Standard errors are clustered at the country pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	$CAR_{[-1,+1]}$	$ALT\_CAR_{[-1,+1]}$
	(1)	(2)
SCI	0.002**	0.003**
	(2.212)	(2.246)
Geo Distance	-0.000	-0.000
	(-0.139)	(-0.256)
Share Border	-0.001	-0.001
	(-0.477)	(-0.491)
Same Law	0.000	0.001
	(0.112)	(0.377)
Same Language	-0.007*	-0.008**
	(-1.875)	(-2.101)
Same Religion	0.002	0.001
	(0.364)	(0.129)
Cultural Distance	-0.000	-0.000
	(-0.655)	(-0.714)
Political Discord	0.001	0.001
	(0.696)	(0.658)
Signed Treaty	0.002	0.001
	(0.572)	(0.344)
Trade Flow	-0.001	-0.001
	(-1.134)	(-1.263)
Δ*GDP Growth*	-0.001*	-0.001*
	(-1.736)	(-1.702)
Δ*GDP per capita*	0.001	0.001
	(0.826)	(0.766)
Δ*GDP*	-0.003***	-0.003***
	(-4.040)	(-4.230)
Δ*Openness*	-0.000	-0.000
	(-0.552)	(-0.403)
Δ*Exchange*	-0.002	-0.003
	(-0.171)	(-0.277)
Δ*Institution Quality*	-0.000	-0.000
	(-0.956)	(-0.921)
Δ*Business Env*	0.000	0.000
	(0.448)	(0.480)
Δ*Disclosure Quality*	-0.010**	-0.011**
	(-2.318)	(-2.427)

Deal Value	-0.007	-0.007
	(-1.359)	(-1.341)
Tender Offer	0.004	0.003
	(0.860)	(0.751)
Financial Acquirer	0.001	0.001
	(0.371)	(0.351)
Non-Cash Deal	0.001	0.002
	(0.192)	(0.249)
Attitude	0.000***	0.000***
	(4.937)	(4.364)
Leverage	-0.000	-0.000
	(-0.716)	(-1.053)
ROA	0.004***	0.004***
	(6.280)	(6.388)
Size	-0.007***	-0.007***
	(-11.941)	(-11.247)
Constant	0.060*	0.065**
	(1.892)	(2.041)
Year Fixed Effects	YES	YES
Industry Fixed Effects	YES	YES
N	6136	6136
adj. R-sq	0.048	0.046

1.4.2 Robustness Tests

1.4.2.1 Alternative return measures

We conduct robustness tests to examine the validity of our baseline findings. To begin, we use different measures of acquirers' announcement performance, including the cumulative market-adjusted return (CMR) in the three days centered around the M&A announcement date ($CMR_{[-1,+1]}$), and the cumulative abnormal returns in the five days centered around the M&A announcement date ($CAR_{[-2,+2]}$). The CMR estimates the stocks' performance over the benchmark index. The benchmark index is the acquirer's primary market index, which is collected from DataStream. The results are reported in Table 1-3 Panel A columns (1) and (2). The regression coefficients of social connectedness are still positive and statistically significant. Our baseline finding is robust to various measures of acquirers' announcement performance.

Table 1-3 Robustness test

Panel A: Adjusted model

This table presents OLS regressions for the sample of 6,136 completed cross-border M&As between 2009 and 2018, estimating the impact of social connectedness on the acquirer's announcement stock return. These robustness tests use additional measures for the announcement stock return (columns (1) and (2)), adjusted samples (columns (3) and (4)), and alternative fixed effect model (column (5)). The independent variables in columns (1)-(5) are *SCI*, the logarithm of the Social Connectedness Index (SCI) between the acquirer country and target country. In column (1), the dependent variable $CMR_{[-1,+1]}$ is the acquirer's cumulative market-adjusted return in the three days centered around the announcement date. In column (2), the dependent variable $CAR_{[-2,+2]}$ is the acquirer's cumulative abnormal return in the five days centered around the announcement date, which is estimated from the market model using a [-240, -41] day estimation period. In columns (3)-(5), the dependent variables are $CAR_{[-1,+1]}$, acquirer's cumulative abnormal return in the three days centered around the announcement date, which is estimated from the market model using a [-240, -41] day estimation period. In column (3), the sample excludes the cross-border M&As involving the U.S. acquirers/targets. In column (4), the sample excludes the cross-border M&As between the U.S., the U.K., Australia, and Canada. In columns (1) to (4), Year fixed effect and acquirer industry fixed effect are included. In column (5), the Year × Industry fixed effect is included to control the industry's time-varying characteristics. The remaining country pair controls, deal controls, and acquirer firm controls are explained in Appendix Table A1-1. *Constant* is the constant term. *N* is the number of observations. Standard errors are clustered at the country pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Dependent variable		*Adjusted sample*		*Fixed effects*
	different estimation model	*different cumulative window*	*U.S. firms removed*	*'Anglosphere' removed*	*industry's time-varying characteristics*
	$CMR_{[-1,+1]}$	$CAR_{[-2,+2]}$	$CAR_{[-1,+1]}$	$CAR_{[-1,+1]}$	$CAR_{[-1,+1]}$
	(1)	(2)	(3)	(4)	(5)
SCI	0.003**	0.005**	0.002*	0.002*	0.003**
	(2.245)	(2.438)	(1.765)	(1.913)	(1.993)
Geo Distance	-0.000	-0.002	-0.001	-0.001	-0.000
	(-0.156)	(-1.104)	(-0.412)	(-0.781)	(-0.232)
Share Border	-0.001	-0.009*	0.002	0.000	-0.003
	(-0.309)	(-1.883)	(0.582)	(0.037)	(-0.852)
Same Law	0.001	-0.000	-0.001	0.000	0.002
	(0.243)	(-0.046)	(-0.142)	(0.042)	(0.449)
Same Language	-0.007*	-0.006	-0.008*	-0.008**	-0.006
	(-1.933)	(-1.173)	(-1.915)	(-2.101)	(-1.451)
Same Religion	0.001	0.004	-0.000	0.001	0.004
	(0.132)	(0.560)	(-0.052)	(0.116)	(0.691)
Cultural Distance	-0.000	-0.000	-0.000	-0.000	0.000
	(-0.646)	(-0.693)	(-0.153)	(-0.303)	(0.297)
Political Discord	0.002	0.004*	0.003	0.003	0.001
	(0.926)	(1.702)	(1.170)	(1.377)	(0.734)
Signed Treaty	0.001	0.001	0.001	0.001	0.001
	(0.351)	(0.249)	(0.186)	(0.344)	(0.308)
Trade Flow	-0.001	-0.001	-0.001	-0.002*	-0.001
	(-0.956)	(-0.962)	(-0.883)	(-1.824)	(-0.778)
Δ*GDP Growth*	-0.001*	-0.001*	-0.001	-0.001**	-0.001*
	(-1.958)	(-1.885)	(-1.240)	(-2.383)	(-1.839)
Δ*GDP per capita*	0.002	0.004*	0.001	0.000	0.002
	(1.218)	(1.784)	(0.491)	(0.116)	(1.108)
Δ*GDP*	-0.003***	-0.003***	-0.002*	-0.003***	-0.003***
	(-4.339)	(-3.166)	(-1.811)	(-3.482)	(-4.392)
Δ*Openness*	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.261)	(-0.434)	(-0.158)	(-0.276)	(-0.862)
Δ*Exchange*	-0.006	0.010	-0.027*	-0.017	0.001

	(-0.483)	(0.744)	(-1.829)	(-1.430)	(0.038)
ΔInstitution Quality	-0.000	-0.000	-0.000	-0.000*	-0.000
	(-1.258)	(-1.088)	(-0.696)	(-1.766)	(-0.865)
ΔBusiness Env	0.000	-0.000	-0.000	0.000	0.000
	(0.178)	(-0.183)	(-0.024)	(1.394)	(0.215)
ΔDisclosure Quality	-0.013***	-0.014**	-0.016***	-0.011**	-0.010**
	(-2.806)	(-2.339)	(-2.815)	(-2.494)	(-2.180)
Deal Value	-0.007	-0.005	-0.013	-0.013**	-0.005
	(-1.238)	(-0.862)	(-1.446)	(-2.080)	(-1.017)
Tender Offer	0.003	0.001	0.001	0.000	0.005
	(0.809)	(0.308)	(0.265)	(0.072)	(1.315)
Financial Acquirer	0.001	-0.000	-0.000	0.001	0.001
	(0.426)	(-0.089)	(-0.058)	(0.289)	(0.468)
Non-Cash Deal	-0.000	-0.002	-0.005	-0.000	0.005
	(-0.053)	(-0.276)	(-0.504)	(-0.049)	(0.686)
Attitude	0.000***	0.000***	0.000*	0.000***	0.000***
	(4.726)	(3.580)	(1.828)	(2.961)	(4.663)
Leverage	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.817)	(-0.689)	(-0.235)	(-0.415)	(-0.516)
ROA	0.004***	0.004***	0.004***	0.005***	0.004***
	(6.538)	(5.297)	(3.575)	(6.903)	(5.815)
Size	-0.008***	-0.009***	-0.008***	-0.008***	-0.007***
	(-12.610)	(-8.844)	(-7.963)	(-9.684)	(-11.383)
Constant	0.061*	0.066*	0.077*	0.073**	0.045
	(1.852)	(1.651)	(1.855)	(2.143)	(0.523)
Year fixed effects	YES	YES	YES	YES	NO
Industry fixed effects	YES	YES	YES	YES	NO
Year × Industry	NO	NO	NO	NO	YES
N	6136	6136	2958	4039	6136
adj. R-sq	0.058	0.052	0.042	0.060	0.041

Panel B: Two-stage least square (2SLS) approach

This table presents the two-stage least square (2SLS) approach for the sample of 6,136 completed cross-border M&As between 2009 and 2018. Column (1) is the first stage of 2SLS, estimating the effect of the instrumental variable ΔAge on social connectedness. The independent variable ΔAGE is the absolute difference in population median ages between the acquirer and target country. The dependent variable is *SCI*, the logarithm of the Social Connectedness Index (SCI) between the acquirer and target countries. Columns (2) and (3) are the second stage, estimating the effect of instrumented social connectedness $\widehat{SCI}$ on acquirers' announcement stock returns. The independent variable is $\widehat{SCI}$, estimated from the first stage. The dependent variable in column (2) $CAR_{[-1,+1]}$ is the acquirer's cumulative abnormal return in the three days centered around the announcement date, which is estimated from the market model using a [-240, -41] day estimation period. The dependent variable in column (3) $ALT\_CAR_{[-1,+1]}$ is the acquirer's cumulative abnormal return in the three days centered around the announcement date, which is estimated from the market model using a [-240, -21] estimation period. The remaining country pair controls, deal controls, and acquirer firm controls are explained in Appendix Table A.1. Year fixed effect and acquirer industry fixed effect are included. *Constant* is the constant term. *N* is the number of observations. Standard errors are clustered at the country pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	First-stage	*Second-stage*	
	SCI	$CAR_{[-1,+1]}$	$ALT\_CAR_{[-1,+1]}$
	(1)	(2)	(3)
ΔAge	-0.043***		
	(-2.682)		
$\widehat{SCI}$		0.008**	0.008**
		(2.210)	(2.298)
Geo Distance	-0.467***	0.002	0.002
	(-5.480)	(1.339)	(1.373)
Share Border	-0.103	-0.001	-0.001
	(-0.383)	(-0.224)	(-0.243)
Same Law	0.206	-0.001	-0.000
	(1.403)	(-0.248)	(-0.025)
Same Language	0.666***	-0.011**	-0.012**
	(3.839)	(-2.281)	(-2.498)
Same Religion	0.320	-0.000	-0.001
	(1.378)	(-0.005)	(-0.215)
Cultural Distance	0.007	-0.000	-0.000
	(0.540)	(-0.783)	(-0.823)
Political Discord	-0.226***	0.003	0.003
	(-2.594)	(1.210)	(1.206)
Signed Treaty	-0.709***	0.007*	0.006*
	(-4.323)	(1.747)	(1.648)
Trade Flow	-0.189***	-0.000	-0.000
	(-3.755)	(-0.030)	(-0.151)
Δ*GDP Growth*	-0.004	-0.001*	-0.001*
	(-0.502)	(-1.699)	(-1.661)
Δ*GDP per capita*	0.054	-0.003***	-0.003***
	(1.106)	(-4.180)	(-4.356)
Δ*GDP*	0.021	0.001	0.001
	(0.231)	(0.890)	(0.837)
Δ*Openness*	0.002*	-0.000	-0.000
	(1.723)	(-1.128)	(-1.019)
Δ*Exchange*	0.108	-0.003	-0.004
	(0.599)	(-0.207)	(-0.316)
Δ*Institution Quality*	-0.009	-0.000	-0.000
	(-1.272)	(-0.726)	(-0.669)
Δ*Business Env*	-0.001	0.000	0.000
	(-0.209)	(0.459)	(0.492)
Δ*Disclosure Quality*	0.105	-0.011**	-0.012***
	(0.449)	(-2.493)	(-2.604)
Deal Value	0.119	-0.008	-0.008
	(1.583)	(-1.475)	(-1.460)
Tender Offer	-0.100**	0.004	0.004
	(-2.005)	(0.964)	(0.858)

Financial Acquirer	0.010	0.001	0.001
	(0.440)	(0.329)	(0.310)
Non-Cash Deal	-0.077	0.001	0.002
	(-0.583)	(0.213)	(0.270)
Attitude	-0.001*	0.000***	0.000***
	(-1.932)	(5.021)	(4.443)
Leverage	0.001***	-0.000	-0.000
	(2.746)	(-0.819)	(-1.164)
ROA	-0.010	0.004***	0.004***
	(-1.149)	(6.295)	(6.398)
Size	-0.034***	-0.007***	-0.007***
	(-2.632)	(-11.667)	(-10.948)
Constant	16.401***	-0.025	-0.026
	(9.883)	(-0.503)	(-0.531)
Year Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
N	6136	6136	6136
adj. R-sq	0.622	0.047	0.046

1.4.2.2 Alternative sample

Next, we estimate the baseline model within adjusted samples to alleviate the concern of sample bias. First, acquirer firms from the U.S. are involved in 21.92% of the cross-border M&As in our sample, as seen in Table 1-1 Panel A. We eliminate cross-border M&As that involve the U.S. acquirers or U.S. targets from the sample to ensure that our baseline findings are not driven by U.S. firms. The positive and significant result in Table 1-3 Panel A column (3) suggests that our baseline finding still holds. Then we eliminate cross-border M&As between the U.S., the U.K., Australia, and Canada from the sample. They are the top four countries involved in cross-border M&As as seen in Table 1-1 Panel A. The number of cross-border M&As between them is 2,097, making up 34.2% of the total observations. The four countries are part of the 'Anglosphere', which has similar languages, cultures, and social norms (Li and Wang, 2023). To ensure that our results are not driven by this proximity, we exclude the deals between these countries. In Table 1-3 Panel A column (4), our baseline finding holds.

1.4.2.3 Alternative fixed effect

We use a *Year*× *Industry* fixed effect model. This more granular fixed effect model controls the industry's time-varying characteristics, which further alleviates the omitted variable concerns. The regression result in Table 1-3 Panel A column (5) is statistically significant and positive. Our baseline finding still holds.

1.4.2.4 Endogeneity

Two endogeneity concerns may plague our analysis. First, our result may be driven by the reverse causality that cross-border M&As foster social connections between two countries. Indeed, cross-border M&As can form some connections. However, Facebook links are formed by all Facebook users across countries (Bailey *et al*., 2020), which is mainly shaped by historical factors and characteristics of the population (Bailey *et al*., 2018a; Kuchler and Stroebel, 2021). Therefore, cross-border M&As are unlikely to significantly increase Facebook users' connectedness. Second, one may argue that the results are potentially driven by observed correlated variables (like countries' cultural proximity) and/or by unobserved omitted variables that significantly affect both social connectedness and cross-border M&As simultaneously.

To address the endogeneity concern, we employ an instrumental variable (IV) approach. The instrumental variable is the difference in population median age (ΔAge) between pair countries (acquirer minus target). Age is an important factor affecting individuals' social networks (Wrzus *et al*., 2013). According to the similarity-attraction theory in psychological studies, people are more likely to meet and actively select others with similarities (Byrne *et al*., 1967; Wrzus *et al*., 2013). Similar people share similar interests and views and thus feel pleasant in the interactions, which in turn facilitates the forming of social networks. Besides, social homogamy theory suggests that people are more likely to form networks with those sharing similar sociodemographic backgrounds such as education, age, or leisure activities (McPherson *et al*., 2001; Wrzus *et al*., 2013). Bailey *et al*. (2020) provide empirical evidence that countries with similar population median ages have larger social connectedness. Following Bailey *et al*. (2020), our instrumental variable (ΔAge) is measured by the absolute value of the difference in population median ages between pair countries. The data are collected from the United Nations' World Population Prospects 2022. In our sample, the variable ranges from 0.003 to 28.221 with a mean value of 4.422. The variable ΔAge serves the relevance condition for a valid IV. According to similarity-attraction theory and social homogamy theory, age differences should reduce social connectedness between pair countries. In addition, the variable ΔAge very likely serves the exclusion condition for a valid IV. In general, we find limited evidence that firms make M&A-investment decisions based on the population age differences between their country and another country. Intuitively, the population median age differences are unlikely to directly affect acquirers' announcement return in cross-border M&As.

The results from the two-stage least squares (2SLS) regressions are reported in Table 1-3 Panel B. In the first stage, we regress *SCI* on ΔAge and control variables as in the baseline regression. In Table 1-3 Panel B column (1), ΔAge has a significantly negative effect on social connectedness, indicating that a larger distance in population ages leads to a lower degree of social connectedness. The *F*-statistic for the weak instrument test is 209.341, indicating that the weak instrument problem is not a threat. The relevance condition of the IV is fulfilled. In the second stage, we regress the acquirer announcement returns on the instrumented social connectedness $\widehat{SCI}$. In Table 1-3 Panel B columns (2) and (3), the instrumented social connectedness has a significant and positive influence on acquirer announcement returns. Taken together, our baseline results are unlikely to be driven by endogeneity.

1.5 Mechanism

In this section, we explore how social connectedness influences cross-border M&As. We predict that social connectedness increases acquirers' announcement returns through an information dissemination channel, allowing acquirers to reduce target premiums and achieve long-run success.

1.5.1 Informational Role of Social Connectedness

If social connectedness facilitates information dissemination and reduces information asymmetry, we should observe a more pronounced effect of social connectedness on acquirers' announcement returns when the information asymmetry problem in cross-border M&As is bigger. We use the following model and focus on the interaction terms between social connectedness and various information asymmetry proxies.

$$Return_{k,t} = \beta_0 + \beta_1 SCI_{ij} + \beta_2 IA + \beta_3 IA \times SCI_{ij} + \beta_4 PAIR\_CONTROL_{ij,t} + \beta_5 DEAL\_CONTROL_{k,t} + \beta_6 FIRM\_CONTROL_{k,t} + T + I + \varepsilon_{k,ij,t} \quad (1-2)$$

where IA refers to the proxies for information asymmetry; $IA \times SCI_{ij}$ is the interaction term between information asymmetry proxies and social connectedness. The information asymmetry proxies are measured by characteristics of acquirer firms, target firms, and country pairs, respectively. The other variables are the same as in the regression model (1-1).

1.5.1.1 Board networks and foreign investors

Literature documents significant financial consequences of personal networks of board members, executives, and shareholders. One key mechanism is that these networks provide better access to knowledge, ideas, and private information (Renneboog and Zhao, 2014; El-Khatib *et al*., 2015). In this case, strong personal networks reduce information asymmetry. In our cross-border setting, we focus on the nationalities of board members of acquirer firms. Foreign investment studies suggest that market participants are familiar with their home markets and benefit from personal connections (e.g., educational connections) with their home countries (Huberman, 2001; Cohen *et al*., 2008). An acquirer firm that does not have any board members from the target country is more likely to face severe information asymmetry. The informational role of social connectedness should be bigger. We set the dummy variable (*Non-Target Country Board*) to one if no board members of the acquirer firm are from the target country, and zero otherwise. As shown in Table 1-4 column (1), the interaction term between *Non-Target Country Board* and social connectedness is positive and significant, indicating that social connectedness has a larger impact on acquirers, when none of their board directors come from the foreign target country.

Foreign institutional investors can bridge the informational gap between acquirers and targets (Ferreira *et al*., 2010). If the acquiring firm has a foreign institutional shareholder who is from the target country, the shareholder could help the acquirer better access and process the target's information. Social connectedness is more influential for acquirers that are not owned by institutional investors in the target country. We calculate an acquirer's ownership by foreign institutional investors from the target country and construct a variable *Non-Target Country IO* as one minus this ownership ratio. A higher value of *Non-Target Country IO* reflects a lower target country shareholders' ownership and greater information asymmetry. The interaction term between social connectedness and *Non-Target Country IO* in Table 1-4 column (2) is positive and significant. The result suggests that the effect of social connectedness is larger when the acquirer is owned less by foreign institutional investors in the target country.

Table 1-4 Informational role of social connectedness

This table presents the OLS regressions (2) for the sample of 6,136 completed cross-border M&As between 2009 and 2018. The analysis estimates the effect of social connectedness on acquirers' stock returns, considering different levels of information asymmetry. The dependent variable in the columns (1)-(6) is $CAR_{[-1,+1]}$, acquirer's cumulative abnormal return in the three days centered around the announcement date, which is estimated from the market model using a [-240, -41] day estimation period. The independent variable *SCI* is the logarithm of the Social Connectedness Index between the acquirer and target countries. *Non-Target Country Board* is a dummy variable that equals one if no board members in the acquirer firm originate from the target country, and zero otherwise. *Non-Target Country IO* is one minus the acquirer's institutional ownership composition originating in target countries. *Non-Public Target* is a dummy variable that equals one if the target firm is a non-public firm, and zero otherwise. Δ*Disclosure Quality* is the difference in disclosure quality index between the acquirer and target countries. The interaction terms between *SCI* and these information asymmetry proxies are included. The remaining country pair controls, deal controls, and acquirer firm controls are consistent with the baseline regression. Year fixed effect and acquirer industry fixed effect are included. Standard errors are clustered at the country pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Acquirer firm		*Target firm*	*Countries*
	$CAR_{[-1,+1]}$	$CAR_{[-1,+1]}$	$CAR_{[-1,+1]}$	$CAR_{[-1,+1]}$
	(1)	(2)	(3)	(4)
SCI	-0.001	0.003**	-0.003	0.003***
	(-0.619)	(2.330)	(-1.007)	(2.586)
Non-Target Country Board	-0.031			
	(-1.479)			
Non-Target Country Board × SCI	0.004*			
	(1.704)			
Non-Target Country IO		0.171*		
		(1.818)		
Non-Target Country IO × SCI		0.018*		
		(1.789)		
Non-Public Target			-0.041	
			(-1.499)	
Non-Public Target × SCI			0.006*	
			(1.922)	
Δ*Disclosure Quality*				-0.064**
				(-2.511)
Δ*Disclosure Quality × SCI*				0.006**
				(2.153)
Controls & Constant	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES
N	4715	3337	6136	6136
adj. R-sq	0.037	0.021	0.050	0.048

1.5.1.2 Target firm's public status

We examine the differential effect of social connectedness between public targets and private targets. Public firms are required to disclose more information to the market. Private firms are more informationally opaque than public firms. M&A literature suggests that acquirers face greater information asymmetry problems when acquiring private targets (Erel *et al*., 2012). We expect that the impact of social connectedness is bigger for private targets in cross-border M&As. To test the conjecture, we employ a dummy variable *Non-Public Target* that equals one if the target is private and zero otherwise. The positive and significant coefficient on the interaction between *Non-Public Target* and *SCI* in Table 1-4 column (3) indicates that social connectedness has a larger effect on deals involving private targets.

1.5.1.3 Countries' information disclosure quality

We focus on the information asymmetry arising from bilateral differences in accounting information disclosure quality between pair countries. The quality of financial disclosures is highly related to corporate transparency (Bushman *et al*., 2004). In M&As, larger differences in accounting standards between pair countries make it difficult for acquirers to process the foreign target's financial statement information and make accurate valuations (Rossi and Volpin, 2004; Erel *et al*., 2012). We use the acquirer country's accounting standards index minus the target country's accounting standards index (Δ*Disclosure Quality*) as the proxy for information asymmetry (La Porta *et al*., 1998; Erel *et al*., 2012). In Table 1-4 column (4), the coefficient on the interaction between Δ*Disclosure Quality* and social connectedness is positive and significant, suggesting that the effect of social connectedness is more pronounced when the two countries have a bigger difference in accounting standards.

1.5.2 Economic Channels

We have presented evidence supporting the informational role of social connectedness in cross-border M&As. Based on this, several economic channels can explain the observed improvement in announcement returns for acquirers. Better-informed acquirers (1) are likely to value targets more accurately, thereby avoiding overpayment; (2) are more likely to successfully complete the deal; (3) achieve better long-term performance; and (4) rely less on financial advisors, resulting in lower advisory fees and reduced transaction costs. Consequently, stock investors respond favorably to these acquisitions.

1.5.2.1 Target valuation

Social connectedness enhances information flows, enabling acquiring firms to better understand the target firms' financial health, operational capabilities, and potential risks. This helps acquirers evaluate the targets accurately and gain a bargaining advantage. As a result, acquirers are less likely to overpay, leading to superior performance in announcement returns. To verify this prediction, we replace the dependent variable in the model (1) with the target premium to estimate how it is affected by social connectedness. Following Lim *et al*. (2016), we calculate the target premium as the per-share offer price divided by the stock price of the target firm one week before the announcement date (*Premium 1-Week*) or four weeks before the announcement date (*Premium 4-Week*). Because these variables depend on the target firm's stock price, our sample for this test includes only events involving public target firms. In Table 1-5 Panel A, we find that SCI significantly reduces the target premium, suggesting a positive role played by social connectedness in lowering acquirers' risk of overpaying for public targets.

Table 1-5 Economic channels

This table estimates the economic channels of social connectedness: target valuation channel (Panel A), completion rate channel (Panel B), long-run success channel (Panel C), and transaction costs channel (Panel D). The key independent variable *SCI* is the logarithm of the Social Connectedness Index between the acquirer and target countries. Panel A examines the impact of social connectedness on target premiums. *Premium 1-Week* and *Premium 4-Week* are calculated by the deal share price divided by the target stock price 1 week and 4 weeks before the announcement date, respectively. Panel B examines the impact of social connectedness on the likelihood of the completion of cross-border M&As, using both the probit model and the logit model. We extend the sample by including uncompleted cross-border M&As during the period. *Completion* is a dummy variable that equals one if the deal is complete, and zero otherwise. *CompletionW* is a dummy variable that equals one if the deal is complete, and zero if withdrawn. Panel C examines the impact of social connectedness on acquirers' stock performance and operating performance in the long run. *BHAR[0,36]* and *BHAR[0,24]* are the buy-and-hold abnormal returns of the acquirer firm in the 36-month and 24-month window after the announcement date. $\Delta ROA[0,3]$ and $\Delta ROA[0,1]$ are the increase in the acquirer's industry-adjusted ROA 3 years and 1 year after the announcement relative to the announcement year. Panel D examines the impact of social connectedness on transaction costs. In column (1), *Time-to-Close* is the calendar days from the date of announcement to closure. In column (2), *Fee* is the fee in million USD paid by the acquirer and target. In column (3), the dependent variable is the ratio of *Fee Combined* to *Time-to-Close*. The remaining country pair controls, deal controls, and acquirer firm controls are consistent with the baseline regression. Year fixed effects and acquirer industry fixed effects are included. *The constant* is the constant term. *N* is the number of observations. Standard errors are clustered at the country pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

Panel A: Target valuation

	Target premium	
	Premium 1-Week	*Premium 4-Week*
	(1)	(2)
SCI	-0.109**	-0.074**
	(-2.329)	(-2.236)
Controls & Constant	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
N	447	449
adj. R-sq	0.108	0.110

Panel B: Deal completion

	Probit model		Logit model	
	Completion	*CompletionW*	*Completion*	*CompletionW*
	(1)	(2)	(3)	(4)
SCI	0.392***	0.158*	0.781***	0.366*
	(5.073)	(1.664)	(4.863)	(1.790)
Controls & Constant	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	7058	5888	7058	5888
pseudo. R-sq	0.911	0.938	0.911	0.940

Panel C: Long-run success

	Stock performance		Operating performance	
	BHAR[0,36]	*BHAR[0,24]*	*ΔROA[0,3]*	*ΔROA*[0,1]
	(1)	(2)	(3)	(4)
SCI	0.016*	0.026**	0.261**	0.145*
	(1.659)	(1.986)	(2.067)	(1.887)
Controls & Constant	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	6136	6136	4001	5544
adj. R-sq	0.134	0.107	0.058	0.027

Panel D: Transaction cost

	Time Costs	Fees	Ratio
	Time-to-Close	*Fee*	*Fee /Time-to-Close*
	(1)	(3)	(5)
SCI	2.146	3.630	0.048
	(0.795)	(0.428)	(0.852)
Controls & Constant	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
N	6136	174	174
adj. R-sq	0.132	0.590	0.362

1.5.2.2 Completion rate

In the aftermath of an M&A deal's announcement, acquirers, targets, and other involved parties continually receive updated information as the negotiation process unfolds (Dikova *et al*., 2010). This evolving information profoundly influences both the associated risks and returns of the deal (Dikova *et al*., 2010). Social connectedness between two countries can reduce information asymmetry and streamline negotiations, enhancing the likelihood of a deal's successful closure. Consequently, enhanced social connectedness could potentially improve the completion rates of cross-border M&As between countries. M&As involve substantial costs. The successful consummation of a deal can have a favorable effect on the acquirers' financial health, thereby prompting positive reactions from the market.

To test the conjecture, we further collect incomplete cross-border M&As from 2009 to 2018 and filter the deals following similar steps. Jointly with the baseline sample, the new sample includes 6,136 completed deals, 308 withdrawn deals, and 692 deals with other incomplete statuses (i.e., intended, pending, and intended withdrawn). The observations would be lost due to the use of the probit model and fixed effects. We employ a probit model of baseline regression (1-1) to estimate the impact of social connectedness on the likelihood of a cross-border M&A to be completed. Following Dikova *et al*. (2010), we construct a dependent variable *Completion*, a dummy variable that equals one if the deal is complete, and zero otherwise. We also use an alternative variable *CompletionW*, a dummy variable that equals one if the deal is complete, and zero if withdrawn. Other variables and fixed effects are consistent with regression (1-1). The results are reported in Table 1-5 Panel B columns (1) and (2). The regression coefficients of *SCI* are positive and statistically significant at a 1% significance level. It suggests that stronger social connectedness is associated with a larger likelihood of deal completion. When we use alternative dependent variables or logit models, the findings are robust.

1.5.2.3 Long-run success

Another channel driving the announcement performance is the acquirers' long-run success. Information flows provide acquirers with access to local markets and maintain relationships. This can increase the likelihood of a successful post-M&A operation and contribute to long-run performance. Following Zhou *et al*. (2015) and Lyon *et al*. (1999),[7] we use 36-month and 24-month buy-and-hold abnormal returns ($BHAR[0,36]$, $BHAR[0,24]$) to measure the long-run stock performance of the acquirers. The benchmark stocks are the market indexes of each acquirer country. We replace the dependent variable in the model (1) with $BHAR[0,36]$ and $BHAR[0,24]$, respectively, and estimate the model. The results are reported in Table 1-5 Panel B columns (1) and (2), suggesting that social connectedness has a positive and significant impact on acquirers' long-run stock performance. To estimate acquirers' long-run operating performance, we use acquirers' increase in industry-adjusted return on assets (ΔROA) (Cai and Sevilir, 2012; Hu *et al*., 2020). The ΔROA is the increase in acquirers' industry-adjusted ROA three years ($\Delta ROA[0,3]$) and one year ($\Delta ROA[0,1]$) after the M&A announcement year. We adjust acquirers' ROA by deducting the mean ROA of acquirers' industry peers in a given year. We replace the dependent variable in the model (1) with $\Delta ROA[0,3]$ and $\Delta ROA[0,1]$, and estimate the model. The regression results in Table 1-5 Panel C columns (3) and (4) suggest that social connectedness is associated with a significant increase in acquirers' industry-adjusted ROA in the long run. Overall, our results in Panel C show that social connectedness is associated with better long-run stock performance and operating performance.

[7] The buy-and-hold return of a stock is calculated as $BHR = \prod_{t=s}^{s+T}(1 + R_t) - 1$. The buy-and-hold abnormal return ($BHAR$) is the difference between the buy-and-hold returns of acquirers' stocks and benchmark stocks.

1.5.2.4 Transaction costs

Transaction costs are generated from the bargaining process between acquirers and targets, which typically manifest in the advisor fees and execution time of the deal (Boeh, 2011). Lower information asymmetry offers a better understanding of acquirers and targets, which mitigates the need for advisory services and shortens the execution time. Following Boeh (2011), we use time-to-close (*Time-to-Close*), transaction fees (*Fee*), and the ratio of advisor fees to time-to-close (*Fee/Time-to-Close*) to examine the impact of social connectedness on transaction costs. *Time-to-Close* is defined as the number of calendar days from the date of announcement to the closure of a deal. *Fee* represents the total fees in million USD paid by the acquirer and the target to advisors, dealer-managers, and other agents. However, the regression coefficients reported in Table 1-5 Panel D are insignificant. We find no significant evidence supporting the transaction costs channel.

Overall, our results support the target valuation, completion rate, and long-run success channels. Information flows facilitated by social connectedness incur acquirers' superior announcement stock returns by avoiding overpayment, increasing the likelihood of completion, and improving long-run stock returns and operating profitability.

1.6 Additional Analysis

1.6.1 Effect of Social Connectedness on Cross-Border M&A Volume

In this section, we examine the effect of social connectedness on two countries' aggregate cross-border M&As. The findings in the previous section show that social connectedness facilitates information dissemination, which benefits acquirers in the accurate valuation and long-run success. Therefore, acquirers are more willing to invest in socially connected countries. In addition to acquirers' willingness, familiarity breeds foreign investments (Huberman, 2001). Information about informationally-opaque countries is easier to transfer to acquirers in socially connected countries. As a result, acquirers are more likely to observe M&A investment opportunities in connected countries. Taken together, we predict that social connectedness leads to a larger volume of cross-border M&As between pair countries. To test the conjecture, we aggregate cross-border M&As in our baseline sample to the country level and estimate the following regression models (1-3) and (1-4).

$$NUMBER_{ij,t} = \beta_0 + \beta_1 SCI_{ij} + \beta_2 PAIR\_CONTROL_{ij,t} + T + \varepsilon_{ij,t} \qquad (1-3)$$

$$VALUE_{ij,t} = \beta_0 + \beta_1 SCI_{ij} + \beta_2 PAIR\_CONTROL_{ij,t} + T + \varepsilon_{ij,t} \qquad (1-4)$$

where $NUMBER_{ij,t}$ is the natural logarithm of one plus the total number of M&As between acquirer country i and target country j in year t; $VALUE_{ij,t}$ is the natural logarithm of one plus the total dollar value of M&As between acquirer country i and target country j in year t. SCI_{ij} is the natural logarithm of one plus the Social Connectedness Index between acquirer country i and target country j. $PAIR\_CONTROL_{ij,t}$ are the pair-level control variables between acquirer country i and target country j in year t. β_0 is the constant. T is the year fixed effect. $\varepsilon_{ij,t}$ is the error term. The country fixed effect is not included in the equation because the country fixed effect can absorb the time-invariant variable SCI_{ij}.

We analyze the effect of social connectedness on cross-border M&A numbers between pair countries in Table 1-6 column (1). The result shows that social connectedness significantly increases the cross-border M&A numbers between pair countries. Table 1-6 column (2) reports the effect of social connectedness on cross-border M&A transaction values. The coefficient of social connectedness is positive and significant at the 1% significance level. The effects of the control variables are also consistent with our expectations, such as the positive effect of the same language and bilateral trade and the negative effect of Hofstede's cultural distance. Overall, the findings suggest that social connectedness positively affects both M&A numbers and values between pair countries.

Table 1-6 Social connectedness and cross-border M&A volume

This table presents the OLS regressions for the sample of cross-border M&As between 2009 and 2018 at the country pair-year level. The analysis estimates the effect of social connectedness on the volume of cross-border M&As between pair countries. The dependent variable *Number* in column (1) is the logarithm of one plus the annual number of M&A deals between the acquirer and target countries in a year. The dependent variable *Value* in column (2) is the logarithm of one plus the annual dollar value of M&A deals between the acquirer and target countries in a year. *SCI* is the logarithm of the Social Connectedness Index between the acquirer and target countries. The country pair controls are included and explained in Appendix Table A.1. Year fixed effects are included. *Constant* is the constant term. *N* is the number of observations. Standard errors are clustered at the country pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Number	Value
	(1)	(2)
SCI	0.063***	0.197***
	(3.901)	(4.025)
Geo Distance	0.059***	0.234***
	(2.676)	(3.281)
Share Border	0.028	0.120
	(0.334)	(0.509)
Same Law	-0.048	-0.293**
	(-1.454)	(-2.443)
Same Language	0.159***	0.398**
	(2.911)	(2.360)
Same Religion	-0.129**	-0.017
	(-2.364)	(-0.096)
Cultural Distance	-0.015***	-0.046***
	(-4.704)	(-4.395)
Political Discord	0.093***	0.323***
	(4.624)	(4.493)
Signed Treaty	-0.200***	-0.828***
	(-6.642)	(-8.189)
Trade Flow	0.191***	0.719***
	(14.168)	(18.019)
Δ*GDP Growth*	-0.003*	-0.014*
	(-1.656)	(-1.695)
Δ*GDP per capita*	-0.004	0.007
	(-0.370)	(0.175)
Δ*GDP*	-0.000	-0.038
	(-0.016)	(-0.648)
Δ*Openness*	0.000	0.000
	(0.074)	(0.275)
Δ*Exchange*	0.070	0.216
	(1.203)	(0.913)
Δ*Institution Quality*	0.003**	0.011*
	(2.000)	(1.766)
Δ*Business Env*	-0.000	0.001
	(-0.190)	(0.154)
Δ*Disclosure Quality*	-0.236***	-0.701***
	(-4.039)	(-3.492)
Constant	-3.216***	-11.901***
	(-9.224)	(-10.474)
Year Fixed Effects	YES	YES
N	8788	8788
adj. R-sq	0.321	0.268

1.6.2 Effect of Cross-Country Differences in Institutional Characteristics

A variety of country-level institutional characteristics may shape the impact of social connectedness on cross-border M&A volume between countries. One such characteristic is countries' affiliation with the same Customs Union (CU). Aleksanyan *et al*. (2021) discuss that acquirers and targets operating within the same CU encounter reduced investment uncertainty. We thus anticipate that social connectedness plays a lesser role in facilitating cross-border M&As between acquirers and targets from the same CU. We include a variable *Common Customs Union*, assigned a value of one if the two countries are members of the same CU, and zero otherwise. Our sample includes countries from the Andean Community (CAN), Common Market for Eastern and Southern Africa (COMESA), East African Community (EAC), European Union Customs Union (EUCU), Southern Common Market (MERCOSUR), and Southern African Customs Union (SACU). The results are reported in Table 1-7 column (1) and column (2). We include the variable *Common Customs Union* and its interaction term with *SCI* into our equation. The regression coefficients for the interaction terms between *Common Customs Union* and social connectedness are negative and statistically significant at a 1% significance level. The result suggests that the effect of social connectedness on cross-border M&As is alleviated by the Customs Union.

Another bilateral factor is the two countries' disagreement on political affairs. Following Garmaise and Natividad (2013) and Bertrand *et al*. (2016), we measure political disagreement (*Political Discord*) using the United Nations members' voting results on resolutions in the General Assembly. A larger value of the variable *Political Discord* reflects a bigger political disagreement between the two countries, which in turn hinders the information communication between them. In these circumstances, social connectedness should help bridge the informational gap. In Table 1-7 column (3) and column (4), the regression coefficients for the interaction terms between *Political Discord* and social connectedness are positive and statistically significant, suggesting that the effect of social connectedness is stronger for pair countries with bigger political disagreement.

Countries with a large time zone difference are geographically distant and have fewer overlapped working hours. This raises information acquisition costs and reduces communication efficiency. Large time zone differences adversely affect bilateral trade (Bacidore and Sofianos, 2002; Stein and Daude, 2007). In Table 1-7 column (5) and column (6), we construct the variable ΔUTC as the difference in time zones between the acquirer and target countries. The regression coefficients for the interaction terms between ΔUTC and SCI are positive and statistically significant at a 1% significance level, indicating that the effect of social connectedness on cross-border M&A volume is stronger for pair countries with a larger time zone difference.

Finally, we examine bilateral trust, which is important in international trade and investment (Guiso *et al*., 2009; Ahmad *et al*., 2022). Individuals who trust each other are more willing to share information with them. This improves the efficiency of information dissemination, strengthening the effect of social connectedness. We use Guiso *et al*.'s (2009) trust index (*Trust*) to measure the level of bilateral trust between the acquirer and target countries. In Table 1-7 column (7) and column (8), the regression coefficients on the interaction terms are positive and statistically significant at a 1% significance level, suggesting that the effect of social connectedness on cross-border M&As is improved by bilateral trust between pair countries.

Table 1-7 Cross-Sectional analysis

This table presents the OLS regressions for the sample of cross-border M&As between 2009 and 2018 at the country pair-year level. The analysis estimates the cross-sectional variations in the effect of social connectedness on the volume of cross-border M&As between pair countries. The dependent variables *Number* and *Value* are the logarithm of one plus the annual number and dollar value of M&As between the acquirer and target countries in a year. *SCI* is the logarithm of the Social Connectedness Index between the acquirer and target countries. *Common Customs Union* is a dummy variable that equals one if two countries are Customs Union members, and zero otherwise. *Political Discord,* Δ*UTC,* and *Trust* are the political disagreement, the difference in Coordinated Universal Time, and the Guiso Trust Index between the acquirer and target countries. The remaining country pair controls are included but not reported. Year fixed effect is included. Standard errors are clustered at the country pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Number	Value	Number	Value	Number	Value	Number	Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SCI	0.085***	0.250***	0.027	0.059	-0.007	-0.043	-1.025**	-3.766***
	(5.064)	(4.555)	(1.108)	(0.839)	(-0.278)	(-0.533)	(-2.605)	(-3.035)
Common Customs Union	0.504**	1.213**						
	(2.553)	(2.034)						
Common Customs Union × SCI	-0.063**	-0.141**						
	(-2.567)	(-1.974)						
Political Discord			-0.224	-0.896**				
			(-1.596)	(-1.984)				
Political Discord × SCI			0.041**	0.156***				
			(2.231)	(2.669)				
Δ*UTC*					-0.082***	-0.286***		
					(-2.867)	(-3.100)		
Δ*UTC × SCI*					0.013***	0.045***		
					(3.450)	(3.665)		
Trust							-3.621***	-12.597***
							(-2.808)	(-3.148)
Trust × SCI							0.374***	1.323***
							(2.904)	(3.316)
Controls & Constant	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	8788	8788	8788	8788	8788	8788	1710	1710
adj. R-sq	0.325	0.269	0.324	0.271	0.334	0.277	0.392	0.336

1.6.3 Effect of Social Connectedness on M&As within the U.S.

In our baseline test, we employ control variables or an instrumental variable to differentiate the impact of social connectedness from countries' distances in culture, language, legal systems, institutions, etc. In this section, we further address the concerns and provide a broad pattern of social connectedness by examining domestic M&As within the U.S. The benefit of this granular setting is that interregional differences in culture, institutions, and language are quite smaller than in cross-countries (Ahern *et al.*, 2015).

We construct of sample of the U.S. domestic M&As from 2009 to 2018 following similar steps to the baseline sample. The final sample includes 1,924 observations at the M&A deal level, 1,784 city pairs, 1029 unique acquirers, and 1,920 unique targets. The sample size is comparable to previous M&A studies, such as Adra *et al*. (2020). We estimate the impact of social connectedness on acquirers' announcement returns. Facebook provides a Social Connectedness Index of zip-code pairs. We employ two approaches to aggregate the index to the city-pair level: (1) a population-weighted average of the social connectedness across the zip codes (*i* and *j*) in cities *I* and *J* (Bailey *et al.*, 2021), PW_SCI^{CITY};[8] (2) an equal-weighted average of the social connectedness across the zip codes in cities *I* and *J*, EW_SCI^{CITY}.[9]

We re-estimate the baseline model (1-1). The dependent variable is still the cumulative abnormal return in three days centered around the announcement date $CAR_{[-1,+1]}$. The independent variable is the logarithm of PW_SCI^{CITY} or EW_SCI^{CITY}. The deal level, firm level control variables, and fixed effects are unchanged. Standard Errors are clustered at a city pair level. We replace the country-pair controls with city-pair controls. In line with our

[8] $PW\_SCI^{CITY} = \sum_{i \in I} \sum_{j \in J} PopShare_i \times PopShare_j \times SCI_{ij}^{ZIP}$

[9] $EW\_SCI^{CITY} = \frac{1}{N \times M} \times \sum_{i \in I} \sum_{j \in J} SCI_{ij}^{ZIP}$, where *N*, *M* are numbers of zip codes in city *I* and *J*, respectively.

baseline model, we incorporate the same set of deal- and firm-level control variables, as well as year and industry fixed effects. We cluster standard errors at the city-pair level and replace country-pair controls with relevant city-pair controls. Specifically, $Geo\ Distance$ is the natural logarithm of the geographical distance (in km) between the acquirer and target cities, based on their latitude and longitude data and the great-circle distance formula (Uysal *et al.*, 2008). $Same\ State$ is a dummy variable that equals one if the acquirer and target are headquartered in the same state, and zero otherwise. In light of Ahern *et al.*'s (2015) study, we control for the cultural differences in trust ($Cultural\ Distance^{Trust}$), individualism ($Cultural\ Distance^{Individualism}$), and hierarchy ($Cultural\ Distance^{Hierarchy}$) at the Census division-pair level (the natural logarithm of one plus the absolute difference between acquirer and target).[10] Additionally, we account for differences in economic indicators such as GDP growth rate ($\Delta GDP\ Growth$), GDP per capita ($\Delta GDP\ per\ capita$), and GDP (ΔGDP) between cities (acquirer minus target).

The results reported in Table 1-8 show that both the population-weighted and equal-weighted average SCI between U.S. cities have a significantly positive effect on acquirers' announcement returns. This relation holds while controlling for interregional cultural differences. This finding demonstrates that the effect of social connectedness is distinct from that of cultural distance. The robust positive impact of social connectedness on acquirers' announcement returns, observed within the relatively homogeneous environment of a single large country, underscores the importance of social connectedness in improving M&A outcomes.

[10] Following Ahern *et al.* (2015), we calculate these cultural dimensions using data from the World Values Survey (WVS). Wave 4 of the WVS includes the three survey questions necessary for constructing the measures: trust (versus distrust) derived from question Q25, individualism (versus collectivism) derived from question Q141, and hierarchy (versus egalitarianism) derived from question Q105. Survey responses are normalized on a 0 to 1 scale to calculate the average for each Census region, and then interregional cultural distance is computed. Due to the omission of Q105 for hierarchy in subsequent WVS waves 5, 6, 7, our measures rely on wave 4 data. For robustness, we focus on trust and individualism and use data from the most recent waves. Our conclusion remains unchanged.

Table 1-8 M&As within the U.S.: acquirer's announcement stock return

This table presents the regressions for the sample of 1,924 completed M&As in the U.S. between 2009 and 2018, estimating the impact of social connectedness on the acquirer's announcement stock return. The dependent variables $CAR_{[-1,+1]}$ $ALT\_CAR_{[-1,+1]}$ are the acquirer's cumulative abnormal return in the three days centered around the announcement date. In columns (1)-(2), PW_SCI^{City} is the population-weighted average of the social connectedness across the zip-codes (i and *j*) in cities *I* and *J*. In columns (3)-(4), EW_SCI^{City} is the equal-weighted average of the social connectedness across the zip-codes in cities *I* and *J*. City controls, deal controls and acquirer firm controls are included, explained in Appendix Table A.1. Year fixed effects and acquirer industry fixed effects are included. *Constant* is the constant term. *N* is the number of observations. Standard errors are clustered at the city pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Population-weighted average SCI		Equal-weighted average SCI	
	$CAR_{[-1,+1]}$	$ALT\_CAR_{[-1,+1]}$	$CAR_{[-1,+1]}$	$ALT\_CAR_{[-1,+1]}$
	(1)	(2)	(3)	(4)
PW_SCI^{City}	0.003*	0.004*		
	(1.882)	(1.923)		
EW_SCI^{City}			0.004**	0.004**
			(2.132)	(2.186)
$Geo\ Distance$	0.003*	0.003*	0.003*	0.003**
	(1.750)	(1.851)	(1.884)	(1.995)
Same State	-0.002	-0.002	-0.003	-0.003
	(-0.402)	(-0.373)	(-0.473)	(-0.448)
$Culture\ Distance^{Turst}$	-0.077	-0.070	-0.076	-0.069
	(-1.442)	(-1.325)	(-1.424)	(-1.307)
$Culture\ Distance^{Individu}$	0.149	0.135	0.149	0.136
	(1.538)	(1.385)	(1.544)	(1.393)
$Culture\ Distance^{Hierarc}$	0.015	0.005	0.014	0.004
	(0.164)	(0.053)	(0.152)	(0.040)
Δ*GDP Growth*	0.010*	0.010*	0.010*	0.010*
	(1.685)	(1.749)	(1.677)	(1.741)
Δ*GDP per capita*	0.000	0.000	0.000	0.000
	(0.898)	(0.975)	(0.915)	(0.992)
Δ*GDP*	0.001	0.001	0.001	0.001
	(1.492)	(1.426)	(1.522)	(1.457)
Deal Value	-0.000	-0.000	-0.000	-0.000
	(-0.135)	(-0.139)	(-0.158)	(-0.162)
Tender Offer	-0.005	-0.004	-0.005	-0.004
	(-0.715)	(-0.576)	(-0.724)	(-0.585)
Financial Acquirer	0.017	0.013	0.016	0.013
	(0.990)	(0.749)	(0.963)	(0.724)
Non-Cash Deal	-0.001	-0.001	-0.001	-0.001
	(-0.442)	(-0.399)	(-0.435)	(-0.391)
Attitude	0.002	0.002	0.002	0.002
	(0.052)	(0.059)	(0.052)	(0.059)
Leverage	0.000***	0.000***	0.000***	0.000***
	(4.232)	(4.194)	(4.243)	(4.206)
ROA	0.000*	0.000*	0.000*	0.000*
	(1.704)	(1.824)	(1.721)	(1.842)
Size	-0.004***	-0.004***	-0.004***	-0.004***
	(-3.299)	(-3.320)	(-3.300)	(-3.321)
Constant	-0.175***	-0.177***	-0.180***	-0.182***
	(-2.878)	(-2.745)	(-2.955)	(-2.820)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	1924	1924	1924	1924
adj. R-sq	0.054	0.053	0.055	0.054

Whether the information mechanism still play a role in M&As within domestic M&As? To answer this question, we conduct heterogeneity analyses based on cities' information flows. We conjecture that if the information mechanism is the case, the effect of social connectedness would be smaller if the target city is a financial hub. Following Global Financial Center Index 32, we identify the following cities as financial hubs: Boston (Massachusetts), Chicago (Illinois), Philadelphia (Pennsylvania), Washington (District of Columbia), Minneapolis (Minnesota), Atlanta (Georgia), Charlotte (North Carolina), Dallas (Texas), Los Angeles (California), Houston (Texas), San Francisco (California), San Diego (California), and New York (New York). In our dataset, 273 M&A observations are associated with target firms headquartered in these designated financial hubs. The dummy variable *Financial Hub* equals one if the target city is a financial hub, and zero otherwise. We estimate the impact of interaction terms between *Financial Hub* and PW_SCI^{CITY} or EW_SCI^{CITY} on the announcement of stock performance. As shown in Table 1-9 columns (1) and (2), the regression coefficients are negative and statistically significant. The impact of social connectedness is smaller when the target city is a financial hub. In columns (3) and (4), we replace the population-weighted social connectedness index with the equal-weighted social connectedness index. The results are consistent.

Overall, this section suggests that social connectedness is positively associated with acquirers' announcement stock return performance within the U.S. domestic M&As through an information mechanism. This is consistent with our baseline finding.

Table 1-9 M&As within the U.S.: financial hub

This table presents the analysis for the sample of 1,924 completed M&As in the U.S. between 2009 and 2018, estimating the effect of social connectedness on acquirers' stock returns, considering different levels of information asymmetry. The dependent variables $CAR_{[-1,+1]}$ $ALT\_CAR_{[-1,+1]}$ are the acquirer's cumulative abnormal return in the three days centered around the announcement date. We employ two approaches to aggregate the zip code-pair Social Connectedness Index to the city-pair level. In columns (1)-(2), PW_SCI^{City} is the population-weighted average of the social connectedness across the zip-codes (i and j) in cities I and J. In columns (3)-(4), EW_SCI^{City} is the equal-weighted average of the social connectedness across the zip-codes in cities *I* and *J*. The proxy for the information asymmetry is *Financial Hub*, a dummy variable that equals one if the target city is recognized as a financial hub, and zero otherwise. We primarily focus on the interaction terms between social connectedness and *Financial Hub*. City controls, deal controls and acquirer firm controls are included, explained in Appendix Table A.1. Year fixed effects and acquirer industry fixed effects are included. *Constant* is the constant term. *N* is the number of observations. Standard errors are clustered at the city pair level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Population-weighted SCI		Equal-weighted SCI	
	$CAR_{[-1,+1]}$	$ALT\_CAR_{[-1,+1]}$	$CAR_{[-1,+1]}$	$ALT\_CAR_{[-1,+1]}$
	(1)	(2)	(3)	(4)
PW_SCI^{City}	0.004*	0.004*		
	(1.929)	(1.960)		
EW_SCI^{City}			0.004**	0.004**
			(2.169)	(2.210)
Financial Hub	0.071*	0.072*	0.071*	0.072*
	(1.716)	(1.710)	(1.662)	(1.665)
PW_SCI^{City} × *Financial Hub*	-0.007*	-0.007*		
	(-1.711)	(-1.691)		
EW_SCI^{City} × *Financial Hub*			-0.007*	-0.007*
			(-1.666)	(-1.657)
$Geo\ Distance$	0.003	0.003*	0.003*	0.003*
	(1.582)	(1.671)	(1.717)	(1.812)
Same State	-0.002	-0.001	-0.002	-0.002
	(-0.283)	(-0.263)	(-0.346)	(-0.327)
$Culture\ Distance^{Turst}$	-0.075	-0.069	-0.075	-0.068
	(-1.422)	(-1.304)	(-1.407)	(-1.289)
$Culture\ Distance^{Individualism}$	0.142	0.128	0.143	0.129
	(1.468)	(1.313)	(1.475)	(1.321)
$Culture\ Distance^{Hierarchy}$	0.015	0.005	0.016	0.006
	(0.172)	(0.060)	(0.175)	(0.063)
Δ*GDP Growth*	0.010*	0.011*	0.010*	0.011*
	(1.754)	(1.806)	(1.747)	(1.799)
Δ*GDP per capita*	0.000	0.000	0.000	0.000
	(0.985)	(1.051)	(1.002)	(1.068)
Δ*GDP*	0.001	0.001	0.001	0.001
	(1.419)	(1.430)	(1.423)	(1.436)
Deal Value	-0.000	-0.000	-0.000	-0.000
	(-0.113)	(-0.125)	(-0.131)	(-0.143)
Tender Offer	-0.006	-0.005	-0.006	-0.005
	(-0.828)	(-0.682)	(-0.816)	(-0.671)
Financial Acquirer	0.018	0.014	0.017	0.014
	(1.037)	(0.815)	(1.001)	(0.781)
Non-Cash Deal	-0.001	-0.001	-0.001	-0.001
	(-0.434)	(-0.395)	(-0.433)	(-0.393)
Attitude	0.004	0.004	0.004	0.004
	(0.099)	(0.105)	(0.098)	(0.104)
Leverage	0.000***	0.000***	0.000***	0.000***
	(4.215)	(4.184)	(4.221)	(4.190)
ROA	0.000*	0.000*	0.000*	0.000*
	(1.708)	(1.836)	(1.723)	(1.851)
Size	-0.004***	-0.004***	-0.004***	-0.004***
	(-3.227)	(-3.255)	(-3.227)	(-3.255)
Constant	-0.178***	-0.180***	-0.182***	-0.184***
	(-2.901)	(-2.764)	(-2.976)	(-2.836)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	1924	1924	1924	1924
adj. R-sq	0.055	0.054	0.056	0.055

1.7 Conclusion

In this paper, we use the Facebook Social Connectedness Index to investigate the effect of social connectedness on cross-border M&As. Using worldwide cross-border M&A data from 2009 to 2018, we provide robust evidence that social connectedness has a significantly positive and economically meaningful impact on acquirers' announcement returns. To address potential endogeneity concerns, we employ the population's media age difference of country pairs as an instrumental variable for social connectedness and confirm the same conclusion. We further validate the main finding by altering sample compositions, using different announcement return measures, and incorporating additional fixed effects. Then we show that social connectedness improves acquirers' announcement returns through an information dissemination channel. Enhanced information flows enable acquirers to reduce target premiums, increase deal completion rates, and achieve long-term success. At the country level, we report that social connectedness increases the volume of cross-border M&As. This effect is amplified for country pairs with greater political disagreement, larger time zone differences, and greater bilateral trust but attenuated for country pairs within the same Customs Union. Finally, we document a positive effect of social connectedness on acquirers' announcement returns in the context of U.S. domestic M&As. However, this effect is reduced when the target firm is located in a financial hub city, where information flows more easily.

Although social connectedness between countries is generally thought to change minimally over time, a limitation of the Social Connectedness Index (SCI) is that it provides a time-invariant snapshot based solely on data from 2020. Future studies could focus on developing more dynamic methods to better capture and analyze social connectedness across countries over time.

Appendix

Table A1-1 Variable definitions and sources

Variable	Definition	Source
Dependent		
$CAR_{[-1,+1]}$	Cumulative abnormal return of acquirer's stock in the three-day announcement period (-1, +1) where day 0 is the announcement day. The abnormal return is calculated through a market model with [-240, -41] window	Datastream
$ALT\_CAR_{[-1,+1]}$	Cumulative abnormal return of acquirer's stock in the three-day announcement period (-1, +1) where day 0 is the announcement day. The abnormal return is calculated through a market model with [-240, -21] window	Datastream
$CMR_{[-1,+1]}$	Cumulative market-adjusted return of the acquirer's stock in the three-day announcement period (-1, +1) where day 0 is the announcement day. The return is subtracting the acquirer country's market return from the stock return	Datastream
$CAR_{[-2,+2]}$	Cumulative abnormal return of acquirer's stock in the five-day announcement period (-2, +2) where day 0 is the announcement day. The abnormal return is calculated through a market model with [-240, -41] window	Datastream
Premium 1-Week	Deal share price divided by target stock price 1 week before the announcement date	Thomson One
Premium 4-Week	Deal share price divided by target stock price 4 weeks before the announcement date	Thomson One
Completion	Dummy variable that equals one if the deal is complete, and zero otherwise	Thomson One
CompletionW	Dummy variable that equals one if the deal is complete, and zero if withdrawn	Thomson One
BHAR[0,36]	Buy-and-hold abnormal return of the acquirer firm in the 36-month window after the announcement date	DataStream
BHAR[0,24]	Buy-and-hold abnormal return of the acquirer firm in the 24-month window after the announcement date	Datastream
ΔROA[0,3]	The increase in the acquirer's industry-adjusted ROA 3 years after the announcement relative to the announcement year	Datastream
ΔROA[0,1]	The increase in the acquirer's industry-adjusted ROA 1 year after the announcement relative to the announcement year	Datastream
Time-to-Close	Calendar days from the date of announcement to the closure of a deal	Thomson One
Fee	Combined total fees in million USD paid by acquirer and target	Thomson One
Number	The natural logarithm of one plus the total number of M&A between the acquirer country and target country	Thomson One
Value	The natural logarithm of one plus the total value of M&A between the acquirer country and target country	Thomson One
Pair-level		
SCI	The natural logarithm of the Social Connectedness Index (SCI) between the acquirer and target countries	Humanitarian Data Exchange[11]
Geo Distance	The natural logarithm of geographical distance (in Kilometers) between the acquirer and target countries	CEPII[12]
Share Border	Dummy variable that equals one if the acquirer country and target country share a common border, and zero otherwise	CIA Factbook[13]
Same Law	Dummy variable that equals one if the acquirer country and target country have the same law origin, and zero otherwise	CEPII
Same Language	Dummy variable that equals one if the acquirer country and target country have the same official language, and zero otherwise	CEPII

[11] Available at : https://data.humdata.org/dataset/social-connectedness-index.
[12] Centre D'Etudes Prospectives et D'Informations Internationales. Available at: http://www.cepii.fr/CEPII/fr/bdd_modele/bdd_modele.asp
[13] Central Intelligence Agency World Factbook. Available at: https://www.cia.gov/the-world-factbook/

Same Religion	Common religion index between the acquirer country and target country	CEPII
Cultural Distance	Hofstede's four-dimension cultural distance between the acquirer and target country	Hofstede Insight[14]
Political Discord	Voting disagreement constructed by Voeten and Merdzanovic (2009), the data set containing the roll call votes of all countries in the U.N. General Assembly over the entire sample period	UN General Assembly Voting Data[15]
Signed Treaty	Dummy variable that equals one if the acquirer country and target country signed a bilateral investment treaty, and zero otherwise	UNCTD[16]
Trade Flow	The natural logarithm of the bilateral trade (in USD) in a year between the acquirer and target countries	CEPII
Δ*GDP Growth*	The difference in GDP growth rate between the acquirer and target countries	World Bank
Δ*GDP per capita*	The difference in the logarithm of GDP per capita between the acquirer and target countries	World Bank
Δ*GDP*	The difference in the logarithm of GDP between the acquirer and target countries	World Bank
Δ*Openness*	The difference in openness between the acquirer and target countries. Openness is the ratio of a country's total imports and exports to GDP	World Bank
Δ*Exchange*	The difference between the acquirer and target countries in the annual average exchange rate's growth rate (local currency to USD) relative to the year before an M&A announcement	World Bank
Δ*Business Env*	The difference in the business environment between the acquirer and target countries, proxied by the business freedom score	Index of Economic Freedom[17]
Δ*Institution Quality*	The difference in institution quality between the acquirer and target countries, proxied by the overall score	Index of Economic Freedom
Δ*Disclosure Quality*	The difference in disclosure quality index between the acquirer and target countries	La Porta *et al.* (1998)
Deal-level		
Deal Value	The logarithm of the deal transaction value (million USD)	Thomson One
Tender Offer	Dummy variable that equals one if the merger is a tender offer, and zero otherwise	Thomson One
Financial Acquirer	Dummy variable that equals one if the acquirer is a financial firm, and zero otherwise	Thomson One
Attitude	Dummy variable that equals one if the attitude is friendly, and zero otherwise	Thomson One
Firm-level		
Leverage	The ratio of acquirer's liability to total assets (in percentage)	DataStream
ROA	The ratio of acquirer's net income to total assets (in percentage)	DataStream
Size	The logarithm of acquirers' total assets (million USD)	DataStream
Others		
Δ*Age*	The absolute difference in the population's median ages between the acquirer and target countries in a given year	UN's World Population Prospects 2022[18]
Non-Target Country Board	Dummy variable that equals one if no board members in the acquirer firm originate from the target country, and zero otherwise	BoardEX
Non-Target Country IO	One minus acquirer's institutional ownership composition originating in the target country	Thomson/Refinitiv
Non-Public Target	Dummy variable that equals one if the target firm is a non-public firm, and zero otherwise	Thomson One

[14] Available at: https://www.hofstede-insights.com/
[15] Voeten, E and A. Merdzanovic (2009) '*United Nations General Assembly voting data*', Available at: https://dataverse.harvard.edu/dataverse/Voeten
[16] United Nations Conference on Trade and Development. Available at: https://unctad.org/search?keys=investment+treaty
[17] Available at: https://www.heritage.org/index/explore
[18] United Nations, Department of Economic and Social Affairs, Population Division (2022). World Population Prospects 2022, Online Edition.

Common Customs Union	Dummy variable that equals one if the acquirer and target countries are members of the same Custom Union, and zero otherwise.	World Trade Organization and Website of the Custom Unions
ΔUTC	The difference in Coordinated Universal Time between the acquirer and target countries	CIA Factbook
Trust	Guiso's Trust Index between the acquirer and target countries	Guiso *et al*. (2009)
U.S. domestic level		
PW_SCI^{City}	The population-weighted SCI between the acquirer and target cities	Self-calculation
EW_SCI^{City}	The equal-weighted SCI between the acquirer and target cities in the U.S.	Self-calculation
$\Delta GDP\ Growth$	The difference in GDP growth rate between the acquirer and target cities	US Cities Database[19]
$\Delta GDP\ per\ capita$	The difference in the logarithm of GDP per capita between the acquirer and target cities	US Cities Database
ΔGDP	The difference in the logarithm of GDP between the acquirer and target cities	US Cities Database
$Culture\ Distance^{Turst}$	The cultural difference in the dimension of trust between the acquirer and target Census divisions. The natural logarithm of one plus the absolute difference between acquirer and target.	World Values Survey[20]
$Culture\ Distance^{Individualism}$	The cultural difference in the dimension of individualism between the acquirer and target Census divisions. The natural logarithm of one plus the absolute difference between acquirer and target.	World Values Survey
$Culture\ Distance^{Hierarchy}$	The cultural difference in the dimension of hierarchy between the acquirer and target Census divisions. The natural logarithm of one plus the absolute difference between acquirer and target.	World Values Survey
Same State	Dummy variable that equals one if the acquirer and target are in the same state, and zero otherwise	Thomson One
Geo Distance	The natural logarithm of geographical distance (in Kilometers) between the acquirer and target cities.	US Cities Database
Financial Hub	Dummy variable that equals one if the target city is a financial hub, and zero otherwise	Global Financial Centres Index 32[21]

[19] Available at: https://simplemaps.com/data/us-cities
[20] Available at: https://www.worldvaluessurvey.org/
[21] Available at: https://en.cdi.org.cn/images/research/gfci/GFCI32.pdf

2. Remote or Face-to-Face: CEO Interviews and Investor Disagreement

Abstract

This study examines the financial implications of CEOs' information disclosure modalities. Using a sample of televised media interviews with public firm CEOs in the United States on CNBC, we find that compared to face-to-face interviews, remote interviews are associated with larger investor disagreement around the interview date. The lack of medium richness, specifically non-verbal cues in remote interviews, can lead to increased dispersion in information interpretation among investors, resulting in larger investor disagreement around the interview date. This effect is mitigated when the information recipient has a high degree of familiarity with CEOs and is amplified for firms with broader public attention, larger analyst following, and institutional holdings as well as when interviews contain more information. Overall, our study underscores the significant role of CEOs' disclosure mediums in shaping investors' interpretation of information delivered by CEOs.

Keywords: CEO interview; information disclosure; investor disagreement; non-verbal cues

2.1 Introduction

CEOs' public disclosures and media appearances serve as influential communication channels for firm-specific information. These interactions contribute to the formation of sentiments and expectations of investors, analysts, regulators, and other stakeholders, thereby shaping financial outcomes (Elliott *et al*., 2012; Kuhnen and Niessen, 2012; Blankespoor *et al*., 2017). Further, the behavior exhibited by CEOs, such as tone, beauty, and non-verbal cues, are subject to market scrutiny and interpretation, potentially leading to material financial implications (Mayew and Venkatachalam, 2012; Kim, 2013; Blankespoor *et al*., 2017; Cao *et al*., 2020; Li *et al*., 2020; Harrison *et al*., 2020; Hsieh *et al*., 2020; Momtaz, 2021; Huang *et al*., 2023). Consequently, an investigation into CEOs' communications on financial performance is of significant academic interest and practical importance in financial studies. In our study, we focus on CEOs' communication modalities, such as face-to-face and remote, and their differential market responses.

Following the COVID-19 pandemic, the importance of remote communication has grown exponentially, extending its influence into both practical and academic spheres. Emerging literature explores the effectiveness of remote communications in financial activities, such as shareholding meetings (Brochet *et al*., 2021) and board meetings (Cai *et al*., 2023). However, our understanding of the financial impacts of CEO communication modalities, specifically remote versus face-to-face, remains limited. Various factors could account for the potential financial consequences. For example, the quality and reception of information may vary with different communication modalities. Non-verbal cues, particularly prevalent in face-to-face interactions, can influence investor interpretations, while technological issues inherent to remote communication may affect the information's clarity, thus shaping market responses.

CEOs' information disclosure modalities can influence investor disagreement around the announcement of the interview. Investor disagreement has long been central to trading in financial markets (Cookson and Niessner, 2020). Leading theories document two key sources of disagreement: investors' different information sets and different information interpretations (Hong and Stein, 2007; Cookson and Niessner, 2020). When a new disclosure of the CEO comes, investors access and interpret this information. The CEO's communication modality can influence the accuracy, clarity, and perception of the information disseminated. In face-to-face interactions, non-verbal cues such as body language and facial expressions contribute to reducing ambiguity and interpretation discrepancies. However, the lack of such cues in remote communication potentially leads to divergent interpretations, thereby escalating investor disagreement. In addition to this information-related influence, the technological issues in remote communications can affect CEOs' expression efficiency, leading to the information recipient's divergent perceptions of CEOs. Understanding the link between CEO communication modalities and investor disagreement can shed light on the mechanisms through which corporate communications influence financial market outcomes.

Following Kim (2013) and Banker *et al*. (2021), we use a sample of CEO interviews on CNBC to empirically examine the impact of remote or face-to-face interviews on investor disagreement. As a leading business and financial news television channel in the United States, CNBC has become a major venue for companies to share information. CNBC interviews CEOs regularly regarding their business and performance. Their most recent appearances can be seen in the interviews. CEOs are engaged in interviews by journalists either remotely or through face-to-face interactions. During remote interviews, conducted via video calls, the information recipient views CEOs directly addressing the cameras, with their faces and upper bodies prominently displayed. Conversely, face-to-face interviews involve CEOs communicating in person with journalists within the broadcast environment of CNBC's studio. Our main sample consists of 868 interviews, 272 unique firms, and 282 unique CEOs during the period from January 2017 to March 2020. The numbers of remote interviews and face-to-face interviews are 393 and 475, respectively. Due to the outbreak of COVID-19, all the interviews are forced to be remotely conducted from the end of March 2020. We construct a post-shock sample from April 2020 to December 2020. This sample, jointly with the main sample, allows us to perform a difference-in-differences analysis in the following section.

We first identify the determinants of remote interviews. CEOs may save excessive travel time and money costs by attending remote interviews (Cai *et al*., 2023). CEOs situated far from the interview location are more likely to select remote interviews to avoid the time and resource expenditure associated with travel. Additionally, the busyness of CEOs, characterized by their numerous responsibilities, further facilitates their choices of remote interviews. The flexibility of remote interviews allows them to seamlessly integrate these sessions into their tight schedules without the need to allocate additional time for commuting. Thus, both the challenges posed by distance and the high demand for their time contribute to a preference for remote interviews among CEOs, and thereby we predict that the location and busyness of CEOs are associated with their remote attendance. Besides, face-to-face interviews allow for more immediate feedback and can help to build stronger relationships between people. CEOs who currently have limited relationships with CNBC tend to prefer face-to-face interviews. This can potentially facilitate the establishment of more robust relationships with the information recipient and the journalistic team. To empirically test the conjecture, we employ three variables. *CEO distance* is the logarithm of one plus the distance (in km) between the states of headquarters of the firm and the CNBC live studio. The dummy variable, *CEO busy*, indicates whether the CEO is also a board member. The dummy variable, CEO relation, indicates whether the CEO is first interviewed by CNBC. After controlling for a host of firm-level, CEO-level, interview video-level characteristics and fixed effects (i.e. year and industry), our findings suggest that the interviews are more likely to be remotely conducted if the CEO is geographically distant, busy, or have a limited relationship with the CNBC team.

Next, we examine the market reactions to remote and face-to-face interviews. We find that remote interviews significantly increase investor disagreements on firms around the interview date. The measure of investor disagreement is *ABS*, the daily average bid-ask spreads during a [0, 2] day window around the interview date minus the daily average bid-ask spreads during the [-55, -6] day window prior to the interview date. Our results are robust for various measures of investor disagreements, calculated from bid-ask spreads estimated from different windows, trading volumes (Brochet *et al*., 2020; Cookson and Niessner, 2020), and abnormal stock price volatility (Landsman *et al*., 2012). Next, the baseline findings are robust when using granular quarter fixed effects. We next consider the interview topics. Prior literature often focuses on the market response to an announcement regarding earnings or stocks. We divide our interviews into two groups based on their topics: discussing earnings or stocks for their firms; and discussing the macro-economy or external events related to their firms or industries. Our baseline findings hold when the topic fixed effects are included. We also test the baseline regression within each group. The results hold. Furthermore, our results are unchanged when we combine the main sample and the post-shock sample. Finally, we control the pre-interview disagreement, where the results are unchanged. To measure the pre-interview disagreement, we include 1-month and 1-quarter lagged average daily trading volumes and 1-month lagged abnormal log trading volume. Overall, our baseline findings are robust to alternative measures of dependent variables, alternative samples, and alternative models.

Our findings have potential endogeneity concerns, such as omitted variable bias and selection bias. Omitted variable bias occurs when other variables simultaneously impact CEOs' selections of remote interviews and market reactions are not adequately included in the regression. Selection bias arises from the non-random decision of CEOs to choose between remote and face-to-face interviews. This decision is likely influenced by unobserved factors correlated with the firms' or CEOs' underlying conditions, which may drive the market reactions. We employ a difference-in-differences (DiD) approach, a Heckman treatment effect model, and a propensity score matching (PSM) approach to alleviate endogeneity concerns. In our DiD approach, the COVID-19 pandemic forced interviews to be remotely conducted after March 2020. We use pre-shock (baseline) and post-shock samples. The control group consists of CEOs and firms interviewed face-to-face in both the pre- and post-shock periods. The treatment group comprises CEOs and firms interviewed remotely in the pre-shock period and face-to-face in the post-shock period. If the impact of remote interviews holds, we will observe an increase in investor disagreement within the treatment group. The results are consistent with our hypothesis.

Heckman treatment effect model has two steps. First, we employ a probit model and instrumental variables to estimate the inverse Mills Ratio (IMR). The instrumental variables for remote interviews include *CEO distance*, *CEO busy*, and *CEO relation*, which are identified as determinants of remote interviews in the previous section. These variables are very likely to serve the exclusion condition as well. CEOs' location, dual roles, and relation to media are less likely to be directly perceived thus leading to different market reactions around the interview date. In the second step, we incorporate the IMR into the baseline regression. The positive impact of remote interviews on investor disagreement remains unchanged. The Heckman treatment effect model indicates that the baseline finding is less likely to be affected by self-selection bias. PSM approach balances the distribution of observed characteristics across the remote interviews and face-to-face interviews, thereby minimizing the impact of confounding variables that could affect the outcome. The results provide further supporting evidence for our baseline findings. Overall, the endogeneity tests suggest that our baseline findings are less likely to be driven by endogeneity problems.

Then we examine how remote interviews are associated with a larger investor disagreement. Theories suggest that investors' differential beliefs stem from both pre-announcement beliefs and the interpretation of the new announcement (Kim and Verrecchia, 1991; Dontoh and Ronen, 1993; Bamber *et al.*, 2011). Our findings suggest that the impact can be attributed to increased diversity in the interpretation of the information during the interview. In a remote interview, the absence of certain non-verbal cues and potential adaptability constraints give rise to varied interpretations of the same information. Such interpretative diversity can lead to a divergence in investor sentiments and expectations, resulting in increased investor disagreement. We employ multiple methods to identify the information interpretation channel. First, information recipients' familiarity with the CEO mitigates uncertainty and enhances the clarity of the communicated information, reducing the scope for divergent interpretations. We find a smaller impact of remote interviews on investor disagreement when information recipients' familiarity with the CEOs is higher. Second, higher public attention to a firm amplifies the dissemination and discussion of the information, leading to varied interpretations and opinions among a broader information recipient. Using firms' size and Google Trend Index as measures of public attention, we find a stronger impact of remote interviews on investor disagreement. Third, firms with larger analyst following and institutional holding attract greater attention and scrutiny from the public and stakeholders, which leads to varied interpretations of the information presented. Consistent with this conjecture, we find a greater impact of remote interviews when firms have larger analyst following or institutional holdings. Finally, more material or substantive information presented results in heightened disagreement among investors. This is likely because substantial information provides more content for analysis and interpretation, leading to a wider range of opinions and expectations. In addition to different information interpretations, different information sets also lead to investor disagreement (Cookson and Niessner, 2020). We reject an alternative explanation that remote interviews affect investor disagreement by creating new information.

Our contribution is twofold. First, our study enhances the body of research concerning CEO disclosure and its financial implications. Traditional studies primarily focus on the impact of verbal content conveyed by CEOs. However, emerging studies highlight the significance of CEOs' non-verbal cues. Pioneering research by Mayew and Venkatachalam (2012) indicates the informative nature of managers' vocal cues. Subsequently, managers' facial cues are found to influence firm outcomes (He *et al.*, 2018; Hsieh *et al.*, 2020; Flam *et al.*, 2020). To our knowledge, our study is the first to explore the market reactions to CEOs' communication modalities. The COVID-19 pandemic has catalyzed the rise of remote communication across multiple contexts. We contribute to this burgeoning field by identifying the informational and perception-based influences of CEO communication modalities on investor disagreement. These insights carry significant real-world implications, particularly in informing the ongoing debate about the merits of remote versus face-to-face interaction.

Second, our study contributes to the literature on investor disagreement. Although investor disagreement is acknowledged as fundamental in financial markets, existing literature primarily focuses on its financial consequences. In contrast, these are less known about the factors leading to investor disagreement (Cookson and Niessner, 2020). Theoretical frameworks propose that differences in formation sets and different information interpretations are the main sources of disagreement (Hong and Stein, 2007; Cookson and Niessner, 2020). Our empirical findings corroborate this theoretical perspective by suggesting that CEO communication modalities influence how investors interpret and perceive CEO disclosures.

The rest of the chapter is organized as follows. Section 2.2 introduces the related studies and hypotheses development. Section 2.3 introduces our data and sample. Section 2.4 reports the main results. In Section 2.5, multiple approaches are employed to address the endogeneity problems. In Section 2.6, we explore the channels. Section 2.7 reports the results of the post-interview analysis. Section 2.8 concludes the paper.

2.2 Literature Review

2.2.1 CNBC Interview

CNBC (Consumer News and Business Channel) is an American commercial television business news channel. It is a major business news network in the United States and worldwide, reaching millions of households. CNBC's coverage spans various sectors of business, finance, technology, and the economy. This broad coverage enables them to cater to diverse information recipients with varying interests, ranging from individual investors to corporate leaders. Prior literature suggests that the market reacts to the information on CNBC. Busse and Green (2002) investigate the efficient market hypothesis using CNBC's Morning Call and Midday Call segments. The study leverages real-time data from these segments, which broadcast analysts' views on individual stocks during market hours, to explore how quickly and effectively stock prices incorporate new information. Chen *et al*. (2011) examine the differing reactions of stock and option markets to the arrival of noisy information, using CNBC's Mad Money recommendations as a case study. The show's large viewership and the immediate availability of its recommendations provide a unique opportunity to observe market reactions in near real-time. Engelberg *et al*. (2012) examine the effects of media-driven attention shocks on stock prices, using CNBC's Mad Money as a primary data source. Using the dataset of 1,149 first-time buy recommendations aired between July 28, 2005, and February 9, 2009, the study documents that stock recommendations lead to large overnight returns that subsequently reverse over the next few months.

CEOs regularly participate in interviews on CNBC, a platform that facilitates additional disclosure of information to the stakeholders. These discussions often touch upon topics such as earnings forecasts, industry projections, and significant corporate events. For example, Marvell CEO Matt Murphy was invited to talk about their earnings and AI growth in August 2023. The CEO Matt Murphy discusses the firm's robust performance in the second quarter and attributes to the rapid growth in its data center and artificial intelligence deployments. CEO interviews on CNBC have been utilized as a novel dataset to examine the financial consequences of the characteristics and information conveyed by these CEOs. Kim (2013) investigates the concept of self-attribution bias (SAB) in CEOs and its implications for corporate decision-making and market outcomes. This study focuses on the cognitive biases that influence executive behavior, particularly overconfidence. The study uses CEO interviews broadcasted on CNBC as a novel dataset to measure and analyze the self-attribution bias of CEOs. The method involves parsing the transcripts of 6,931 CEO interviews aired on CNBC from 1997 to 2006. By examining CEOs' causal statements, particularly those that follow the words "because" or precede "hence", CEOs who frequently attribute positive outcomes to their own actions, rather than external factors like the economy or industry trends, exhibit higher levels of SAB. It documents a non-linear relation between SAB and the market response to acquisition announcements. Kamiya *et al*. (2019) explore the relationship between CEO facial masculinity, as measured by facial width-to-height ratio (*fWHR*), and the riskiness of corporate financial and investment policies. focus on CEOs who appear on CNBC between 1997 and 2009. CEOs' images collected from CNBC interviews effectively address the challenge of obtaining a large, diverse sample of CEO photographs that could be analyzed for facial metrics. The study finds a significant positive association between *fWHR* and corporate risk-taking. CEOs with higher *fWHR*, indicative of higher testosterone levels, are associated with greater stock return volatility, higher leverage ratios, more frequent acquisition, and larger Vega of compensation. Flam *et al*. (2020) examine the degree of investor response to CEO interviews on CNBC, suggesting that investors negatively react to CEOs' facial expressions of anger. This effect is strong enough to nullify the benefits of positive messaging from journalists.

Huang *et al*. (2023) explore how first impressions of entrepreneurs, as conveyed through their facial traits during televised pitches, influence angel investors' decisions. The study utilizes video stills from two prominent sources: the Shark Tank TV show and the TechCrunch Startup Battlefield competitions. CNBC, through its broadcast of Shark Tank episodes, is one of the platforms where entrepreneurs pitch their business ideas to a panel of angel investors in front of a national audience. The study finds that first impressions, particularly those related to charm and perceived general ability, significantly influence the likelihood of an entrepreneur receiving an investment offer or winning a competition round. The study also reveals that while charm may increase the probability of receiving an initial offer, it does not necessarily correlate with long-term business success. Banker *et al*. (2024) analyze how investors respond to CEOs' facial expressions, particularly the asymmetry between the left and right sides of their faces during video interviews. This study employs CNBC interviews as a critical data source to investigate whether these facial cues, especially dynamic hemifacial asymmetry *(HFAsy*), influence market reactions and investor behavior. The results suggest a negative relationship between *HFAsy* and market reactions. Specifically, the study finds that higher levels of *HFAsy* in CEOs during earnings interviews are associated with negative cumulative abnormal returns (CARs) over the three-day window surrounding the interview. This suggests that investors perceive CEOs with higher *HFAsy* as less trustworthy, leading to adverse market reactions, particularly when these CEOs announce favorable earnings news. The study also documents a positive association between *HFAsy* and abnormal bid-ask spreads, indicating higher investor disagreement for firms led by high *HFAsy* CEOs.

Overall, CNBC has emerged as a critical resource in financial research, particularly in studies examining the influence of media on market dynamics and investor behavior. CNBC's real-time broadcasting provides researchers with a unique and rich dataset to analyze how information dissemination through widely viewed media platforms affects market outcomes. CEO interviews become a tool for capturing CEOs' characteristics unobserved in traditional datasets. We can observe CEOs' communication styles and their subsequent market impact, which makes CNBC an ideal support for our research.

2.2.2 Non-Verbal Cues

Psychological studies divide human interactions into two ways: verbal interaction and non-verbal interaction (Duncan, 1969). Verbal interaction is the use of words to convey information, while non-verbal interaction is expressed by body language, facial expressions, gestures, voice, proxemics, eye gaze, haptics, appearance, and artifacts. Verbal information and non-verbal information are perceived and interpreted by receivers during verbal interaction and non-verbal interaction, respectively.

Traditional research in accounting and finance primarily focuses on verbal behaviors or verbal information, such as financial reports, conference presentations, press releases, and news, which are delivered through texts. The verbal information has been widely found to be related to firm fundamentals and investor behaviors. However, according to psychological studies (Birdwhistell, 1970), two-thirds of all meaning in human interactions is derived from non-verbal behaviors. Recent literature in accounting and finance finds the importance of the information contained in non-verbal behaviors including vocal and facial behaviors. Mayew and Venkatachalam (2012) explore the role of non-verbal cues, particularly vocal expressions, in conveying information about a firm’s future performance. The study specifically focuses on how the emotional states of CEOs, as inferred from their vocal cues during earnings conference calls, influence market perceptions and predict future firm outcomes. The authors argue that vocal cues, which reflect a manager’s affective states, such as excitement, anxiety, or stress, contain valuable information that goes beyond spoken words. These non-verbal cues can reveal insights into a manager’s confidence or concerns about the firm’s future that may not be explicitly stated in the verbal content of the conference call. first found that managers’ vocal cues are informative, which extended the finance and accounting literature from verbal information to non-verbal information. The study employs Layered Voice Analysis (LVA) technology to measure the emotional content of managers’ voices during these calls. This software analyzes various vocal attributes to detect emotional states such as stress, cognitive dissonance, and excitement. The findings reveal that the stock market responds to both positive and negative affective states conveyed through vocal cues. Positive emotional expressions are associated with immediate positive stock returns, while negative emotions correlate with poorer long-term firm performance.

Since the study by Mayew and Venkatachalam (2012), growing research has focused on the impacts of non-verbal cues, among which facial cues have drawn the most attention from researchers. Blankespoor *et al*. (2017) investigate the role of non-verbal cues, such as gestures, body movement, facial expressions, and vocal qualities, in shaping investor perceptions and influencing firm valuation during IPO roadshows. These non-verbal cues are believed to convey critical information about a CEO's competence, trustworthiness, and overall managerial quality, which investors then integrate into their valuation of the firm. Using a "thin slice" approach, the study extracts 30-second content-filtered video clips from IPO roadshow presentations, ensuring that only the CEOs' non-verbal cues are available for evaluation, with the verbal content made indiscernible. Then, Amazon's Mechanical Turk (MTurk) is used to assess these video clips. MTurk participants rate the CEOs on perceived competence, trustworthiness, and attractiveness using a seven-point Likert scale. These ratings are averaged to create a composite measure of overall perception for each CEO, which is then linked to various stages of IPO valuation, including the proposed price, offer price, and the closing price after the first day of trading.

Choudhury *et al*. (2019) explore both verbal and non-verbal communication cues from CEOs. To analyze these non-verbal cues, the study employs a convolutional neural network (CNN)-based machine learning algorithm to code facial expressions from video interviews of CEOs. The algorithm categorizes facial expressions into eight distinct emotions: anger, contempt, disgust, fear, happiness, neutral, sadness, and surprise. This approach allows the researchers to quantify the intensity and frequency of these emotions as they appear on the CEO's face during the interviews collected from Harvard Business School's Creating Emerging Markets project. The study identifies five distinct communication styles based on the analysis of both verbal and non-verbal cues: Excitable, Stern, Dramatic, Rambling, and Melancholy. One of the key findings is that CEOs with a "Dramatic" communication style, characterized by a wide range of facial emotions and fluctuating verbal sentiment, are less likely to pursue major acquisitions. This suggests that non-verbal cues can significantly influence strategic decision-making. Cade *et al*. (2020) explore the impact of nonverbal cues displayed by CEOs during video disclosures on investor perceptions and judgments. The study emphasizes how visual and vocal nonverbal cues, including facial expressions, body language, and tone of voice, can significantly influence investors' reactions to forward-looking information. The study employs two experimental designs to investigate the impact of nonverbal cues on investor judgments. The authors created video disclosures where a professional actor, playing the role of a CEO, was instructed to deliver the same verbal content while exhibiting different nonverbal cues—either conveying certainty or uncertainty. The results reveal an asymmetric reaction to nonverbal cues: while investors did not react more positively to video disclosures featuring a CEO displaying nonverbal cues of certainty compared to written disclosures, they reacted significantly more negatively when the CEO displayed nonverbal cues of uncertainty. This suggests that investors are particularly sensitive to cues of uncertainty, which can undermine their confidence in the firm's future prospects and lower their valuation assessments.

Davila and Guasch (2021) focus on the role of body language in managerial communication, particularly in the context of corporate financial presentations. Their study highlights the under-researched area of body language, emphasizing its impact on the perception of managers during presentations and its subsequent effect on firm outcomes. The authors argue that body language, when combined with other non-verbal cues such as tone of voice and facial expressions, significantly influences investor perceptions and decision-making. Further, Barcellos and Kadous (2022) investigate the impact of nonnative accents on investment decisions, particularly in the context of earnings conference calls. The study documents that nonnative accents, a subtle yet significant non-verbal cue, can trigger stereotypes related to social status and intellectual ability. These stereotypes are often in conflict with the high-status, dominant image typically associated with CEOs, leading to a cognitive dissonance that investors must reconcile. Rennekamp *et al*. (2022) explore non-verbal cues within earnings conference calls, specifically analyzing the engagement levels between managers and analysts. They suggest that engagement often reflected through verbal coordination, can serve as a proxy for understanding the importance of the discussed topics. This study posits that non-verbal signals, alongside verbal ones, contribute to how market participants interpret and integrate information during these calls. Peng *et al*. (2022) investigate how the facial traits of CEOs, as perceived through their public appearances, influence investor perceptions and market outcomes. The study documents that non-verbal cues conveyed through facial expressions, such as perceived competence and trustworthiness, play a significant role in shaping investor judgments. These impressions can drive firm valuation and affect market performance, underscoring the power of non-verbal cues in financial markets.

In summary, the expanding research in the field consistently demonstrates the significant influence of non-verbal cues on financial outcomes.

2.2.3 Remote vs. Face-to-Face Interviews

Remote communication is increasingly popular in business and daily life. Recent studies have documented the different influences of remote and face-to-face communication channels in business activities (Brochet *et al*., 2023; Cai *et al*., 2023). Brochet *et al*. (2023) examine the rise of virtual shareholder meetings (VSMs) and their impact on shareholder engagement and corporate transparency. The authors analyze both the voluntary adoption of virtual meetings before the COVID-19 pandemic and the forced adoption due to the pandemic. Virtual meetings are typically motivated by cost savings and increased shareholder participation. These meetings are generally shorter, with less frequent and less detailed business presentations compared to face-to-face meetings. This trend is more pronounced among voluntary adopters. The study finds no evidence that firms use virtual meetings to avoid shareholder scrutiny, and the reduced activity in virtual meetings does not lead to a loss of information content. Cai *et al*. (2023) investigate the characteristics and consequences of remote board meetings in Chinese firms, focusing on their impact on corporate governance. Remote board meetings, both synchronous and nonsynchronous, are associated with more objective judgment and improved board monitoring effectiveness. These meetings are viewed as a viable alternative to face-to-face interactions without compromising governance quality. Our paper contributes to this emerging stream of literature by focusing on CEOs' interviews, which is a widely received information disclosure method. CEOs can attend the interviews remotely or face-to-face. In remote interviews, CEOs talk with journalists through video calls. In face-to-face interviews, CEOs talk with the journalists in the living studio. We investigate how markets differently react to these two communication channels.

The decision to conduct remote interviews, as opposed to face-to-face interviews, is influenced by a variety of factors, particularly those related to cost, time efficiency, and strategic objectives. Prior research suggests that remote interviews offer significant advantages in terms of cost reduction and flexibility (Cai *et al*., 2023). These benefits are particularly relevant for high-profile individuals such as CEOs, whose schedules are often constrained by multiple demands on their time, including travel and participation in various corporate activities. One of the primary determinants of remote interviews is the geographic distance between the CEO and the interview location. The further the CEO is from the interview site, the higher the time and travel costs. CEOs with demanding schedules are likely to prioritize remote interviews as they allow for more efficient time management, enabling them to fulfill their numerous obligations. In addition to CEOs' location and busyness, CEOs who have not yet established strong relationships with media outlets may prefer face-to-face interviews to foster a more personal connection with journalists. This personal interaction can be critical for shaping public perception and ensuring that the media accurately conveys the CEO's message. The relationship-building aspect of face-to-face interviews can be particularly important for CEOs looking to establish or enhance their public image. In other words, CEOs who have limited relationships with the media are more willing to develop a robust relationship with the information recipient and the journalist team through face-to-face interviews. We have the following hypothesis H1.

H1: ***CEOs who are geographically distant, busy, and have established relationships with the media are more likely to participate in remote interviews than face-to-face interviews.***

Next, we conjecture that remote interviews can lead to a larger investor disagreement around the interview date. Investor disagreement is central to trading in financial markets (Cookson and Niessner, 2020). It reflects the diversified opinions of investors regarding financial assets, which are related to market inefficiencies that can lead to price discrepancies and opportunities for profitable trade. Theoretical literature explores the sources of investor disagreements. Differences in information sets and differences in information interpretation are the two main sources of investor disagreement (Hong and Stein, 2007). However, we know less empirical evidence of the sources of disagreement (Cookson and Niessner, 2020).

Organizational communication theory suggests that channels with greater "richness" can minimize ambiguity and improve communication efficiency (Daft and Lengel, 1986). This "richness" refers to multiple cues, diverse language, and opportunities for interaction. Skinner (2024) documents that the richness of these channels helps reduce investors' information processing costs. When managers do not match complex information with a rich disclosure channel, the market response to the firm's quarterly disclosures is less pronounced, suggesting that investors struggle to process the information efficiently. Additionally, prior literature discussed above suggests that the non-verbal cues of CEOs matter in the information disclosure process. Face-to-face interviews, characterized by immediate feedback, multiple cues, and natural language, are considered a richer communication channel. Remote interviews, a less rich communication channel, have limitations in providing immediate feedback and transmitting non-verbal cues, such as body language, gestures, proxemics, and haptics. In remote interviews, CEOs usually directly face cameras and display their face and upper body. For example, as shown in Appendix Figure A2-1, CEOs can deliver their information only through linguistic, vocal, and facial expressions. In face-to-face interviews, as shown in Appendix Figure A2-2, CEOs talk with the journalists in the living studio. Information recipients not only observe their linguistic, vocal, and facial expressions but also their gestures, body language, and eye contact. As a result, the accuracy and clarity of CEOs' disclosures in remote interviews may lead to a larger dispersion of the interpretation of the information, resulting in a larger investor disagreement around the interview date. We have the following hypothesis H2.

H2: ***Remote CEO interviews are associated with a larger investor disagreement around the interview.***

2.3 Data

2.3.1 Sample

We collect CEO interview videos by searching 'CEO interview' on the CNBC website.[22] We refine the sample of CEO interviews by implementing the following exclusion criteria: (1) We exclude interviews from firms not publicly traded or not U.S. based; (2) Interviews of non-CEO executives are excluded, as our research focus is on the CEOs; (3)

[22] There are 31,516 interview videos, starting in 2011 and ending in 2021.

We remote interviews where CEOs discuss other firms exclusively as well as financial firms solely discussing their portfolio firms, as these do not provide insights into their own firms; (4) We focus on live interactions and exclude interviews pre-recorded; (5) We exclude instances where there are multiple interviews for the same CEO on the same day, to avoid repetition and potential bias; (6) Phone interviews are removed due to their unique communication characteristics which could complicate the comparison between remote and face-to-face interviews; (7) Lastly, we remove interviews falling in the bottom and top one percentile of video length, to mitigate the impact of outliers.[23] We primarily focus on the interviews starting from 2017, before which the interview frequency is significantly lower. The lower interview frequency may lead to lower investors' attention, leading to the bias of our results.

Our main sample starts in January 2017 and ends in March 2020. The steps reduce the number of interviews to 868 interviews, 272 unique firms, and 282 unique CEOs. The larger number of CEOs than firms means that some firms changed CEOs during the sample period. In the sample, only one CEO for a firm is interviewed on a certain date. There are 475 face-to-face interviews and 393 remote interviews. The numbers of unique CEOs only participating in face-to-face interviews or remote interviews are 131 and 74, respectively. The number of unique CEOs who have participated in both face-to-face and remote is 77. Table 2-1 reports the distribution of interview videos. The interviews from April 2020 to December 2020 are noted as a post-shock sample. Since the end of March 2020, all interviews have been conducted via video calls, because of the outbreak of COVID-19. In the post-shock sample, all interviews are remotely conducted. However, the total number of interviews remains similar to previous years. This sample allows us to perform the

[23] Our main finding still holds without the step (7).

difference-in-differences analysis in the endogeneity tests.

Table 2-1 Distribution of interview types

This table reports the distribution of remote and face-to-face interviews in our sample. The main sample covers the interviews from January 2017 to March 2020. The post-shock sample covers the interviews from April 2020 to December 2020. The number of interviews in each dimension is reported.

	Pre-Shock					Post-Shock	
	2017	2018	2019	Jan2020 to Mar2020	Total	Apr2020 to Dec2020	Total
Remote	97	127	125	44	393	249	642
Face-to-face	107	156	175	37	475	0	475
Total	204	283	300	81	868	249	1,117

2.3.2 Variables

We define an interview as a remote interview if it is conducted via CEO video calls. Conversely, face-to-face interviews indicate CEOs interacting directly with journalists in the CNBC live studio. We use an indicator variable at the interview level, *Remote*, to denote the interview types. The variable equals 1 if the interview is remotely conducted, and 0 otherwise.

We primarily measure investor disagreement around the interview date by the abnormal bid-ask spreads. The variable *ABS* is the daily average bid-ask spreads during a [0, 2] day window around the interview date minus the daily average bid-ask spreads during the [-55, -6] day window prior to the interview date. For robustness, we use alternative measures for investor disagreement, which are introduced in the following Section 2.4.3.

Firm-level, CEO-level, and interview video-level variables are included to capture the characteristics of the firm, CEO, and interview, respectively. Following prior studies, firm-level variables measure a firm's cumulative abnormal return during the past month (*Recent return*), return-on-asset ratio (*ROA*), Book-to-market ratio (*Book-to-Market*), firm size (*Size*), leverage ratio (*Leverage*), loss in earnings (*Loss*) at the most recent quarter-end, and analyst coverage (*Analyst*) at the most recent fiscal year-end prior to the interview. These financial characteristics can have an impact on the firm financial outcomes. CEO-level variables include *CEO Age*, *CEO Gender*, and *CEO Edu*, measuring the age, gender, and education level of CEOs, respectively. These CEO characteristics have a potential influence on CEO behaviors thereby affecting firm outcomes and the information recipient's perceptions. Therefore, the CEO-level variables are controlled. Interview-level variables include *Video date*, *Video length*, *Video time*, *Negative sentiment*, and *Uncertainty sentiment*, which control the interview characteristics that affect information recipient perceptions and market reactions (Flam *et al*., 2020; Banker *et al*.,2021). *Video date* is the month from the interview month to the current fiscal year-end month. *Video length* measures the length of the videos in seconds of the interview. *Video time* is a dummy variable that equals 1 if the interview is announced in the morning, and 0 in the afternoon. Prior studies document that tones expressed by the management are significantly associated with market reactions (Loughran and McDonald, 2011). Compared to positive tones, negative tones have a more pronounced effect on market reactions, especially among individual investors. *Negative sentiment* measures the verbal sentiment of the interview, which is the difference between the number of negative and positive words, divided by the number of total words. The verbal information is derived from the video subtitles. In addition, we control for *Uncertainty sentiment*, which is the frequency of uncertainty words scaled by the number of total words in the interview. The details of the variables are explained in Appendix A2-2.

2.3.3 Summary Statistics

The summary statistics for the variables in our main sample are reported in Table 2-2 Panel A. The dependent variables and firm characteristics are similar to the prior related studies. In terms of CEO characteristics, the largest before-log age of CEOs is 75, while the smallest is 27. The mean value for *CEO Gender* is 0.067, indicating that the majority of CEOs in our sample are male. The mean value for *CEO Edu* is 0.476, indicating that the number of CEO observations with a master’s degree or above is smaller than those without. In terms of interview video characteristics, the mean value of the *Video date* is 5.915. The minimum value is 0, indicating that some CEOs are interviewed during the fiscal year-end month. The before-log mean value of the length of videos is about 300 seconds (5 minutes). The shortest interview video is about 100 seconds (1.7 minutes), while the longest interview video is about 900 seconds (15 minutes). The mean value of the variable *Video time* is 0.471, indicating that more than half of interview videos are published in the afternoon.

Table 2-2 Summary statistics

Panel A: Descriptive statistics

This table reports the summary statistics for the dependent variables, firm-level characteristics, CEO-level characteristics, and interview video-level characteristics, including the number of observations, mean, standard deviation, 25 percentile, 50 percentile, 75 percentile, minimum, and maximum values.

Variable	N	Mean	SD	p25	p50	p75	Min	Max
Independent								
Remote	868	0.453	0.498	0.000	0.000	1.000	0.000	1.000
Dependent								
ABS	868	0.580	0.922	-0.113	0.283	1.109	-0.452	2.487
ABS[0, 4]	868	0.437	0.772	-0.123	0.198	0.879	-0.473	2.025
ABS[-2, 2]	866	0.344	0.614	-0.095	0.171	0.672	-0.419	1.588
TVOL	866	1.670	2.627	-0.127	0.553	2.514	-0.888	7.518
TVOL[-2, 2]	866	1.125	1.973	-0.164	0.347	1.840	-0.945	5.636
ALTVOL	866	0.526	0.569	0.041	0.418	1.001	-0.246	1.484
ATVOL	866	0.335	0.449	-0.059	0.301	0.713	-0.293	1.055
AVAR	866	0.323	1.266	-0.687	0.322	1.353	-1.648	2.263
Firm controls								
Recent return	868	0.008	0.057	-0.037	0.010	0.051	-0.084	0.097
ROA	868	0.026	0.049	0.004	0.023	0.058	-0.065	0.107
Book-to-market	868	6.379	5.823	1.976	3.936	8.973	1.155	18.660
Size	868	9.847	1.420	8.602	9.882	11.070	7.652	12.020
Leverage	868	0.249	0.144	0.121	0.249	0.371	0.029	0.471
Loss	868	0.206	0.405	0.000	0.000	0.000	0.000	1.000
Analyst	868	1.550	1.472	0	1.946	2.996	0	3.584
CEO controls								
CEO age	868	4.023	0.143	3.951	4.043	4.111	3.332	4.344
CEO gender	868	0.067	0.250	0.000	0.000	0.000	0.000	1.000
CEO education	868	0.476	0.500	0.000	0.000	1.000	0.000	1.000
Video controls								
Video date	868	5.915	3.555	3.000	6.000	9.000	0.000	11.000
Video length	868	5.656	0.492	5.284	5.660	6.038	4.481	6.824
Video time	868	0.471	0.499	0.000	0.000	1.000	0.000	1.000
Negative sentiment	868	-0.012	0.021	-0.024	-0.012	0.000	-0.086	0.080
Uncertainty sentiment	868	0.012	0.009	0.006	0.011	0.016	0.000	0.062
Remote determinants								
CEO distance	857	2.697	1.086	1.511	2.742	3.826	0.000	4.444
CEO busy	866	0.595	0.491	0.000	1.000	1.000	0.000	1.000
CEO relation	664	0.224	0.417	0.000	0.000	0.000	0.000	1.000

Panel B Univariate tests

This table reports the univariate test results for firm, CEO, and interview video-level characteristics between face-to-face interviews and remote interviews, including observation, standard deviation, and mean value. The last column reports the t-statistics for the differences. Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

	Remote Interview			Face-to-Face Interview			Difference
	N	SD	Mean	N	SD	Mean	t-statistics
Market reactions							
ABS	393	1.857	1.061	475	1.269	0.395	6.35***
ABS[0, 4]	393	1.423	0.795	475	1.102	0.282	5.99***
ABS[-2, 2]	393	1.294	0.640	475	1.056	0.274	4.58***
TVOL	393	7.343	3.791	475	5.064	1.532	5.34***
TVOL[-2, 2]	393	5.429	2.569	475	3.911	0.860	5.37***
ALTVOL	393	0.696	0.715	475	0.794	0.429	5.57***
ATVOL	393	0.528	0.462	475	0.559	0.256	5.54***
AVAR	393	1.503	0.573	475	1.487	0.069	4.94***
Firm characteristics							
Recent return	393	0.056	0.003	475	0.057	0.013	-2.52**
ROA	393	0.050	0.031	475	0.047	0.022	2.88***
Book-to-market	393	5.859	6.183	475	5.793	6.541	-0.90
Size	393	1.370	9.762	475	1.458	9.917	-1.60
Leverage	393	0.148	0.247	475	0.142	0.250	-0.29
Loss	393	0.387	0.183	475	0.418	0.225	-1.52
Analyst	393	1.475	1.661	475	1.465	1.459	2.009**
CEO characteristics							
CEO age	393	0.135	4.032	475	0.150	4.015	1.77*
CEO gender	393	0.220	0.051	475	0.272	0.080	-1.71*
CEO education	393	0.501	0.511	475	0.498	0.446	1.91*
Video characteristics							
Video date	393	3.480	6.003	475	3.619	5.842	0.66
Video length	393	0.465	5.618	475	0.512	5.688	-2.07**
Video time	393	0.500	0.468	475	0.500	0.474	-0.16
Negative sentiment	393	0.023	-0.015	475	0.020	-0.010	-3.88***
Uncertainty sentiment	393	0.011	0.012	475	0.009	0.013	-1.21

In Table 2-2 Panel B, we conducted a univariate test between face-to-face interviews and remote interviews. There are 475 face-to-face interviews and 393 remote interviews. In firm characteristics, the firms that are remotely interviewed have significantly lower recent stock performance, higher ROA, and higher analyst coverage. However, the average values of firm size, leverage ratio, and earnings have no significant differences between the two groups. The two groups have significant differences in CEOs' characteristics. CEOs in the remote interview group are older and better educated. CEOs also show a significant gender disparity between the groups, with the proportion of male CEOs being significantly higher in the remote interview group as compared to the face-to-face group. In video characteristics, remote interviews are significantly shorter and deliver more negative sentiments. However, there are insignificant differences in the months to fiscal year-end month, published time, and uncertainty word frequency between the two groups. To capture these characteristics, we include these variables as control variables in the regressions.

2.4 Main Results

2.4.1 Determinants of Remote Interview

To better understand the interview behaviors, we investigate the determinants of a CEO being remotely interviewed. We estimate the probit model of equation (2-1) using our main sample.

$$\begin{aligned} Remote_{ijt} &= \beta_0 + \beta_1 CEO\ distance_{j,t} + \beta_2 CEO\ busy_{i,t} + \beta_3 CEO\ relation_{i,t} \\ &\quad + \beta_4 \chi\_Firm_{j,t} + \beta_5 \chi\_CEO_{i,t} + \beta_6 \chi\_Video_{j,t} + Y + I + T + \varepsilon_{ijt} \quad (2-1) \end{aligned}$$

where $Remote_{ijt}$ is a dummy variable that equals 1 if the interview for CEO i in firm j on interview date *t* is remotely conducted, and 0 otherwise. The key determinants of interest are $CEO\ distance_{j,t}$, $CEO\ busy_{i,t}$, and $CEO\ relation_{i,t}$. $CEO\ distance_{j,t}$ is the distance between the states of headquarters of CEO's firm j and CNBC live studio on date t. $CEO\ busy_{i,t}$ is a dummy variable that equals 1 if the CEO *i* also sits on the board of directors, and 0 otherwise. In regression (2-1), $CEO\ relation_{i,t}$ is a dummy variable that equals 1 if the CEO is interviewed by CNBC for the first time in the last 12 months prior to the interview date, and 0 otherwise.[24] $\chi\_Firm_{j,t}$ are a series of firm characteristics for firm *j* on interview date *t*. $\chi\_CEO_{i,t}$ are a series of CEO characteristics for CEO *i* on interview date *t*. $\chi\_Video_{j,t}$ are a series of interview video characteristics for firm *j* on interview date *t*. *Y* is the year-fixed effect. *I* is the industry-fixed effect. *T* is the topic-fixed effect. We divide interviews into two topic groups: group (1) discloses firm-specific information, such as their firms' earnings, stocks, outlook, business events, and strategies; group (2) discusses macro-economy, industrial outlook, policies, political events, and environments related to their firms. β_0 is the constant. $\beta_1 - \beta_6$ are regression coefficients. ε_{ijt} is the error term.

Table 2-3 reports the results of the probit model of regressions (2-1).[25] Firstly, we separately examine the impact of the determinants, the results of which are reported in columns (1)-(3). In column (1), the regression coefficient for *CEO distance* is positive and statistically significant at a 1% significance level. It suggests that a larger geographic distance to a CNBC studio leads to a higher likelihood that the CEOs are remotely interviewed. In column (2), the regression coefficient for *CEO busy* is positive and statistically significant at a 5% significance level. The results suggest that busier CEOs are more likely to participate in remote interviews. One standard deviation increase in *CEO distance* and *CEO busy* are associated with an average increase in *Remote* of 0.286

[24] Because our sample starts from 2017, the observations for $ceo\_relation_{i,t}$ are omitted in 2017.
[25] The results estimated using the logit model reported in Appendix 3 Table A2 remain similar.

(1.086×0.263) and 0.141 (0.491×0.287), respectively. Given the mean of *Remote* is 0.453, the impact of *CEO distance* and *CEO busy* are economically significant. In column (3), the regression coefficient for *CEO relation* is negative and statistically significant at a 1% significance level. It suggests that CEOs without previous interview experience in CNBC are less likely to participate in remote interviews and more likely to attend face-to-face interviews to establish a relationship with CNBC journalists. This impact is also economically significant. One standard deviation increase in *CEO relation* is associated with a decrease in *Remote* of 0.221 (0.417×0.531). In column (4) and column (5), we include these variables simultaneously, and the results are unchanged. When we further consider the within-topic effect, the results still hold. Overall, these results are consistent with hypothesis *H1* that CEOs who are geographically distant, busy, and have established relationships with media are more likely to participate in remote interviews than face-to-face.

Table 2-3 Determinants of remote interview

This table presents the probit regression (2-1) estimating the determinants of remote interviews. *Remote* is a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. In columns (1), (2), and (3), the independent variables of interest are separately included in the model, *CEO distance*, *CEO busy*, and *CEO relation*, respectively. In column (4), the two variables, *CEO distance* and *CEO busy*, are both included. In columns (5) and (6), all three variables are included. Firm, CEO, and video control variables are consistent. Year fixed effects and industry fixed effects are included. In column (6), we further control the interview topic fixed effect. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Remote (1)	Remote (2)	Remote (3)	Remote (4)	Remote (5)	Remote (6)
CEO distance	0.263***			0.272***	0.300***	0.304***
	(3.219)			(3.337)	(3.403)	(3.479)
CEO busy		0.287**		0.321**	0.340**	0.322*
		(2.077)		(2.322)	(2.034)	(1.943)
CEO relation			-0.531***		-0.488***	-0.461***
			(-3.190)		(-2.870)	(-2.706)
Firm Control						
Recent return	-1.486**	-1.637***	-0.753	-1.551**	-1.007	-0.933
	(-2.433)	(-2.699)	(-1.102)	(-2.520)	(-1.414)	(-1.305)
ROA	2.088***	1.789**	2.482***	1.904**	2.202**	2.263**
	(2.720)	(2.456)	(2.636)	(2.453)	(2.296)	(2.344)
Book-to-market	-0.002	-0.001	-0.006	-0.001	-0.006	-0.006
	(-0.572)	(-0.258)	(-1.134)	(-0.361)	(-1.162)	(-1.154)
Size	-0.116**	-0.106*	-0.150**	-0.096*	-0.106	-0.096
	(-2.020)	(-1.779)	(-2.260)	(-1.661)	(-1.617)	(-1.478)
Leverage	-0.597	-0.561	-1.337***	-0.414	-0.842*	-0.812
	(-1.476)	(-1.306)	(-2.737)	(-0.998)	(-1.692)	(-1.636)
Loss	0.006	0.015	-0.068	-0.075	-0.251	-0.308
	(0.025)	(0.060)	(-0.244)	(-0.330)	(-0.936)	(-1.140)
Analyst	0.012	-0.003	-0.014	0.008	-0.008	-0.004
	(0.215)	(-0.054)	(-0.226)	(0.155)	(-0.142)	(-0.071)
CEO Control						
CEO age	0.281	0.214	-0.138	0.163	-0.259	-0.521
	(0.482)	(0.384)	(-0.213)	(0.281)	(-0.380)	(-0.750)
CEO gender	-0.260	-0.398	-0.252	-0.246	-0.105	-0.158
	(-0.961)	(-1.479)	(-0.952)	(-0.837)	(-0.328)	(-0.480)
CEO education	0.077	0.054	-0.060	0.061	-0.062	-0.101
	(0.494)	(0.345)	(-0.355)	(0.405)	(-0.383)	(-0.634)
Video Control						
Video date	0.004	0.010	-0.004	0.008	-0.000	0.001
	(0.257)	(0.686)	(-0.202)	(0.508)	(-0.015)	(0.032)
Video length	-0.149	-0.147	-0.139	-0.146	-0.126	-0.138
	(-1.507)	(-1.537)	(-1.217)	(-1.484)	(-1.070)	(-1.164)
Video time	0.020	0.008	-0.016	0.028	0.033	0.073
	(0.157)	(0.063)	(-0.116)	(0.217)	(0.225)	(0.510)
Negative sentiment	-9.696***	-9.947***	-9.675***	-9.703***	-9.930***	-8.994***
	(-3.690)	(-3.838)	(-3.012)	(-3.711)	(-2.996)	(-2.635)
Uncertainty sentiment	-6.477	-6.626	-1.121	-6.828	-3.047	-5.654
	(-1.042)	(-1.102)	(-0.154)	(-1.101)	(-0.412)	(-0.765)
Constant	1.177	1.657	4.774*	1.223	3.885	5.054*
	(0.489)	(0.740)	(1.792)	(0.514)	(1.381)	(1.753)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	-	-	-	-	-	Yes
N	817	826	629	815	621	616
pseudo-R-sq	0.178	0.164	0.185	0.185	0.212	0.219

2.4.2 Remote Interview and Investor Disagreement

Using the pre-covid sample and the following regression, we investigate how the choice of remote versus face-to-face interviews affects investor disagreement.

$$Disagree_{ijt} = \beta_0 + \beta_1 Remote_{ijt} + \beta_2 \chi\_Firm_{j,t} + \beta_3 \chi\_CEO_{i,t} + \beta_4 \chi\_Video_{ij,t} + Y + I + \varepsilon_{ijt} \qquad (2-2)$$

where $Disagree_{ijt}$ refers to measures of investor disagreement on the stocks of firm *j* with CEO *i* on interview date *t.* We primarily focus on ABS, daily average bid-ask spreads during [0, 2] day window around the interview date minus the daily average bid-ask spreads during the [-55, -6] day window prior to the interview date. $\chi\_Video_{ij,t}$ are a series of interview video characteristics for the interview of CEO *i* in firm *j* on date *t*. $\chi\_Firm_{j,t}$ are a series of firm characteristics for firm *j* on interview date *t*. $\chi\_CEO_{i,t}$ are a series of CEO characteristics for CEO *i* on interview date *t*. $\chi\_Video_{j,t}$ are a series of interview video characteristics for firm *j* on interview date *t*. *Y* is year-fixed effects. *I* is industry-fixed effects. β_0 is the constant. $\beta_1 - \beta_4$ are regression coefficients. ε_{ijt} is the error term.

Table 2-4 reports the results for regression (2-2). In column (1), the regression coefficient on the key independent variable *Remote* is positive and statistically significant at a 1% significance level. It suggests that remote interview is associated with higher abnormal bid-ask spreads on the firm around the interview date compared to the face-to-face interview. One standard deviation increase in *Remote* leads to an increase in *ABS* of 0.362 (0.727×0.498). This impact is also economically significant given the mean value of *ABS* in our sample is 0.580. Next, we include the determinants of remote interviews discussed in Section 2.4.1 and re-estimate the regression (2-2). In column (2), all three determinants of the remote interview, *CEO distance*, *CEO busy*, and *CEO relation*, are all included. In column (3), *CEO distance* and *CEO busy* are included. The regression coefficients for the variable *Remote* are still positive and significant at a 1% significance level, and the economic magnitude is similar to that in column (1).

Table 2-4 Remote interview and investor disagreement

This table reports the results for regression (2-2) estimating the impact of the remote interview on firms' investor disagreements around the interview date. The dependent variable is *ABS*, the abnormal daily average bid-ask spreads for the firms [0, 2] days around the interview date. The key independent variable is *Remote,* a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. Column (1) reports the result of the regression. Columns (2) and (3) include the determinants for remote interviews: *CEO distance*, *CEO busy*, and *CEO relation*. Firm, CEO, and video control variables are consistent in the columns. Year fixed effects and industry fixed effects are included. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Baseline	*Remote determinants included*	
	ABS	ABS	ABS
	(1)	(2)	(3)
Remote	0.727***	0.742***	0.699***
	(4.078)	(3.540)	(4.091)
CEO distance		0.041	0.061
		(0.419)	(0.787)
CEO busy		0.221	0.186
		(1.109)	(1.194)
CEO relation		-0.109	
		(-0.485)	
Firm Control			
Recent return	0.375	0.694	0.580
	(0.452)	(0.754)	(0.703)
ROA	3.217***	4.550***	3.708***
	(3.099)	(3.335)	(3.241)
Book-to-market	-0.004	-0.008	-0.004
	(-0.671)	(-0.995)	(-0.660)
Size	0.019	0.016	0.031
	(0.323)	(0.225)	(0.546)
Leverage	0.240	0.528	0.364
	(0.516)	(0.853)	(0.772)
Loss	0.401	0.311	0.380
	(1.543)	(0.939)	(1.454)
Analyst	0.072	0.125	0.073
	(1.083)	(1.540)	(1.102)
CEO Control			
CEO age	-0.427	-1.108	-0.711
	(-0.761)	(-1.625)	(-1.191)
CEO gender	-0.103	-0.117	-0.067
	(-0.242)	(-0.248)	(-0.168)
CEO education	0.242	0.428**	0.295*
	(1.418)	(1.974)	(1.693)
Video Control			
Video date	-0.011	0.008	-0.008
	(-0.661)	(0.354)	(-0.466)
Video length	0.047	0.098	0.077
	(0.395)	(0.653)	(0.669)
Video time	-0.032	-0.013	-0.011
	(-0.280)	(-0.092)	(-0.091)
Negative sentiment	-3.469	-5.759*	-3.739
	(-1.530)	(-1.891)	(-1.637)
Uncertainty sentiment	-3.415	-6.201	-2.272
	(-0.613)	(-0.787)	(-0.391)
Constant	-1.388	0.405	-0.991
	(-0.634)	(0.151)	(-0.438)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	868	656	855
adj R-sq	0.111	0.131	0.120

2.4.3 Additional Robustness Tests

2.4.3.1 Alternative dependent variable

To ensure that our results are robust, we estimate the regression (2-2) using alternative measures for investor disagreement, adjusted fixed effects, sub-groups by topics, and adjusted sample. We calculate the abnormal bid-ask spreads using different day windows, [0, 4] day window and [-2, 2] day window, noted as *ABS[0,4]* and *ABS[-2,2]*, respectively. Furthermore, we measure investor disagreement around the interview date by trading volumes estimated from different estimation windows following Brochet *et al*. (2020) (*TVOL[-1,1]* and *TVOL[-2,2]*). Prior research documents that investors' differential interpretation of information can lead to a larger trading volume. We also calculate abnormal log trading volume (*ALTVOL*) (Cookson and Niessner, 2020) and abnormal trading volume (*ATVOL*) (Landsman *et al*., 2012). Following Landsman *et al*. (2012), we employ abnormal stock price volatility around the interview date (*AVAR*), where the abnormal return is calculated as a mean value of the squared market model adjusted returns. The abnormal stock price volatility reflects the information perceived by the investors around the interview date, the larger value of which reflects a higher investor disagreement. The calculation follows Brochet *et al*. (2020), Cookson and Niessner (2020), and Landsman *et al*. (2012).

Table 2-5 Panel A reports the results. In columns (1) and (2), we use alternative measures for abnormal bid-ask spreads. The regression coefficients in columns (1) and (2) are positive and statistically significant at a 1% significance level. In columns (3) and (4), the dependent variables are trading volumes estimated from different estimation windows following Brochet *et al*. (2020). The results in both columns are positive and statistically significant at a 1% significance level. Remote interviews are associated with a larger trading volume than face-to-face interviews. The dependent variables in columns (5) and (6) are abnormal log trading volume (Cookson and Niessner, 2020) and abnormal trading volume (Landsman *et al*., 2012), respectively. The results in columns (5) and (6) suggest that remote interviews lead to higher abnormal trading volume around the interview date. In column (7), the dependent variable is abnormal stock price volatility around the interview date (Landsman *et al*., 2012). The regression coefficient in column (7) is positive and statistically significant, indicating that remote interview has a positive and significant impact on abnormal stock price volatility around the interview date.

2.4.3.2 Adjusted model or sample

Next, we re-estimate the baseline regression (2-2) using adjusted fixed effects, sub-groups by topics, and adjusted sample. In Table 2-5 Panel B column (1), we restrict our year fixed effects to quarter fixed effects. Our baseline findings are unchanged when using this more granular time fixed effect. To control the time-invariant within-topic characteristics, we include the topic fixed effect in Table 2-5 Panel B column (2) and find a consistent result. Further, we divide our sample into two sub-groups according to their topics and re-estimate the regression (2-2). Group one includes the interviews in which CEOs discuss firm-specific information, such as their firms' earnings, stocks, and business events, while group two includes interviews where CEOs discuss macro-economy, industrial outlook, policies, political events, and environments. The impact of remote interviews exhibits a significant impact in both groups, as shown in Table 2-5 Panel B columns (3) and (4). However, remote interviews exhibit a stronger impact than firm-specific interviews. A possible reason is that the firm-specific information receives a larger amount of information recipients leading to larger information interpretation dispersion. In column (5), we estimate the regression using the sample combining the main sample and the post-covid sample. The results still hold in this sample.

2.4.3.3 Additional control

A potential concern is that the firm recently experienced or is experiencing other events simultaneously, which drive the changes of investor disagreement. Though we already include the recent stock performance as a control variable, we further control the pre-interview disagreement. Our measures of pre-interview disagreement include 1-month and 1-quarter lagged average daily trading volumes (*TVOL[-1,1]_lagged*), and 1-month lagged abnormal log trading volume (*ALTVOL_lagged*). Table 2-5 Panel C presents the estimation after including these pre-interview disagreement control variables. All regression coefficients in the three columns are positive and significant, which are consistent with our baseline findings.

Taken together, our baseline findings are consistent across various measures of investor disagreement. More specifically, remote interviews are associated with a significantly higher level of investor disagreement than face-to-face interviews.

Table 2-5 Robustness tests

This table reports the robustness test results for regression (2). The key independent variable is *Remote,* a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. Panel A uses alternative measures for investor disagreement. *ABS[0,4]* and *ABS[-2,2]* are abnormal daily average bid-ask spreads [0,4] and [-2,2] days around the interview date. *TVOL[-1,1]* and *TVOL[-2,2]* are abnormal average daily trading volume [-1,1] and [-2,2] days centered on the interview date. *ALTVOL* is Cookson and Niessner (2020)'s abnormal log trading volume on the interview date. *ATVOL* is Landsman *et al*. (2012)'s abnormal trading volume around the interview date. *AVAR* is Landsman *et al*. (2012)'s abnormal return volatility. Panel B uses adjusted fixed effects, sub-groups, and adjusted samples. In column (1), the year fixed effect is replaced by the quarter fixed effect. In column (2), the topic fixed effect is included. Columns (3) and (4) report the results for sub-groups by topics: firm-specific information and macro-economic information, respectively. Column (5) uses a full sample with both pre- and post-Covid samples. In Panel C, we use additional control variables: the 1-month lagged *TVOL[-1,1]* and *ALTOVL*, and 1-quarter lagged *TVOL[-1,1]*. Firm, CEO, and video control variables are consistent with Table 2-4 column (1). Year fixed effects and industry fixed effects are included. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

Panel A: Using alternative measures

	ABS[0,4]	ABS [-2,2]	TVOL [-1,1]	TVOL [-2,2]	ALTVOL	ATVOL	AVAR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Remote	0.543***	0.393***	2.310***	1.704***	0.270***	0.202***	0.488***
	(4.221)	(3.961)	(3.403)	(3.674)	(3.590)	(4.065)	(3.509)
Firm Control							
Recent return	0.478	0.007	-3.963*	-3.719*	-0.513	-0.640**	-0.610
	(0.722)	(0.011)	(-1.728)	(-1.846)	(-1.495)	(-2.508)	(-0.944)
ROA	2.122***	2.054**	3.956	2.712	0.843**	0.619**	2.818***
	(2.610)	(2.523)	(1.045)	(0.885)	(2.041)	(2.023)	(3.201)
Book-to-market	-0.004	-0.002	0.004	0.003	-0.001	-0.001	-0.003
	(-0.896)	(-0.424)	(0.280)	(0.246)	(-0.430)	(-0.802)	(-0.811)
Size	-0.013	-0.008	0.764***	0.431***	-0.137**	-0.055**	-0.000
	(-0.295)	(-0.197)	(3.931)	(3.360)	(-2.073)	(-2.244)	(-0.003)
Leverage	0.169	0.128	-2.909*	-2.153*	-0.143	-0.098	-0.535
	(0.486)	(0.419)	(-1.859)	(-1.960)	(-0.630)	(-0.600)	(-1.337)
Loss	0.258	0.119	2.300***	1.642***	0.169	0.105	0.376*
	(1.374)	(0.762)	(2.936)	(3.046)	(1.274)	(1.139)	(1.742)
Analyst	0.033	0.016	-0.206	-0.127	0.029	0.008	0.015
	(0.646)	(0.332)	(-0.770)	(-0.700)	(1.215)	(0.438)	(0.332)
CEO Control							
CEO age	-0.206	-0.161	1.354	1.794	-0.073	-0.111	-0.490
	(-0.511)	(-0.467)	(0.590)	(1.147)	(-0.216)	(-0.576)	(-1.083)
CEO gender	-0.051	-0.078	-0.691	-0.459	-0.021	-0.031	-0.147
	(-0.144)	(-0.328)	(-0.989)	(-0.908)	(-0.196)	(-0.339)	(-0.521)
CEO education	0.200	0.234*	0.067	0.158	0.023	0.064	0.184
	(1.504)	(1.963)	(0.122)	(0.449)	(0.340)	(1.395)	(1.610)
Video Control							
Video date	-0.022*	-0.024**	0.007	-0.039	0.008	0.003	0.015
	(-1.766)	(-2.011)	(0.079)	(-0.550)	(1.091)	(0.443)	(0.922)
Video length	0.051	0.119*	0.220	0.170	0.028	0.035	0.076
	(0.602)	(1.699)	(0.507)	(0.545)	(0.492)	(0.852)	(0.664)
Video time	-0.017	-0.051	0.767	0.666	0.059	0.007	-0.171
	(-0.178)	(-0.585)	(1.564)	(1.636)	(0.753)	(0.130)	(-1.344)
Negative sentiment	-2.983	-0.937	5.923	4.948	-1.206	-0.873	0.366
	(-1.561)	(-0.522)	(0.537)	(0.573)	(-0.962)	(-0.878)	(0.142)
Uncertainty	-1.810	-4.120	-37.495**	-26.346*	-7.191**	-3.251	2.494
sentiment	(-0.405)	(-1.010)	(-1.979)	(-1.857)	(-2.546)	(-1.607)	(0.478)
Constant	-1.462	-1.667	-15.670*	-13.802**	0.790	0.523	0.535
	(-0.917)	(-1.229)	(-1.696)	(-2.208)	(0.692)	(0.681)	(0.308)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	868	866	866	866	866	866	866
pseudo R-sq	0.128	0.148	0.184	0.134	0.119	0.099	0.081

Panel B Using adjusted fixed effects, sub-groups, and adjusted samples

	Quarter-FE	*Topic-FE*	*Sub-groups by topic*		*Full sample*
	ABS	ABS	ABS	ABS	ABS
	(1)	(2)	(3)	(4)	(5)
Remote	0.783***	0.708***	0.783***	0.352*	0.470***
	(4.449)	(3.996)	(3.273)	(1.909)	(2.991)
Firm Control					
Recent return	-0.101	0.616	0.011	0.837	0.716
	(-0.116)	(0.726)	(0.009)	(0.597)	(0.885)
ROA	2.591**	3.747***	2.853**	5.097	3.451***
	(2.381)	(3.210)	(2.512)	(1.578)	(3.749)
Book-to-market	-0.003	-0.004	-0.001	-0.006	-0.006
	(-0.500)	(-0.620)	(-0.067)	(-0.430)	(-1.007)
Size	0.036	0.018	0.024	0.016	0.025
	(0.638)	(0.323)	(0.342)	(0.184)	(0.482)
Leverage	0.369	0.220	0.206	-0.078	-0.198
	(0.845)	(0.466)	(0.353)	(-0.122)	(-0.432)
Loss	0.335	0.377	0.517	0.257	0.367*
	(1.319)	(1.464)	(1.649)	(0.561)	(1.897)
Analyst	0.063	0.076	0.055	0.092	-0.009
	(0.940)	(1.147)	(0.645)	(0.990)	(-0.158)
CEO Control					
CEO age	-0.272	-0.643	0.151	-1.254	-0.292
	(-0.476)	(-1.068)	(0.193)	(-1.578)	(-0.645)
CEO gender	-0.072	-0.148	0.136	-0.436	0.062
	(-0.172)	(-0.362)	(0.265)	(-1.105)	(0.176)
CEO education	0.243	0.316*	0.446**	0.271	0.236
	(1.435)	(1.830)	(2.029)	(1.352)	(1.538)
Video Control					
Video date	0.147	-0.010	0.003	-0.026	0.017
	(1.399)	(-0.575)	(0.142)	(-0.974)	(1.111)
Video length	-0.041	0.058	0.063	-0.052	-0.025
	(-0.354)	(0.482)	(0.349)	(-0.352)	(-0.197)
Video time	-3.355	0.007	0.182	-0.234	-0.017
	(-1.383)	(0.057)	(1.325)	(-1.447)	(-0.153)
Negative sentiment	-6.142	-2.564	-4.548	2.747	-5.824***
	(-1.089)	(-1.084)	(-1.272)	(0.715)	(-2.736)
Uncertainty sentiment	0.147	0.541	4.934	-2.320	-5.811
	(1.399)	(0.094)	(0.605)	(-0.269)	(-0.985)
Constant	-1.848	-0.757	-3.847	5.228	-0.211
	(-0.837)	(-0.318)	(-1.256)	(1.382)	(-0.113)
Year FE	-	Yes	Yes	Yes	Yes
Quarter FE	Yes				
Industry FE	Yes	Yes	Yes	Yes	Yes
Topic FE	-	Yes	-	-	-
N	868	845	551	294	1117
adj R-sq	0.072	0.129	0.046	0.296	0.048

Panel C Using additional control variables

	1-month lagged		*1-quarter lagged*
	ABS	ABS	ABS
	(1)	(2)	(3)
Remote	0.719***	0.725***	0.720***
	(4.071)	(4.096)	(4.074)
TOVL[-1,1]_lag	-0.000		-0.000
	(-0.200)		(-0.731)
ALTVOL_lag		-0.175**	
		(-2.071)	
Firm Control			
Recent return	0.622	0.606	0.630
	(0.759)	(0.736)	(0.768)
ROA	3.566***	3.642***	3.562***
	(3.337)	(3.351)	(3.330)
Book-to-market	-0.004	-0.004	-0.004
	(-0.625)	(-0.568)	(-0.621)
Size	0.023	0.024	0.023
	(0.401)	(0.401)	(0.391)
Leverage	0.259	0.247	0.259
	(0.526)	(0.503)	(0.526)
Loss	0.417	0.419	0.415
	(1.571)	(1.579)	(1.564)
Analyst	0.063	0.066	0.063
	(0.947)	(0.989)	(0.949)
CEO Control			
CEO age	-0.509	-0.517	-0.515
	(-0.913)	(-0.905)	(-0.921)
CEO gender	-0.110	-0.059	-0.106
	(-0.260)	(-0.140)	(-0.253)
CEO education	0.257	0.245	0.256
	(1.510)	(1.437)	(1.504)
Video Control			
Video date	-0.010	-0.012	-0.010
	(-0.593)	(-0.697)	(-0.625)
Video length	0.054	0.055	0.056
	(0.454)	(0.457)	(0.471)
Video time	-0.041	-0.043	-0.040
	(-0.356)	(-0.372)	(-0.347)
Negative sentiment	-3.815*	-3.316	-3.822*
	(-1.658)	(-1.407)	(-1.662)
Uncertainty sentiment	-2.703	-2.689	-2.724
	(-0.480)	(-0.478)	(-0.484)
Constant	-1.220	-1.217	-1.202
	(-0.561)	(-0.550)	(-0.551)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	862	859	862
adj R-sq	0.114	0.117	0.115

2.5 Endogeneity

In our main regression, we incorporate control variables and fixed effects to investigate the influence of remote interviews on investor disagreement. Nevertheless, potential concerns with our main regression are that CEOs' remote interviews may not be exogenous, and unobserved factors could drive the findings. We address these endogeneity problems in multiple ways, including a difference-in-differences (DiD) strategy and a Heckman (1979) treatment effect model. Further, a propensity score matching approach is employed to balance the impact of co-founding factors.

2.5.1 Difference-in-Differences Approach

Our sample is allowed to use a DiD model to alleviate the endogeneity problem. Since March 2020, interviews have been forced to be remotely conducted due to the outbreak of COVID-19. As shown in Table 2-1, there are 44 remote interviews and 37 face-to-face interviews from January to March, 2020. After that, there are 249 remote interviews and zero face-to-face interviews, while the total number of interviews is similar to the previous years. Relying on this exogenous shock, we could observe the treatment effect of the forced remote interviews.

Using both the pre-shock (baseline) sample and post-shock sample from January 2017 to December 2020, we construct a treatment group and a control group. We keep the firms that are interviewed both before and after the shock. In our setting, treated firms are forced to transform face-to-face interviews into remote interviews by the shock, while controlled firms are unaffected and have remote interviews continuously. The distribution for the treatment and control observations is shown in Table 2-6 Panel A. There are 570 observations at the interview level in total, 372 of which are interviews within the treated group and 198 of which are interviews within the control group. There are 369 interviews before shock and 201 interviews post shock. The number of which could be reduced due to the missing observations of control variables.

Table 2-6 Endogeneity: Difference-in-Differences (DiD)

Panel A: Distribution for observations of treatment and control groups

This table reports the distribution of observations of treatment and control groups in different periods. In the first column, the number 0 refers to the observations of the control group, and the number 1 refers to the treatment group. In the first row, the number 0 refers to the observations during the pre-shock period, and the number 1 refers to the post-shock period. The total numbers of each column and row are calculated and shown in the table.

	Post		Total
Treat	0	1	
0	137	61	198
1	232	140	372
Total	369	201	570

Panel B: Figure for the trends of investor disagreement of treatment and control group

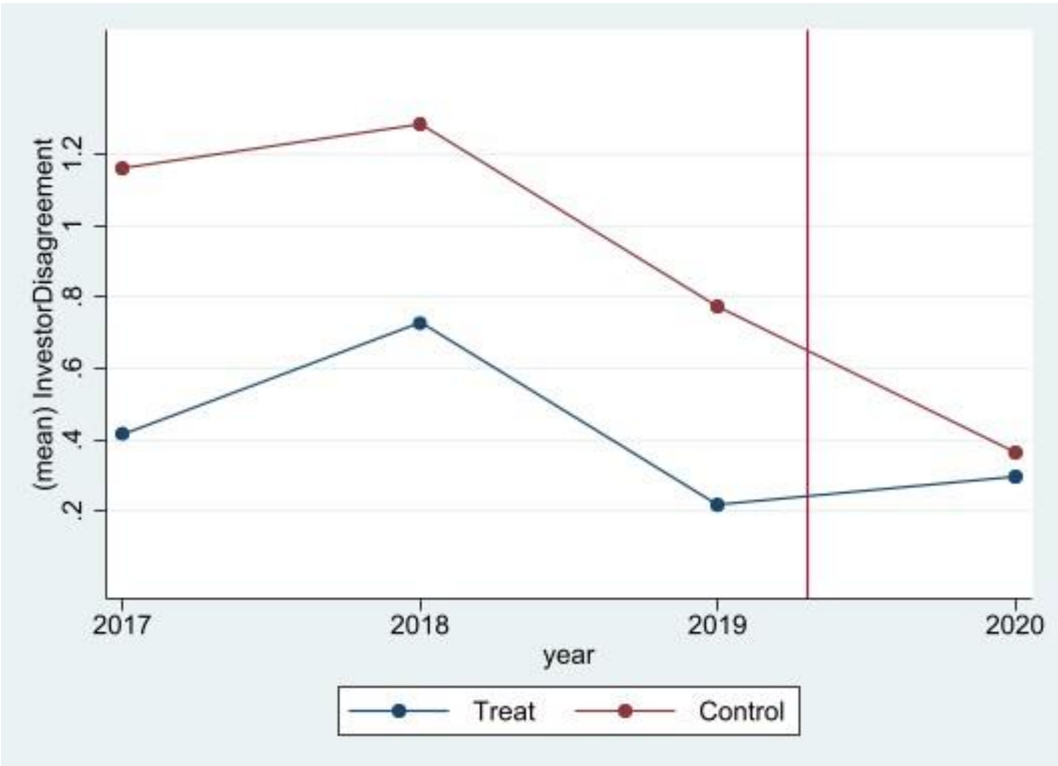


Figure 2-1 Trends of investor disagreements of treatment and control group

Panel C: Results of difference-in-differences (DiD) tests

This table reports the results of the DiD model (2-4). The dependent variable is *ABS*, the abnormal daily average bid-ask spreads for the firms [0, 2] days around the interview date. The exogenous shock is the outbreak of COVID-19, which forces face-to-face interviews to remote interviews since April 2020. Treated firms are those interviewed face-to-face pre- and remotely post-shock. Control firms are those interviewed remotely pre- and post-shock. Column (1) presents the DiD model (4). *Treat* is an indicator variable that equals 1 if the firm belongs to the treatment group, and 0 to the control group. *Post* is an indicator variable that equals 1 if the interview date is after March 2020, and 0 if before. The interaction term between them is also included. Column 2 is the result of DiD parallel test. The variable '*Treat*' and its interaction term between year indicators are included. Firm, CEO, and interview control variables are consistent with baseline regression. Year fixed effects and industry fixed effects are included. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Key DiD Test		Robustness Test	
	DiD Model	*Parallel Test*	*DiD Model*	*Parallel Test*
Treat × Year2019(Benchmark)	ABS	ABS	ABS[0,4]	ABS[0,4]
	(1)	(2)	(3)	(4)
Treat	-0.428	-0.316	-0.421	-0.461
	(-1.376)	(-0.875)	(-1.655)	(-1.550)
Treat × Post	0.793**	0.681*	0.572*	0.612*
	(2.250)	(1.687)	(1.931)	(1.866)
Treat × Year2018		-0.210		0.073
		(-0.486)		(0.196)
Treat × Year2017		-0.195		0.073
		(-0.550)		(0.256)
Firm Control				
Recent return	1.579	1.572	1.151	1.154
	(1.385)	(1.372)	(1.304)	(1.307)
ROA	4.266***	4.163***	2.804***	2.840***
	(3.326)	(3.161)	(2.984)	(2.958)
Book-to-market	-0.024**	-0.024**	-0.016*	-0.015*
	(-2.400)	(-2.419)	(-1.876)	(-1.850)
Size	0.049	0.050	0.016	0.015
	(0.628)	(0.640)	(0.289)	(0.277)
Leverage	1.185**	1.195**	1.074**	1.071**
	(2.192)	(2.177)	(2.548)	(2.542)
Loss	0.571**	0.559**	0.302*	0.306*
	(2.311)	(2.252)	(1.729)	(1.702)
Analyst	-0.086	-0.088	-0.101*	-0.100*
	(-1.216)	(-1.238)	(-1.714)	(-1.696)
CEO Control				
CEO age	-1.418**	-1.409**	-0.990	-0.994
	(-2.082)	(-2.059)	(-1.648)	(-1.655)
CEO gender	-0.425	-0.414	-0.284	-0.288
	(-1.249)	(-1.193)	(-1.058)	(-1.062)
CEO education	0.154	0.158	0.092	0.091
	(0.695)	(0.712)	(0.521)	(0.514)
Video Control				
Video date	-0.017	-0.017	-0.025	-0.025
	(-0.714)	(-0.720)	(-1.267)	(-1.263)
Video length	-0.305*	-0.304*	-0.191	-0.192
	(-1.781)	(-1.769)	(-1.570)	(-1.567)
Video time	0.237	0.231	0.037	0.038
	(1.323)	(1.286)	(0.250)	(0.261)
Negative sentiment	-10.984***	-10.983***	-8.099**	-8.103**
	(-3.157)	(-3.039)	(-2.592)	(-2.502)
Uncertainty sentiment	4.725	4.913	1.225	1.164
	(0.470)	(0.486)	(0.196)	(0.184)
Constant	6.743**	6.760**	5.114**	5.107**
	(2.552)	(2.555)	(2.056)	(2.042)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	495	495	495	495
adj R-sq	0.177	0.174	0.135	0.131

We plot the trends of average investor disagreement for the treatment and control group each year, shown in Figure 2-1. The vertical line presents the shock in 2020. Before the shock, we find that the average investor disagreements of the treatment group each year are lower than the control group, suggesting that firms with face-to-face interviews are associated with less investor agreement. The differences between the treatment and control groups in each year are relatively equal, suggesting a parallel trend. After the shock, the degree of investor disagreement in treated firms rises relative to what happens in control firms. This is caused by the treatment group's transformation from face-to-face interviews to remote interviews.

If remote interviews cause a higher investor disagreement, we should observe that the degree of investor disagreement in treated firms increases relative to the contemporaneous change in control firms after the shock. We use the following DiD model (2-3) to examine this conjecture. The variable *Treat* is an indicator variable that equals 1 if the firm belongs to the treatment group, and 0 to the control group. The variable *Post* is an indicator variable that equals 1 if the interview date is after March 2020, and 0 if before. We include the interaction term between the two variables. The other variables are consistent with the baseline regression (2-2). Additionally,

$$\begin{aligned} Disagree_{ijt} = {} & \beta_0 + \beta_1 Treat_{jt} + \beta_2 Treat_{jt} \times Post_t \\ & + \beta_3 \chi\_Firm_{j,t} + \beta_4 \chi\_CEO_{i,t} + \beta_5 \chi\_Video_{j,t} + Y + I + \varepsilon_{ijt} \qquad (2-3) \end{aligned}$$

The results of DiD model (2-3) are reported in Table 2-7 Panel C column (1). The regression coefficient for the interaction term is positive and statistically significant at a 1% significance level. It indicates that the forced transformation from face-to-face interviews to remote interviews leads to higher investor disagreement. We also perform tests to examine the parallel trend assumption. We replace the variable *Post* with additional dummy variables *Year2017* and *Year2018*, indicating the years of the observations. The interaction terms between *Treat* and these indicators are included. The year 2019 is regarded as a benchmark. Then we re-estimate the model. Table 2-7 column (2) reports the results. The differences pre-shock are insignificant, while the difference post-shock is significant. The results suggest that our DiD test follows the parallel trend assumption. To ensure these results are robust, we re-estimate the regression model in column (1) and column (2) using an alternative dependent variable *ABS[0, 4]*. The results are reported in Table 2-7 Panel C columns (3) and (4), which are unchanged. Overall, the result of DiD approach suggests that our baseline findings are less likely driven by endogeneity problems.

2.5.2 Heckman Treatment Effect Model

A concern is that CEOs' interview modality (remotely or face-to-face) is endogenously selected. We employ a Heckman treatment effect model. In the first stage, a probit model estimates the probability of a remote interview including all control variables in equation (2) as well as variables predicting remote interview but exogenous to investor disagreement. Then it derives a selectivity correction factor: inverse Mills Ratio (IMR). In the second stage, we include *IMR* into equation (2-2) and re-estimate the impact of remote interviews on investor disagreement. The exogenous variables are the determinants of remote interviews discussed in Section 2.4.1, including the distance between their headquarters and CNBC live studio (*CEO distance*), the busyness of CEOs (*CEO busy*), and CEOs' relation with CNBC

(*CEO relation*). These variables significantly predict a CEO to be remotely interviewed in Table 2-3, but they do not have any direct impact on investor disagreement as seen in Table 2-4 because these characteristics are not observable in televised media.

The model in the first stage is the same as the probit model of regression (2-1). The second stage uses the following regression (2-4), where we include a selectivity correction term *IMR* compared to our baseline regression (2-2):

$$Disagree_{ijt} = \beta_0 + \beta_1 Remote_{ijt} + \beta_2 IMR + \beta_3 \chi\_Firm_{j,t} + \beta_4 \chi\_CEO_{i,t} + \beta_5 \chi\_Video_{j,t} + Y + I + \varepsilon_{ijt} \quad (2-4)$$

Table 2-7 reports the results. We have two instrument settings. In columns (1) and (2), our instruments include *distance* and *CEO busy*. In columns (3) and (4), our instruments include *CEO distance*, *CEO busy*, and *CEO relation*. The results for the first stage in columns (1) and (3) are the same as the previous findings. *CEO distance* and *CEO busy* positively predict the remote interview, while *CEO relation* negatively predicts the remote interview. In the second stage, where we further include the *IMR*, the positive impact of remote interviews on investor disagreement is unchanged. Our baseline findings are less likely driven by selection bias.

Table 2-7 Endogeneity: Heckman Treatment Effect

This table presents the Heckman treatment effect approach. *Remote* is a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. *ABS* is the abnormal daily average bid-ask spreads for the firms [0, 2] days around the interview date. We regress *Remote* on instruments and controls, estimating an inverse Mills Ratio (*IMR*), then regress *ABS* on *Remote*, *IMR,* and controls. We have two instrument settings: 1) *CEO distance* and *CEO busy*; 2) *CEO relation* additionally included. Columns (1) and (3) present the first stage. Columns (2) and (4) present the second stage. Controls and fixed effects are included. Year fixed effects and industry fixed effects are included. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Instruments setting 1		Instruments setting 2	
	1st stage	*2nd stage*	*1st stage*	*2nd stage*
	Remote	ABS	Remote	ABS
	(1)	(2)	(3)	(4)
Remote		1.541*		2.066***
		(1.910)		(2.812)
IMR		-0.503		-0.805*
		(-1.107)		(-1.918)
CEO distance	0.272***		0.300***	
	(3.337)		(3.403)	
CEO busy	0.321**		0.340**	
	(2.322)		(2.034)	
CEO relation			-0.488***	
			(-2.870)	
Firm Control				
Recent return	-1.551**	0.969	-1.007	1.267
	(-2.520)	(0.969)	(-1.414)	(1.277)
ROA	1.904**	3.261***	2.202**	3.459**
	(2.453)	(3.074)	(2.296)	(2.535)
Book-to-market	-0.001	-0.004	-0.006	-0.006
	(-0.361)	(-0.639)	(-1.162)	(-0.839)
Size	-0.096*	0.051	-0.106	0.053
	(-1.661)	(0.802)	(-1.617)	(0.735)
Leverage	-0.414	0.447	-0.842*	1.101
	(-0.998)	(0.940)	(-1.692)	(1.568)
Loss	-0.075	0.435	-0.251	0.368
	(-0.330)	(1.577)	(-0.936)	(1.052)
Analyst	0.008	0.075	-0.008	0.131
	(0.155)	(1.124)	(-0.142)	(1.612)
CEO Control				
CEO age	0.163	-0.714	-0.259	-0.848
	(0.281)	(-1.167)	(-0.380)	(-1.260)
CEO gender	-0.246	-0.001	-0.105	-0.053
	(-0.837)	(-0.002)	(-0.328)	(-0.116)
CEO education	0.061	0.281	-0.062	0.434**
	(0.405)	(1.627)	(-0.383)	(2.014)
Video Control				
Video date	0.008	-0.784	-0.000	-1.635
	(0.508)	(-0.227)	(-0.015)	(-0.437)
Video length	-0.146	0.285	-0.126	-3.573
	(-1.484)	(0.043)	(-1.070)	(-0.459)
Video time	0.028	-0.011	0.033	0.010
	(0.217)	(-0.651)	(0.225)	(0.440)
Negative sentiment	-9.703***	0.121	-9.930***	0.140
	(-3.711)	(1.045)	(-2.996)	(0.891)
Uncertainty sentiment	-6.828	-0.010	-3.047	-0.020
	(-1.101)	(-0.085)	(-0.412)	(-0.142)
Constant	1.223	0.240	3.885	0.267
	(0.514)	(0.094)	(1.381)	(0.085)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	815	815	621	621
Pseudo/adj R-sq	0.185	0.131	0.212	0.141

2.5.3 Propensity Score Matching Approach

We employ the Propensity Score Matching (PSM) method to create comparable groups for accurate causal inference. The objective of this approach is to balance the distribution of observed characteristics across the treatment (remote interviews) and control (face-to-face interviews) groups, thereby minimizing the impact of confounding variables that could affect the outcome. The propensity score reflects the probability of an observation being in the treatment group given its observed characteristics. Observations with similar propensity scores across the treatment and control groups were paired. After matching, the average treatment effect on the treated (ATT = 0.558; t-statistics = 4.77 in Table 2-8 Panel A) indicates that the difference between the abnormal bid-ask spreads of remote and face-to-face interviews is statistically significant at a 1% significance level. The investor disagreement on remote interviews is approximately 0.56 points larger than that on face-to-face interviews. Additionally, using the matched sample, we re-estimate the baseline regressions. The results are reported in Table 2-8 Panel B. Our findings are unchanged.

Table 2-8 Endogeneity: Propensity Score Matching Approach

Panel A: Average treatment effect on the treated (ATT)

This table reports the results of the PSM approach. The outcome variable is the abnormal bid-ask spread *ABS*. The mean value of the outcome variable of the treatment interviews and control interviews is reported. ATT and t-statistics are presented in the table.

Outcome = *ABS*	Mean			
	Treated	Controls	Difference	t-statistics
ATT	0.87	0.31	0.56	4.77***

Panel B: Propensity score matching (PSM) approach

We employ the PSM approach to re-estimate the baseline regression (2-2). *Remote* equals one if the interview is remotely conducted, and zero otherwise. *ABS* is the abnormal bid-ask spreads for the firms [0, 2] days around the interview date. Columns (2) and (3) include the determinants for remote interviews. Column (4) includes both pre- and post-Covid observations. Column (5) uses an alternative measure, abnormal average daily trading volume [-1,1] days centered on the interview date. Firm, CEO, and interview control variables are consistent with baseline regression. Year fixed effects and industry fixed effects are included. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Baseline	*Remote determinants included.*		*Full sample*	*Alternative Y*
	ABS	ABS	ABS	ABS	TVOL[-1,1]
	(1)	(2)	(3)	(4)	(5)
Remote	0.914***	1.117***	0.933***	0.662***	2.798***
	(3.665)	(3.521)	(3.757)	(2.821)	(3.397)
CEO distance		-0.013	0.003		
		(-0.112)	(0.035)		
CEO busy		0.008	0.128		
		(0.029)	(0.589)		
CEO relation		-0.045			
		(-0.106)			
Firm Control		-0.013	0.003		
Recent return	-0.601	0.420	0.093	-1.208	-6.620*
	(-0.438)	(0.285)	(0.068)	(-1.072)	(-1.805)
ROA	1.016	3.795*	2.277	1.156	-1.897
	(0.651)	(1.968)	(1.378)	(0.817)	(-0.419)
Book-to-market	0.001	-0.006	0.001	-0.001	-0.001
	(0.131)	(-0.456)	(0.130)	(-0.055)	(-0.061)
Size	-0.035	-0.078	-0.038	-0.043	0.454*
	(-0.471)	(-0.743)	(-0.512)	(-0.627)	(1.961)
Leverage	0.217	0.447	0.063	0.112	1.396
	(0.322)	(0.510)	(0.094)	(0.190)	(0.826)
Loss	-0.131	0.067	-0.046	-0.051	2.167**
	(-0.363)	(0.145)	(-0.123)	(-0.168)	(2.217)
Analyst	0.089	0.135	0.097	0.125	-0.162
	(1.005)	(1.199)	(1.051)	(1.515)	(-0.705)
CEO Control					
CEO age	0.039	-0.513	-0.440	0.867	1.255
	(0.049)	(-0.516)	(-0.539)	(1.278)	(0.544)
CEO gender	-0.001	-0.185	-0.062	-0.097	-1.692*
	(-0.002)	(-0.326)	(-0.117)	(-0.187)	(-1.852)
CEO education	0.236	0.566**	0.361*	0.218	-0.382
	(1.152)	(2.260)	(1.696)	(1.150)	(-0.685)
Video Control					
Video date	-0.010	0.014	-0.002	0.018	0.028
	(-0.404)	(0.473)	(-0.084)	(0.759)	(0.296)
Video length	-0.017	0.073	0.050	-0.125	0.436
	(-0.095)	(0.346)	(0.306)	(-0.753)	(0.789)
Video time	-0.112	-0.085	-0.022	-0.125	1.227**
	(-0.606)	(-0.385)	(-0.119)	(-0.703)	(2.375)
Negative sentiment	-3.654	-5.574	-4.376	-6.110	20.392
	(-0.666)	(-0.769)	(-0.798)	(-1.338)	(1.175)
Uncertainty sentiment	-16.582	-21.622	-15.321	-18.727*	-67.535*
	(-1.478)	(-1.381)	(-1.297)	(-1.913)	(-1.841)
Constant	-0.338	1.603	1.163	-2.787	-14.198
	(-0.095)	(0.361)	(0.321)	(-0.877)	(-1.444)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	454	341	447	543	452
adj R-sq	0.082	0.104	0.098	0.030	0.188

2.6 Information Interpretation and Investor Disagreement

Organizational communication theory indicates that communication mediums differ in their richness, thereby varying in their capacity to facilitate understanding and minimize ambiguity (Daft and Lengel, 1986). Face-to-face communication, characterized by immediate feedback, multiple cues, and natural language, is considered the richest medium. In contrast, remote communication, with limitations in providing immediate feedback and transmitting non-verbal cues, is deemed a less rich medium. Jointly with findings in the existing financial literature (Mayew and Venkatachalam, 2012; Flam *et al*., 2020; Momtaz, 2021; Huang *et al*., 2023), CEOs' non-verbal cues contribute to the information correctly perceived by the information recipient, without which the information could be equivocal. As a result, the perceived clarity of CEOs' disclosures in interviews may lead to a larger dispersion of the interpretation of the information. To better understand the mechanism, we conduct the following analysis on the perspectives of information recipients and interviews.

2.6.1 Information Recipient Familiarity

Should the information interpretation be the mechanism, we predict a variation in the impact of remote interviews on investor disagreement, depending on the information recipient's familiarity with the CEO. Understanding the CEO becomes simpler for information recipients who are already familiar with them.

To test the conjecture, we construct a variable *Familiarity*. The variable *Familiarity* has integer values ranging from 1, each value indicating the sequential count of a CEO's interviews throughout the given sample period. For instance, a value of 1 represents the first interview of a CEO, 2 indicates the second interview, 3 denotes the third, and so on. *Familiarity* measures the extent to which investors are acquainted with a particular CEO, with larger values indicating a higher degree of familiarity. A stronger familiarity should reduce the potential for misinterpretation of the CEOs' information. In Table 2-9, by estimating the interaction term between *Remote* and *Familiarity*, we observe a significant and negative coefficient of the term. It is consistent with our hypothesis.

Table 2-9 Investor familiarity

This table presents the interactive impact of investors' familiarity with CEOs. The dependent variables in columns (1) and (2) are *ABS* and *ABS[0,4]*, the abnormal daily average bid-ask spreads [0,2] and [0,4] days around the interview date, respectively. The key independent variable is *Remote,* a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. The other variable of interest is *Familiarity,* capturing a CEO's information recipient familiarity. The interaction term between *Remote* and *Familiarity* is included. The control variables and fixed effects are consistent with baseline regression (2-2). Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	ABS (1)	ABS[0,4] (2)
Remote	1.275***	0.944***
	(3.070)	(3.483)
Familiarity	-0.000	0.000
	(-0.065)	(0.272)
Remote × Familiarity	-0.001*	-0.001*
	(-1.784)	(-1.953)
Firm Control		
Recent return	0.376	0.475
	(0.456)	(0.725)
ROA	3.207***	2.128***
	(3.085)	(2.619)
Book-to-market	-0.004	-0.004
	(-0.670)	(-0.893)
Size	0.008	-0.017
	(0.142)	(-0.379)
Leverage	0.262	0.179
	(0.565)	(0.509)
Loss	0.403	0.258
	(1.530)	(1.354)
Analyst	0.070	0.032
	(1.055)	(0.623)
CEO Control		
CEO age	-0.458	-0.221
	(-0.814)	(-0.546)
CEO gender	-0.135	-0.059
	(-0.328)	(-0.174)
CEO education	0.228	0.190
	(1.352)	(1.426)
Video Control		
Video date	-0.011	-0.022*
	(-0.651)	(-1.831)
Video length	0.030	0.038
	(0.251)	(0.438)
Video time	-0.010	-0.005
	(-0.090)	(-0.056)
Negative sentiment	-3.617	-3.078
	(-1.580)	(-1.586)
Uncertainty sentiment	-3.686	-2.137
	(-0.662)	(-0.476)
Constant	-1.086	-1.358
	(-0.468)	(-0.804)
Year FE	Yes	Yes
Industry FE	Yes	Yes
N	868	868
adj R-sq	0.120	0.134

2.6.2 Public Attention

If the information interpretation is the case, a larger degree of public attention to a remote interview can lead to greater investor disagreement. Individuals' opinions are various due to their various social and cognitive experiences. As the number of recipients of the CEOs' message increases, the probability of it being interpreted in various ways also rises, resulting in a wider range of interpretations.

We measure a firm's public attention using its size (*Size*) and Google Trend Index (*GTI*). The variable *Size* is the logarithm of the dollar value of total assets, which is used as a control variable in baseline regressions (2-1) and (2-2). Larger firms receive more investors' attention than smaller firms. The other variable *GTI* is the logarithm of the average Google Trend Index of a firm during the past four weeks. Google Trends provides data on the search frequencies of terms on a weekly basis. Scholars used the index to proxy for a stock's investor attention (Ding and Hou, 2015), a larger of which indicates a larger degree of investor attention. To effectively capture investors' searching interests, we track queries using ticker symbols rather than firm names (Ding and Hou, 2015). Nevertheless, this approach could potentially yield ambiguous results; for instance, searching for the ticker 'F' may produce results unrelated to 'Ford Motor'. To mitigate this ambiguity, we refine our search by pairing the ticker symbol with the relevant stock exchange. For example, we utilize 'NYSE: F' to pinpoint interest in 'Ford Motor', a firm listed on the New York Stock Exchange (NYSE). This strategy ensures more accurate results by reducing search ambiguity.

Using regression (2-2), we estimate the regression coefficient of the interaction terms between the remote and the two measures (*Size* and *GTI*). The results are reported in Table

2-10. In column (1), the coefficient of the interaction term is 0.185 and significant at a 5% significance level. It indicates that the impact of *Remote* on *ABS* is stronger when the firm is larger. In column (3), we find consistent results that the impact of *Remote* on *ABS* is stronger when the Google Trend Index is larger. In columns (2) and (4), using an alternative measure of investor disagreement (*ABS[0,4]*) finds consistent results. Overall, the remote interview of a firm with larger investor attention leads to larger investor disagreement.

Table 2-10 Public attention

This table presents the interactive impact of public attention. The key independent variable is *Remote,* a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. The dependent variables in columns are *ABS* and *ABS[0,4]*, the abnormal daily average bid-ask spreads [0,2] and [0,4] days around the interview date, respectively. In columns (1) and (2), the public attention measure is firm size *Size*. In columns (3) and (4), the public attention measure is the firm's Google Trend Index *GTI*. The key variables of interest are *Remote*, public attention measures, and the interaction term between them. The control variables and fixed effects are consistent with baseline regression (2). Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Firm Size		*Attention to Firms*	
	ABS	ABS[0,4]	ABS	ABS[0,4]
	(1)	(2)	(3)	(4)
Remote	-1.089	-0.454	0.406*	0.273*
	(-1.413)	(-0.758)	(1.852)	(1.720)
Size	-0.054	-0.052		
	(-0.994)	(-1.207)		
Remote × Size	0.185**	0.102*		
	(2.259)	(1.703)		
GTI			-0.010*	-0.008*
			(-1.892)	(-1.888)
Remote × GTI			0.018**	0.015**
			(2.240)	(2.368)
Firm Control				
Recent return	0.442	0.515	0.409	0.506
	(0.535)	(0.776)	(0.491)	(0.759)
ROA	3.307***	2.171***	3.277***	2.169***
	(3.137)	(2.635)	(3.137)	(2.659)
Book-to-market	-0.005	-0.005	-0.004	-0.004
	(-0.759)	(-0.966)	(-0.692)	(-0.920)
Size			0.019	-0.013
			(0.312)	(-0.298)
Leverage	0.178	0.135	0.248	0.176
	(0.373)	(0.380)	(0.532)	(0.505)
Loss	0.381	0.247	0.387	0.246
	(1.467)	(1.313)	(1.529)	(1.347)
Analyst	0.064	0.029	0.068	0.029
	(0.973)	(0.556)	(1.022)	(0.580)
CEO Control				
CEO age	-0.459	-0.224	-0.363	-0.152
	(-0.813)	(-0.551)	(-0.645)	(-0.375)
CEO gender	-0.091	-0.044	-0.081	-0.035
	(-0.220)	(-0.128)	(-0.196)	(-0.100)
CEO education	0.225	0.191	0.216	0.179
	(1.332)	(1.436)	(1.264)	(1.337)
Video Control				
Video date	-0.013	-0.023*	-0.012	-0.023*
	(-0.804)	(-1.887)	(-0.705)	(-1.821)
Video length	0.043	0.049	0.055	0.059
	(0.364)	(0.579)	(0.459)	(0.681)
Video time	-0.040	-0.021	-0.030	-0.015
	(-0.346)	(-0.222)	(-0.266)	(-0.161)
Negative sentiment	-3.214	-2.843	-3.367	-2.891
	(-1.413)	(-1.492)	(-1.487)	(-1.498)
Uncertainty sentiment	-3.083	-1.627	-2.998	-1.460
	(-0.553)	(-0.365)	(-0.540)	(-0.328)
Constant	-0.544	-0.998	-1.549	-1.598
	(-0.234)	(-0.597)	(-0.709)	(-1.004)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	868	868	868	868
adj R-sq	0.117	0.131	0.114	0.133

2.6.3 Analyst Following and Institutional Holding

Firms with a larger analyst following and substantial institutional holdings tend to attract greater attention and scrutiny from various stakeholders, owing to their higher market visibility and investment significance. When these firms conduct CEO interviews, the information disseminated is interpreted by a diverse set of investors, each with varying levels of expertise, investment horizons, and risk appetites. This heterogeneity in the investor base can lead to a wider range of interpretations and consequent investment decisions, thereby facilitating greater investor disagreement.

We investigate how our baseline findings vary across different levels of analyst coverage (*Analyst*) and institutional ownership (*Institutional ownership*). The variables *Analyst* is the logarithm of the number of analysts following the firm with a lag of one quarter. The variable *Institutional ownership* is the ratio of the number of shares held by institutional investors to the total outstanding with a lag of one quarter. We estimate the interaction terms between the remote and the two variables. The results are reported in Table 2-11. The regression coefficients for all interaction terms are positive and significant, suggesting that the impact of remote interviews on investor disagreement is stronger when the firms have a higher level of analyst following or institutional holding.

Table 2-11 Analyst following & institutional holding

This table presents the interactive impact of analyst coverage and institutional holding. The key independent variable is *Remote,* a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. The dependent variables are *ABS* and *ABS[0,4],* the abnormal daily average bid-ask spreads [0,2] and [0,4] days around the interview date, respectively. The other variable of interest is analyst coverage (*Analyst*) in columns (1) and (2), and institutional ownership (*Institutional ownership*). The interaction terms between the remote and the variables are included. The control variables and fixed effects are consistent with baseline regression (2). Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Analyst		*Institutional Investor*	
	ABS	ABS[0,4]	ABS	ABS[0,4]
	(1)	(2)	(3)	(4)
Remote	-2.265**	-1.499*	-0.154	-0.151
	(-2.263)	(-1.888)	(-0.308)	(-0.377)
Analyst	-0.759**	-0.494**		
	(-2.253)	(-2.071)		
Remote × Analyst	1.054***	0.707**		
	(2.883)	(2.496)		
Institutional ownership			0.176	0.143
			(0.473)	(0.463)
Remote × Institutional ownership			1.187*	0.948*
			(1.667)	(1.769)
Firm Control				
Recent return	1.188	1.111	0.589	0.759
	(0.870)	(1.032)	(0.599)	(1.017)
ROA	5.452**	3.631**	3.415**	2.538**
	(2.395)	(2.203)	(2.470)	(2.489)
Book-to-market	0.001	-0.003	-0.007	-0.006
	(0.105)	(-0.599)	(-1.062)	(-1.316)
Size	0.017	-0.024	0.005	-0.023
	(0.117)	(-0.235)	(0.071)	(-0.427)
Leverage	-1.399**	-0.845*	0.091	0.052
	(-2.004)	(-1.716)	(0.170)	(0.130)
Loss	0.095	0.019	0.331	0.218
	(0.247)	(0.063)	(1.000)	(0.868)
Analyst			0.061	0.018
			(0.813)	(0.314)
CEO Control				
CEO age	-0.228	-0.034	-0.662	-0.395
	(-0.200)	(-0.042)	(-0.850)	(-0.738)
CEO gender	-0.415	-0.260	-0.130	-0.064
	(-0.846)	(-0.678)	(-0.312)	(-0.185)
CEO education	0.267	0.184	0.336*	0.272*
	(0.993)	(0.863)	(1.710)	(1.766)
Video Control				
Video date	-0.017	-0.025	-0.002	-0.016
	(-0.681)	(-1.302)	(-0.107)	(-1.154)
Video length	0.092	0.127	0.102	0.100
	(0.444)	(0.925)	(0.756)	(1.009)
Video time	-0.065	-0.034	-0.051	-0.053
	(-0.354)	(-0.223)	(-0.386)	(-0.475)
Negative sentiment	0.214	-0.794	-4.846*	-4.467**
	(0.053)	(-0.236)	(-1.837)	(-1.997)
Uncertainty sentiment	-1.914	-2.607	-2.877	-0.888
	(-0.170)	(-0.313)	(-0.432)	(-0.167)
Constant	-0.503	-1.369	-0.950	-1.199
	(-0.110)	(-0.398)	(-0.312)	(-0.556)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	460	460	735	735
adj R-sq	0.144	0.190	0.120	0.146

2.6.4 Interview Contents

The quantity and substance of information disclosed during a CEO's interview can have significant implications for investors' reactions. When more material or substantive information is presented, the level of investors' response is likely to escalate. Consequently, increased disclosure of material information may result in heightened disagreement among investors (Landsman *et al*., 2012), reflecting their varying interpretations and responses to the newly disclosed information. Therefore, it is plausible that a larger volume of material information disseminated through CEO interviews prompts more pronounced reactions from investors.

First, we investigate the topics covered in the CEO interviews. As discussed, the topics have two categories: (1) firm-specific issues such as earnings, stocks, business outlook, events, and strategies; (2) macroeconomic concerns, including industry outlooks, policy impacts, political impacts, and environments related to their firms. The first category is directly related to the stock and the firm's operational performance. For instance, earnings can offer concrete information that directly affects the valuation. In contrast, the second category is less quantifiable or less within the firm's control, reducing its materiality. As a result, the first category is likely to produce stronger investor responses due to its direct impact on firm performance. A dummy variable *Video topic* defines the topics, which equals 1 if the topic is (1), and 0 otherwise. We add the interaction term between the *Remote* and *Video topic* and estimate the regression (2-2). Table 2-12 column (1) shows a positive and significant regression coefficient of the interaction term, indicating that the impact of remote is stronger when the interview is topic one. The result still holds using the alternative measure in column (2).

Next, we use textual analysis to measure the information content of an interview. In natural language processing (NLP), stop words such as ‘the’, ‘so’, and ‘this’ occur frequently but carry little meaningful information. The variable *NonStop* measures the ratio of the number of non-stop words to total words in an interview, a larger of which indicates a larger information content. More content leads to larger divergence in interpretations, resulting in larger investor disagreement. The positive coefficients of the interaction terms in Table 2-12 columns (3) and (4) are consistent with our conjecture.

Table 2-12 Interview contents

This table presents the interactive impact of interview content. The key independent variable is *Remote,* a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. The dependent variables in columns are *ABS* and *ABS[0,4]*, the abnormal daily average bid-ask spreads [0,2] and [0,4] days around the interview date, respectively. In columns (1) and (2), the other variable of interest is *Video topic* which equals 1 if the topic is firm-specific and 0 otherwise. In columns (3) and (4), we investigate information content delivered by CEOs. The interaction terms are included. The control variables and fixed effects are consistent with baseline regression (2). Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Topics		*Contents*	
	ABS	ABS[0,4]	ABS	ABS[0,4]
	(1)	(2)	(3)	(4)
Remote	0.395**	0.292**	-5.872*	-3.917
	(2.292)	(2.172)	(-1.936)	(-1.477)
Video topic	0.303**	0.188*		
	(2.438)	(1.851)		
Remote × Video topic	0.450*	0.351*		
	(1.864)	(1.927)		
NonStop			1.799	1.076
			(1.222)	(0.915)
Remote × NonStop			7.789**	5.265*
			(2.152)	(1.660)
Firm Control				
Recent return	0.566	0.663	0.162	0.338
	(0.675)	(0.983)	(0.205)	(0.514)
ROA	3.643***	2.416***	2.955***	1.951**
	(3.197)	(2.631)	(2.979)	(2.439)
Book-to-market	-0.004	-0.004	-0.004	-0.004
	(-0.567)	(-0.812)	(-0.638)	(-0.864)
Size	0.014	-0.017	0.021	-0.012
	(0.241)	(-0.412)	(0.374)	(-0.282)
Leverage	0.250	0.184	0.243	0.171
	(0.537)	(0.526)	(0.531)	(0.498)
Loss	0.354	0.232	0.322	0.206
	(1.396)	(1.271)	(1.289)	(1.136)
Analyst	0.081	0.039	0.067	0.029
	(1.229)	(0.775)	(1.026)	(0.587)
CEO Control				
CEO age	-0.655	-0.345	-0.430	-0.208
	(-1.100)	(-0.805)	(-0.788)	(-0.531)
CEO gender	-0.140	-0.071	-0.138	-0.074
	(-0.356)	(-0.215)	(-0.345)	(-0.219)
CEO education	0.330*	0.269**	0.263	0.214*
	(1.935)	(2.058)	(1.589)	(1.658)
Video Control				
Video date	-0.010	-0.021*	-0.010	-0.022*
	(-0.598)	(-1.654)	(-0.599)	(-1.715)
Video length	0.058	0.070	0.039	0.047
	(0.484)	(0.806)	(0.332)	(0.545)
Video time	0.005	0.005	0.026	0.020
	(0.047)	(0.057)	(0.226)	(0.213)
Negative sentiment	-2.170	-2.078	-3.506	-3.016
	(-0.907)	(-1.055)	(-1.482)	(-1.508)
Uncertainty sentiment	0.756	0.957	-2.576	-1.282
	(0.131)	(0.209)	(-0.481)	(-0.298)
Constant	-1.155	-1.401	-2.988	-2.420
	(-0.499)	(-0.819)	(-1.218)	(-1.284)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	845	845	868	868
adj R-sq	0.137	0.150	0.130	0.141

2.6.5 Alternative Explanation

In the previous section, we provide evidence that the perceived clarity of CEOs' disclosures in remote interviews may lead to a larger dispersion of the interpretation of the information, thus leading to larger investor disagreement. There is an additional potential explanation for the baseline findings. The different information set is the other channel driving investor disagreement (Cookson and Niessner, 2020). Whether the remote interview create additional information beyond the face-to-face interview, holding other conditions equal? To answer this question, we estimate to what extent remote interviews are associated with new information. We use firms' cumulative abnormal return 3 days (-1, 1) centered around the interview date (*CAR[-1, 1]*) to capture the information contents of the interviews. If remote interview reduces information asymmetry more than face-to-face interviews, we should observe a significantly positive impact of remote interviews on *CAR[-1, 1]*. For robustness, we use various estimation windows or cumulative windows to calculate different CARs. Table 2-13 reports the results. We find an insignificant impact of remote interviews on CARs. It suggests that remote interviews are less likely to create new information or reduce information asymmetry than face-to-face interviews. In summary, investor disagreement is less likely to be derived from different information sets.

Table 2-13 New information

This table presents the impact of remote interviews on new information content. The key independent variable is *Remote,* a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. The dependent variables in columns are *CAR[-1,1] and CAR[-2,2]*, the cumulative abnormal returns [-1,1] and [-2,2] days centered around the interview date, respectively. The control variables and fixed effects are consistent with baseline regression (2-2). Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	CAR[-1,1]	CAR[-2,2]
	(1)	(2)
Remote	0.003	0.004
	(0.733)	(0.808)
Firm Control		
Recent return	0.003	0.004
	(0.733)	(0.808)
ROA	-0.008	-0.031
	(-0.294)	(-1.027)
Book-to-market	0.019	0.022
	(0.632)	(0.625)
Size	0.000	0.000
	(0.348)	(0.013)
Leverage	-0.003**	-0.002
	(-2.274)	(-1.129)
Loss	0.008	0.003
	(0.864)	(0.239)
Analyst	-0.007	-0.002
	(-1.029)	(-0.343)
CEO Control	0.002*	0.002*
CEO age	(1.825)	(1.844)
CEO gender	0.008	0.005
	(0.565)	(0.272)
CEO education	-0.002	-0.005
	(-0.303)	(-0.732)
Video Control	0.007**	0.007*
Video date	(2.091)	(1.853)
Video length	-0.000	-0.000
	(-0.717)	(-0.689)
Video time	0.009***	0.007*
	(2.646)	(1.770)
Negative sentiment	-0.001	-0.004
	(-0.314)	(-0.866)
Uncertainty sentiment	-0.140*	-0.105
	(-1.861)	(-1.110)
Constant	0.104	0.191
	(0.598)	(0.878)
Year FE	Yes	Yes
Industry FE	Yes	Yes
N	868	868
adj R-sq	0.019	0.001

2.7 Post-Interview Analysis

Information recipients possess varying information processing abilities. For instance, sophisticated investors, with their superior resources and insights, tend to respond more adeptly to new information than unsophisticated investors (Amiram *et al.*, 2016; Cookson and Niessner, 2020). This section investigates how different interview recipients react to remote versus face-to-face interviews.

Institutional investors such as banks, insurance companies, and mutual funds tend to rely on sophisticated models to access information and manage large volumes of investment. It remains uncertain whether they respond to interview modalities. To answer the question, we estimate how remote interviews impact institutional holdings in the subsequent quarter. The dependent variable *Total_Holding* is the ratio of institutional holdings of a firm to its outstanding shares in the subsequent quarter following the interview date. Additionally, we separately account for the total holdings of various institutional investor types as defined by Refinitiv: banks (*Banks*), insurance companies (*Insurance*), and investment companies (*Investment*). Upon substituting the dependent variable in regression (2-2), the results are presented in Table 2-14 columns (1)-(4). Remote interviews are associated with negative institutional holdings as shown in column (1). This impact is primarily driven by investment companies while this effect is insignificant within banks and insurance companies. Overall, the results indicate that institutional investors negatively react to remote interviews.

Given the impact of remote interviews on information interpretation, analysts may react differently to the interviews. We focus on analysts' forecast accuracy. The variable *Accuracy* measures how accurate the next quarter's forecasts are for the actual earnings.[26] In Table 2-14 columns (5), we find insignificant impacts of *Remote* on *Accuracy*. We also find insignificant impact when using alternative measures such as next month's or next year's accuracy. Overall, we find no evidence that interview modalities influence analysts' forecast accuracy.

[26] Accuracy = - |(Mean Estimation – Actual Earnings)/Actual Earnings|. Source: I/B/E/S

Table 2-14 Information recipients' heterogeneity

This table presents whether institutional investors and analysts react to remote interviews. The key independent variable is *Remote,* a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. In columns (1)-(4), the dependent variables are institutional holdings of the interviewed firm in the next quarter by all types of investors, banks, insurance companies, and investment companies, respectively. In column (5), the dependent variables are the next quarter's analysts' forecasts accuracy. The control variables and fixed effects are consistent with baseline regression (2-2). Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Institutional Investors				*Analysts*
	Total_Holding	Bank	Insurance	Investment	Accuracy
	(1)	(2)	(3)	(4)	(5)
Remote	-0.032**	-0.007	-0.001	-0.033**	0.129
	(-2.012)	(-1.292)	(-0.472)	(-2.253)	(1.407)
Firm Control					
Recent return	0.017	0.002	-0.003	0.056	0.199
	(0.196)	(0.113)	(-0.692)	(0.725)	(0.380)
ROA	0.581***	0.097**	0.008	0.501***	-1.553*
	(3.866)	(2.355)	(0.903)	(3.586)	(-1.739)
Book-to-market	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.120)	(-0.585)	(-0.625)	(-0.402)	(-0.056)
Size	-0.026**	0.010***	-0.001*	-0.040***	-0.166
	(-2.228)	(3.376)	(-1.835)	(-3.614)	(-1.150)
Leverage	0.140**	-0.017	-0.002	0.140**	-1.358*
	(2.052)	(-1.539)	(-0.561)	(2.339)	(-1.842)
Loss	-0.006	0.000	-0.005**	-0.003	-0.001
	(-0.179)	(0.032)	(-2.183)	(-0.114)	(-0.004)
Analyst	-0.004	-0.002	0.000	-0.007	0.587
	(-0.473)	(-1.248)	(0.660)	(-0.893)	(0.959)
CEO Control					
CEO age	-0.035	-0.011	0.006	-0.042	0.810
	(-0.314)	(-0.427)	(1.019)	(-0.415)	(0.977)
CEO gender	-0.032	0.014*	-0.002	-0.054	-0.012
	(-0.575)	(1.772)	(-0.865)	(-1.045)	(-0.058)
CEO education	-0.010	-0.006	-0.002	-0.007	-0.069
	(-0.420)	(-0.718)	(-1.110)	(-0.326)	(-0.570)
Video Control					
Video date	-0.001	-0.001	0.000	-0.002	0.012
	(-0.388)	(-0.941)	(0.099)	(-0.912)	(1.340)
Video length	-0.009	-0.011	-0.001	-0.006	0.019
	(-0.740)	(-1.261)	(-1.495)	(-0.539)	(0.236)
Video time	-0.016	0.004	-0.002*	0.001	0.030
	(-1.005)	(0.764)	(-1.687)	(0.094)	(0.194)
Negative sentiment	0.065	-0.027	-0.026	-0.130	-0.687
	(0.171)	(-0.191)	(-1.467)	(-0.442)	(-0.390)
Uncertainty sentiment	-0.178	-0.394**	0.005	0.162	-7.343
	(-0.221)	(-2.093)	(0.087)	(0.246)	(-1.423)
Constant	1.189***	0.151	0.002	1.248***	-3.485
	(2.743)	(1.346)	(0.076)	(3.219)	(-1.046)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	812	804	798	789	471
adj R-sq	0.226	0.137	0.135	0.342	0.227

2.8 Conclusion

This study examines the effect of remote CEO interviews on investor disagreement. We focus on CEO interviews on CNBC which is a leading televised media in the United States. There are two types of interviews: face-to-face and remote interviews. We first investigate the determinants of remote interviews. Our findings suggest that CEOs who are geographically distant, busy, and have limited relations with the media are more likely to be remotely interviewed. Next, we examine to what extent remote interviews lead to investor disagreement. We find that a remote interview is associated with a higher investor disagreement around the interview date than a face-to-face interview. The finding is robust to various measures of investor disagreement, including abnormal daily average bid-ask spreads, abnormal trading volume, and abnormal stock price volatility. The finding is also robust to granular fixed effects or adjusted samples. We alleviate the endogeneity concern by using a Heckman treatment effect model, difference-in-differences, and propensity score matching strategy. Our results are less likely driven by endogeneity problems such as selection bias or omitted variables. Remote interviews impact investor disagreement by increasing the dispersion of information interpretation among the information recipients.

We contribute to the line of research on CEOs' media appearances, investor disagreement, and the emerging literature on CEOs' non-verbal behaviors. Our study also has an impact on reality by highlighting the differences between remote and face-to-face communications, a new debate that became popular after the outbreak of COVID-19. Due to the technical limitation, our paper provides limited direct measurement of the content of CEOs' non-verbal cues. This could be further explored in the future.

Appendix

Table A2-2 Variable description

Variables	Definition	Source
Independent		
Remote	Dummy variable that equals one if the interview is conducted by video calls or phones, and zero by face-to-face	CNBC video
Dependent		
ABS	Daily average bid-ask spreads during [0, 2] day window around the interview date minus the daily average bid-ask spreads during the [-55, -6] day window prior to the interview date	Compustat
ABS[0,4]	Daily average bid-ask spreads during [0, 4] day window around the interview date minus the daily average bid-ask spreads during the [-55, -6] day window prior to the interview date	Compustat
ABS[-2,2]	Daily average bid-ask spreads during [-2, 2] day window around the interview date minus the daily average bid-ask spreads during the [-55, -6] day window prior to the interview date	Compustat
TVOL[-1, 1]	Average daily trading volume scaled by shares outstanding over the 3-day window centered on the interview, net of the same measured over the sixty calendar days ending four days before the interview	Compustat
TVOL[-2, 2]	Average daily trading volume scaled by shares outstanding over the 5-day window centered on the interview, net of the same measured over the sixty trading days ending four days before the interview	Compustat
ALTVOL	The difference between the log trading volume on the interview date and the average log trading volume over the 140 trading days ending 20 days before the interview	Compustat
ATVOL	The mean of the trading volume during the [-1, 1] days divided by the average volume during the [-60, -10] estimation window, taken from the natural logarithm	Compustat
AVAR	The mean of the squared market model adjusted returns, divided by the variance of the firm's market model residuals during the [-60, -10] window	Compustat
Firm control		
Recent return	Cumulative abnormal return during the past month	Compustat
ROA	Return-on-asset at the quarter end	Compustat
Book-to-market	The book-to-market ratio at the quarter end	Compustat
Size	The logarithm of one plus the market value at the quarter-end	Compustat
Leverage	Leverage ratio at the quarter-end	Compustat
Loss	Dummy variable that equals one if earnings are negative, and zero otherwise at the quarter end.	Compustat
Analyst	The logarithm of the number of analysts following the firm at the year-end	I/B/E/S
CEO control		
CEO age	The logarithm of CEO age	BoardEX
CEO gender	Dummy variable that equals one if the CEO is female, and zero otherwise	BoardEX
CEO education	Dummy variable that equals one if the CEO has a master's degree or above, and zero otherwise	BoardEX
Video control		
Video date	The number of months between the interview month and the fiscal year-end month	CNBC video

Video length	The logarithm of one plus the number of seconds of the video	CNBC video
Video time	Dummy variable equals one if the video is published on the website in the morning, and zero otherwise	CNBC website
Negative sentiment	The difference between the number of negative and positive words[27], divided by the number of total words	CNBC video
Uncertainty sentiment	The number of uncertainty words[28] divided by the number of total words	CNBC video
Remote determinants		
CEO distance	The logarithm of one plus the distance between the states of headquarters of the firm and CNBC live studio	Bureau of Economic Analysis[29]
CEO busy	Dummy variable that equals one if the CEO is a board member, and zero otherwise	BoardEX
CEO relation	Dummy variable that equals one if the CEO is first interviewed during the sample period, and zero otherwise	CNBC video
Other variables		
Familiarity	Integer values ranging from 1 to X, each value indicating the sequential count of a CEO's interviews throughout the given sample period	Self-calculation
GTI	The logarithm of the average Google Trend Index of a firm during the past four weeks	Google Trend Index
Institutional Ownership	The ratio of the number of shares held by institutional investors to total shares outstanding with a lag of one quarter	Thomson/ Refinitiv
NonStop	The ratio of the number of non-stop words to total words in an interview subtitle	Self-calculation
CAR[-1,1]	The cumulative abnormal returns [-1,1] days centered around the interview date. The returns are estimated from the market model	Compustat
CAR[-2,2]	The cumulative abnormal returns [-2,2] days centered around the interview date. The returns are estimated from the market model	Compustat
Accuracy	The negative absolute value of the difference between mean estimation and actual earnings, then divided by actual earnings	I/B/E/S

[27] From word dictionary of Loughran and McDonald (2011)
[28] From word dictionary of Loughran and McDonald (2011)
[29] Available at: https://www.bea.gov/

Figure A2-1 and Figure A2-2 Two examples of the screenshots for the interviews

The following two figures are screenshots of interview videos. In Figure A1, General Mills CEO, Jeff Harmening, is remotely interviewed. In Figure A2, Vertex Pharmaceuticals CEO, Dr. Jeff Leiden, is participating in a face-to-face interview. The videos are from the CNBC website available at: https://www.cnbc.com/.

Figure A2-1 Interviews for General Mills CEO, Jeff Harmening

Figure A2-2 Interviews for Vertex Pharmaceuticals CEO, Dr. Jeff Leiden

Table A2-2 Determinants of remote interview

This table presents a logit model of regression (2-1) estimating the determinants of remote interviews. *Remote* is a dummy variable that equals one if the interview is remotely conducted by video calls, and zero if face-to-face. We estimate the probit model of the regression (2-1). Firm, CEO, and video control variables are consistent in columns (1)-(5). Year fixed effects and industry fixed effects are included. In column (6), we further control the interview topic fixed effect. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Remote (1)	Remote (2)	Remote (3)	Remote (4)	Remote (5)	Remote (6)
CEO distance	0.466***			0.481***	0.520***	0.535***
	(3.109)			(3.210)	(3.296)	(3.401)
CEO busy		0.459**		0.527**	0.550*	0.521*
		(1.994)		(2.255)	(1.959)	(1.871)
CEO relation			-0.917***		-0.841***	-0.791***
			(-3.118)		(-2.795)	(-2.625)
Firm Control						
Recent return	-2.479**	-2.679***	-1.253	-2.578**	-1.662	-1.508
	(-2.432)	(-2.641)	(-1.081)	(-2.507)	(-1.371)	(-1.223)
ROA	3.447***	2.976**	4.174**	3.190**	3.757**	3.910**
	(2.666)	(2.394)	(2.537)	(2.437)	(2.231)	(2.305)
Book-to-market	-0.004	-0.002	-0.011	-0.002	-0.010	-0.009
	(-0.549)	(-0.222)	(-1.101)	(-0.355)	(-1.158)	(-1.141)
Size	-0.191*	-0.173*	-0.260**	-0.159	-0.192*	-0.177
	(-1.942)	(-1.703)	(-2.274)	(-1.587)	(-1.677)	(-1.570)
Leverage	-0.978	-0.966	-2.276***	-0.697	-1.464*	-1.418*
	(-1.416)	(-1.292)	(-2.725)	(-0.988)	(-1.749)	(-1.701)
Loss	-0.013	0.025	-0.119	-0.139	-0.433	-0.540
	(-0.033)	(0.061)	(-0.247)	(-0.365)	(-0.944)	(-1.173)
Analyst	0.012	-0.013	-0.030	0.006	-0.016	-0.010
	(0.129)	(-0.137)	(-0.287)	(0.064)	(-0.156)	(-0.099)
CEO Control						
CEO age	0.463	0.346	-0.169	0.246	-0.357	-0.831
	(0.487)	(0.371)	(-0.158)	(0.258)	(-0.315)	(-0.720)
CEO gender	-0.522	-0.736	-0.415	-0.532	-0.235	-0.351
	(-1.031)	(-1.443)	(-0.879)	(-0.945)	(-0.394)	(-0.569)
CEO education	0.130	0.092	-0.104	0.102	-0.106	-0.177
	(0.485)	(0.339)	(-0.363)	(0.392)	(-0.380)	(-0.637)
Video Control						
Video date	0.008	0.017	-0.006	0.013	-0.001	0.001
	(0.304)	(0.677)	(-0.206)	(0.511)	(-0.031)	(0.029)
Video length	-0.253	-0.247	-0.241	-0.251	-0.231	-0.262
	(-1.486)	(-1.508)	(-1.210)	(-1.477)	(-1.110)	(-1.240)
Video time	0.028	0.016	-0.031	0.047	0.044	0.126
	(0.128)	(0.078)	(-0.130)	(0.214)	(0.177)	(0.511)
Negative sentiment	-16.450***	-16.686***	-16.154***	-16.380***	-16.392***	-14.548**
	(-3.623)	(-3.790)	(-2.940)	(-3.640)	(-2.870)	(-2.495)
Uncertainty sentiment	-11.226	-10.955	-2.481	-11.606	-5.785	-9.875
	(-1.068)	(-1.074)	(-0.203)	(-1.104)	(-0.467)	(-0.805)
Constant	1.973	2.821	7.925*	2.157	6.456	8.643*
	(0.497)	(0.746)	(1.790)	(0.547)	(1.372)	(1.779)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	-	-	-	-	-	Yes
N	817	826	629	815	621	616
pseudo R-sq	0.180	0.165	0.186	0.187	0.213	0.221

3. Climate Change Exposure and Mutual Fund Ownership

Abstract

This chapter examines the implications of firms' climate change exposure on their mutual fund ownership. Using a sample of firms in the United States between 2002 and 2020 and a measure of climate change exposure estimated from the attention paid by earnings call participants, we find that larger climate change exposure is associated with smaller growth in mutual fund ownership at the firm level. The impact is pronounced in high carbon-emitting and innovative sectors. This aversion stems from mutual funds' concern over heightened transition risks associated with climate change, which introduce substantial uncertainties in investment performance.

Keywords: climate change, climate change exposure, mutual fund ownership, transition risk

3.1 Introduction

Climate change creates a significant impact on the global economy and environment. The intensity of public attention to climate change has experienced an increasing trend over the past 30 years (Engle *et al.*, 2020). The increasing severity and frequency of climate change consequences are forcing market participants to reassess their operations and practices to mitigate associated risks and capitalize on potential opportunities. Institutional investors incorporate their portfolio firms' climate-related information and actively engage in improvements. According to the academic survey by Krueger *et al*. (2020), mutual funds are a type of institutional investor that ranks climate risks higher than others. However, the empirical evidence supporting to what extent and how institutional investors incorporate climate change risk and opportunity is known little. Given the increasing importance of climate change, our study examines the relationship between firms' climate change exposure and mutual funds' investment strategies, an important and unanswered question in the prior literature.

Mutual funds are important institutional investors within the global financial market. In the U.S., approximately 8,807 mutual funds were operating as of the end of 2021, managing assets of $26.82 trillion and serving roughly 100 million investors.[30] Compared to other institutional investors, such as insurance companies and banks, mutual funds exhibit a heightened propensity to gather information and attribute higher importance to climate risks (Ferreira and Matos, 2008; Dyck *et al*., 2019; Krueger *et al*., 2020). Mutual funds consider a range of financial and non-financial factors when incorporating a firm's climate change exposure into their investment decisions. The increased uncertainties associated with a firm's climate change risks add complexity to the evaluation process. Consequently, mutual funds

[30] Investment Company Institute (ICI) 2021. Available at: https://www.ici.org/

may avoid investing in firms with significant climate change exposure due to the heightened information processing costs involved. Second, firms could incur increased expenditures to address the risks and opportunities of climate change. Consequently, mutual funds might be averse to investing in firms with pronounced climate change exposure. Conversely, climate change can also be perceived as an opportunity. Firms significantly exposed to climate change exposure might be promoted to innovate and enhance sustainability practices. In prior studies, the implication of climate change exposure on mutual funds' investment decisions is underexplored. This study explores the potential motivations steering mutual funds' incorporation of climate change and to what extent firms' climate change exposure influences their mutual fund ownership.

Our main empirical analysis investigates the relationship between firms' climate change exposure and the net growth in mutual fund ownership. We use Sautner *et al*. (2023)'s climate change exposure index (*CCExposure*), which identifies participants' attention to a firm's climate change exposure in earnings calls using machine learning approaches. It reflects market participants' assessments of how climate change affects the firms. To construct the index, the research first selects an initial set of bigrams that unambiguously relate to climate change. These bigrams are used as seeds in an algorithm that searches through earnings call transcripts to identify additional bigrams that indicate discussions about climate change. The algorithm helps in capturing more specialized language that may not be covered by pre-specified keywords, especially in the context of niche or evolving terminology. The final climate change exposure measures are derived by counting the frequency of these identified bigrams in each transcript and scaling them relative to the total number of bigrams in the transcript. The resulting index provides a measure of how much attention earnings call participants (both management and analysts) devote to climate change topics at a firm level, reflecting how firms are perceived to be exposed to climate-related risks and opportunities over time. The index is further refined to focus on specific topics like opportunities (*CCExposureOpp*), regulatory risks (*CCExposureReg*), and physical risks (*CCExposurePhy*). Similarly, the research starts with an initial set of bigrams related to each topic and the machine learning algorithm expands the bigrams, following which the frequency of bigrams from these topic-specific sets is calculated. This measure better addresses the challenge that previous approaches are difficult to measure how individual firms are influenced by climate change (Giglio *et al*., 2021b; Sautner *et al*., 2023). The benefit is that it reflects soft information originating from information exchanges between managers and analysts on earnings calls instead of measures based on fundamental information.

We initially focus on all the U.S. firms covered by Sautner *et al*. (2023)'s climate change exposure. The sample period starts in 2002 and ends in 2020. After matching with other databases, our final sample includes 12,628 firm-year observations and 1,825 unique firms in 46 states of the U.S. Empirical results suggest that firms' climate change exposure in the current year negatively affects the net growth in mutual fund ownership in the next year after controlling known determinants of mutual funds' investment decisions, firm fixed effects and year fixed effects. To ensure that our results are robust, we examine the baseline regression using additional measures of mutual fund ownership and climate change exposure. Additional robustness tests suggest that the baseline findings still hold when we (1) adjust the sample by removing the states with the largest or smallest number of firms, (2) adjust the sample by excluding the observations in the year 2002 and year 2003, (3) adjust the sample by excluding industries with a superior number of firms, (4) use alternative dependent or independent variables, (5) adjust the sample by using alternative fixed effect setting.

Next, we identify possible channels through which firms' climate change exposure hinders mutual fund ownership. We separately examine the impact of three aspects of climate change exposure: opportunity, regulation, and physical disasters. Our results suggest that firms' exposure to opportunity and regulation drives the baseline findings. Mutual fund investors primarily incorporate firms' exposure to opportunity and regulation shocks related to climate change, while they are less likely to incorporate the exposure to physical risks. We conjecture that mutual fund investors mainly incorporate the transition risks and stock performance of the firms that have larger climate change exposure. Transition risk related to climate change refers to the risks that arise as economies and industries shift toward a low-carbon future. These risks are associated with the changes required to reduce greenhouse gas emissions and adapt to more sustainable practices. Following Ilhan *et al*. (2021) and Ginglinger and Moreau (2023), we investigate the heterogeneous impact of climate change exposure on mutual fund ownership across different industries. Carbon-emitting industries and innovative industries are largely correlated with climate change, which increases costs, risks, and uncertainties (Bhattacharya *et al*. 2017; Li *et al*., 2023). For firms in these industries, the impact of climate change exposure on mutual fund ownership is amplified. Firms with weaker stock performance or greater downside risks are more vulnerable to the negative effects of climate change exposure. The heightened uncertainties and increased downside risks associated with transition risks significantly impact firms' stock performance. These factors play a crucial role in guiding the investment decisions of mutual fund investors. We find no evidence for other potential explanations: information cost, reputation risks, or financial constraints.[31]

To address endogeneity issues and identify the causal relationship between climate change exposure and the net growth in mutual fund ownership, we rely on climate-related

[31] Specifically, mutual funds have demand for firms' disclosure of climate-related information (Ferreira and Matos, 2008; Dyck et al., 2019; Krueger et al., 2020). When investing in firms with large climate change exposure, mutual funds require more information to identify the potential risks and assess the investment. The increased information collection costs restrict the investment of mutual fund investors. Following Sautner et al. (2023) and Krueger et al. (2020), firms will invest more to hedge climate change exposures such as in human capital and employment environments, which lead to lower reputation or financial constraints. Due to the incentives to make profits, mutual funds may be averse to investing in firms with large climate change exposure.

exogenous shocks. The first is the adoption of climate change adaption plans at the U.S. state-level. Climate change adaptation plans are developed to address the impacts of climate change and to enhance the resilience of communities, infrastructure, and ecosystems. These plans focus on preparing for and mitigating the adverse effects of climate change, such as extreme weather events, rising sea levels, and shifting ecological patterns. As of March 2021, there are 19 states that have adopted the climate change plans. These adaptation plans are one of the leading sources of practical strategies for preparing and responding to the impacts of climate change.[32] The climate change adaption plans increase the resilience of firms in climate change (Heo, 2021). The implementation of state-level climate adaptation plans often leads to new regulations or the enhancement of existing ones aimed at mitigating climate risks. While adaptation plans are primarily focused on risk mitigation, they also create opportunities for firms to innovate and grow. We employ a staggered difference-in-differences approach to empirically test the impact of this shock. The results of DiD regression indicate a significant positive influence on the net growth of mutual fund ownership of firms in states that have adopted climate change adaption plans, relative to firms in non-adopting states, following the policy's implementation. The results are consistent with our conjecture.

The second exogenous shock is the implementation of Renewable Portfolio Standards (RPS) at the U.S. state-level. Renewable portfolio standards (RPS), designed to increase the use of renewable energy sources for electricity generation, encourage electricity suppliers to provide their customers with a stated minimum share of electricity from eligible renewable resources.[33] As of November 2022, RPS has been adopted by 30 states, inclusive of the District of Columbia. Post-RPS implementation, there is an increase in attention to the benefits and costs of climate-related issues. Elevated public focus ensures that firms with

[32] The Georgetown climate center is tracking implementation of these plans: https://www.georgetownclimate.org
[33] The U.S. Energy Information Administration (EIA) (2022). Avaiable at: https://www.eia.gov

RPS-adopting states are conspicuously exposed to climate change. The staggered adoption of RPS across different states provides a viable framework to exploit how heightened climate change exposure changes mutual fund ownership. The results of staggered difference-in-differences (DiD) regression indicate a significant negative influence on mutual fund ownership of firms in states that have adopted RPS, relative to firms in non-adopting states, subsequent to the policy's implementation. The above evidence supports the causal relation and alleviates endogeneity issues.

To better understand the impact of climate change exposure on mutual funds' investment decisions, we examine the variations of baseline findings across different degrees of uncertainties. External uncertainties, such as those related to political uncertainties, can significantly mitigate the influence of a firm's climate change exposure on mutual fund ownership. In periods of heightened uncertainty, investors and fund managers may prioritize short-term risk management and capital preservation over long-term environmental considerations. Our paper focuses on political uncertainties. In times of heightened political uncertainty, investors may place greater emphasis on firms' climate change exposure when evaluating investment opportunities. This heightened scrutiny arises because, under conditions of political uncertainty, the potential for regulatory shifts, policy changes, or market disruptions related to climate change becomes more pronounced. Consequently, firms with high climate risk may face increased pressure from investors to demonstrate resilience and adaptability, leading to a stronger correlation between climate change exposure and mutual fund ownership. This dynamic suggests that in environments characterized by significant external uncertainties, the consideration of climate-related risks becomes even more critical in mutual fund investment decisions. To empirically test our conjecture, we divide the baseline into sub-samples based on whether the year has a presidential election. A year with a presidential election is regarded as a greater political uncertainty. The results suggest that the negative impact of climate change exposure on net growth in mutual fund ownership is strengthened. This is consistent with our hypothesis.

Our study contributes to the literature twofold. First, it adds to the literature on climate change and its economic impacts (Dell *et al*., 2014; Burke, *et al*., 2015; Carleton and Hsiang, 2016; Hsiang and Kopp, 2018). Prior literature documents the impact of climate change on municipal bonds, bank lending, capital structure, etc. Due to the limitation in measurement, these studies usually focus on one aspect of climate change. However, climate change has a comprehensive impact on firms. Sautner *et al*. (2023) construct a measure of climate change capturing the aggregate risk of climate change. This provides us with an opportunity to investigate the impact of climate change exposure on mutual fund investment decisions. Our study highlights that climate change hinders mutual funds investment, which suggests a possible mechanism through which climate change negatively impacts economic and financial markets.

Second, our study provides empirical evidence for the recent call for whether and how institutional investors incorporate climate change (Stroebel *et al*., 2021). Climate change is both a risk and an opportunity. Institutional investors face greater uncertainties in investments. Theoretically, mutual funds have incentives to either more or less invest in firms with large climate change exposure. Our findings provide empirical evidence that mutual funds, on average, are averse to investing in climate change. Further, we find that mutual fund investors primarily focus on the impact of climate change exposure in opportunity and regulation. The exposure heightens the transition risks, which leads to higher investment uncertainties. Overall, we provide new evidence to the literature on how mutual fund investors incorporate climate change as well as the opportunities and risks.

The study proceeds as follows. Section 3.2 summarizes prior literature about climate change and mutual funds, and then proposes our hypothesis. Section 3.3 introduces the sample and data. Section 3.4 reports the results of baseline regression and robustness tests. Section 3.5 explores the economic channels of our key finding. Section 3.6 reports the results of the additional analysis. Section 3.7 concludes the paper.

3.2 Literature Review and Hypothesis Development

We draw on different strands of literature to derive the theoretical predictions on the effect of climate change exposure on mutual funds ownership. This section begins by introducing prior literature on climate change and mutual funds. We then put forward our hypothesis.

3.2.1 Climate Change and Financial Market

Climate change refers to the long-term alteration of temperature and typical weather patterns in a place, largely driven by human activities such as the burning of fossil fuels, deforestation, and industrial processes. These activities increase the concentration of greenhouse gases in the atmosphere, leading to global warming and a range of associated environmental impacts, including more frequent and severe weather events, rising sea levels, and disruptions to ecosystems. The financial markets are increasingly recognizing the implications of climate change, as it introduces significant risks and opportunities for investors. Consequently, climate change is reshaping investment strategies, risk management practices, and regulatory frameworks, underscoring its critical importance to the financial market's stability and future growth.

Climate change has become an increasingly important topic in the field of finance, with a growing body of literature exploring its potential impacts on financial markets and the broader economy. Prior studies have examined the impact of climate change on asset prices, investor decisions, and firm performance. These studies usually focus on one specific aspect of climate change, such as temperature exposure (Pankratz *et al.*, 2023), or focus on regional climate change (Baldauf *et al*., 2020; Painter, 2020; Li *et al*., 2022). Baldauf *et al*. (2020) explored real estate pricing with heterogeneous beliefs, showing that buyers' varying beliefs about the likelihood and severity of long-run climate risks can affect real estate prices. It uses two types of climate change variables: variables that describe the current climate (measured from mean higher high water tidal datum) and variables pertaining to the change in climate (measured by the distance to the coast and risk of an extreme flood). Painter (2020) conducts an empirical analysis of the impact of climate change on municipal bonds, finding that counties more affected by climate change pay more in underwriting fees and initial yields to issue long-term municipal bonds compared to the counties less likely affected by climate change. Climate change increases risks for investors. Individual investors exhibit more behavioral biases due to environmental issues (Li *et al*., 2021). Environmental issues affect human health and reduce individuals' well-being and effectiveness in financial activities, leading to cognitive bias in trading markets. Li *et al*. (2021) document that air pollution significantly increases investors' disposition effects. Climate change also impacts firms' performance. Pankratz *et al*. (2023) explore the market reactions to firms' high-temperature exposure, highlighting that operating income and revenues are reduced by extreme temperatures. Overall, the literature on climate change and finance highlight the need for investors, policymakers, and other stakeholders to consider the potential impacts of climate change on financial markets and the broader economy. As the risks and opportunities associated with climate change continue to evolve, further research in this area is needed to inform sustainable investment strategies and risk management practices.

However, prior literature knows little about the firm-level variation in overall climate change exposure. Although investigating a specific aspect of climate change may offer detailed insights, firm-level climate change exposure illuminates the interconnectedness and interdependencies among various climate change aspects, enhancing systemic understanding. Consequently, investigating the firm-level variation in climate change is meaningful. One key challenge to estimating climate change's overall exposure to the financial outcome at a firm level is the measure of difficulty (Sautner *et al*., 2023), as the effects are multifaceted and originate from multiple sources. For example, physical climate changes might impose costs on some firms, while climate changes can provide opportunities for firms in renewable energy. Using a machine learning approach, Sautner *et al*. (2023) create a measure of firms' exposure to various facets of climate change. It defines the 'exposure' to an issue as the share of the conversation in a transcript devoted to that topic. The study adapts the keyword discovery algorithm to construct four related sets of climate change bigrams in earnings calls, including the overall exposure, opportunities, physical shocks, and regulatory shocks. It captures the attention that financial analysts and management devote to climate change topics at a given point in time. The benefit of the measure is that it reflects soft information from the exchanges between managers and analysts, as well as how market participants assess the impact of climate change on individual firms.

3.2.2 Mutual Fund Investors

Prior research documents that institutional investors should incorporate climate changes into their investments, and they value and demand firms' climate-related information disclosures. According to an academic survey by Krueger *et al*. (2020), (1) institutional investors believe that climate risks have a significant impact on portfolio firms, though the importance follows financial, operating, governance, and social risks. The climate-related uncertainties will materialize not in a distant future; (2) institutional investors have both financial and nonfinancial motivations such as protecting investors' reputation, moral considerations, increasing investment returns, and reducing portfolio risks; (3) most institutional investors actively manage climate risks, though still on the way finding the most effective approaches; (4) institutional investors act as marginal investors affecting asset prices. Among institutional investors, independent institutions such as mutual fund investors value climate risks more than financial risks.

Existing evidence suggests that fund managers incorporate physical disasters and carbon emissions, thereby influencing their allocation to portfolio firms. Alok *et al*. (2020) explore the implications of climatic disasters, highlighting that fund managers close to major disaster regions underweight disaster zone stocks to a much greater degree than managers distant. Ceccarelli *et al*. (2023) document that fund managers actively reduce exposure to firms with high carbon risks. Rohleder *et al*. (2022) explore the financial consequences of mutual fund decarbonization. The study finds that decarbonization contributes to the reduction of portfolio firms' carbon emissions. However, the integration of climate change into institutional investors is still challenging, because the tools and best practices are not yet well established (Krueger *et al*., 2020). Empirically, we have little evidence of the impact of overall climate change on fund managers' decisions, due to the lack of an efficient measure of a firm's overall climate change exposure. This paper fills the gap by identifying to what extent an individual firm's climate change exposure impacts the assessment of mutual fund investors.

3.2.3 Hypothesis Development

Multiple motivations potentially predict mutual funds' reaction to firms' climate change exposure. Mutual funds could be averse to firms' climate change exposure. A transition risk hypothesis suggests that firms face both opportunities and risks due to climate change (Li *et al.*, 2024). Transition risk arises from the economic and operational challenges that firms face as they adapt to the shift toward a low-carbon economy. Opportunity exposure and regulation exposure are central to this risk. Firms that encounter high levels of opportunity exposure are those attempting to capitalize on new markets or technologies related to climate change, such as renewable energy or carbon capture innovations. Regulation exposure, on the other hand, represents the extent to which firms must comply with increasingly stringent climate-related policies, which can impose additional costs and operational burdens. Firms with high transition risks are perceived as facing significant hurdles in adapting to a low-carbon economy, whether due to the costs of regulatory compliance or the uncertainties surrounding new market opportunities. Mutual fund investors may be less inclined to invest in firms that are heavily exposed to these transition risks, leading to a decline in mutual fund ownership.

Another reason for the potential impact is that mutual fund investors incorporate the stock performance affected by climate change (Krueger *et al.*, 2020). The stock performance channel further suggests how opportunity and regulation exposures influence mutual fund ownership by considering a firm's recent financial performance and risk profile. Firms with weaker stock performance or greater downside risks are more vulnerable to the negative effects of climate change exposure. This is because investors may view these firms as already struggling to maintain profitability, making them less capable of absorbing the additional costs or uncertainties associated with climate change. In this context, high opportunity or regulation exposure exacerbates concerns about the firm's future financial stability, leading mutual fund investors to reduce their holdings.

Additionally, an information cost hypothesis indicates that mutual funds' decisions can be impacted by the information processing costs caused by climate change exposure. The uncertainty of climate change increases the complexity of mutual funds to value a firm. Mutual funds may spend more time or money expense on climate-related risks, regulations, opportunities, and so on. As a result, mutual funds may invest less in firms with large climate change exposure to avoid excessive information processing costs. Besides, a financial costs hypothesis indicates that firms' operating costs caused by climate change are negatively associated with mutual funds' investments. Climate changes lead to higher costs for firms, such as more investments in human capital (Stern and Valero, 2021; Sautner *et al*., 2023), employee treatment (Wang *et al*., 2021), costs of sales (Pankratz, *et al*., 2023), etc. The increased costs potentially reduce firm values, thus negatively associated with mutual funds' investment.

H1a**: Ceteris paribus, the firm's climate change exposure is negatively associated with the net growth in mutual fund ownership**.

Conversely, firms' climate change exposure may also attract mutual fund investors. Mutual funds are the least conservative among institutional investors (Bennett *et al*., 2003). Mutual funds bear excessive risks to achieve superior returns that attract customers (Sirri and Tufano, 1998). Thus, mutual funds may prefer firms with risks caused by large climate change exposure. In addition, because of their diversifying nature, mutual funds are least affected by firm-specific risks (O'Neal, 1997; Doellman *et al*., 2020). Overall, we could observe a positive relationship between firms' climate change exposure and mutual funds ownership. We have the following hypothesis H1b that is contrary to H1a:

***H1b*: Ceteris paribus, the firm's climate change exposure is positively associated with the net growth in mutual fund ownership**.

3.3 Data and Sample

This section introduces our variables of interest and the characteristics of the sample. We obtain the data from calculations and several sources, the details of which are explained in Appendix Table A3-1.

3.3.1 Climate Change Exposure Data

We employ Sautner *et al*. (2023)'s measurement to proxy for the firm-level climate change exposure. Our key independent variable, $CCExposure$, is the firms' climate change exposure estimated from the participants' attention to firms' climate change exposures in earnings calls (Sautner *et al*., 2023). To construct the index, the research first selects an initial set of bigrams that unambiguously relate to climate change.[34] These bigrams are used as seeds in an algorithm that searches through earnings call transcripts to identify additional bigrams that indicate discussions about climate change. The algorithm helps in capturing

[34] For example, these bigrams include renewable energy, electric vehicle, clean energy, new energy, climate change, etc. The details can be found in Table II of Sautner *et al.* (2023).

more specialized language that may not be covered by pre-specified keywords, especially in the context of niche or evolving terminology. The final climate change exposure measures are derived by counting the frequency of these identified bigrams in each transcript and scaling them relative to the total number of bigrams in the transcript. The resulting index provides a measure of how much attention earnings call participants (both management and analysts) devote to climate change topics at a firm level, reflecting how firms are perceived to be exposed to climate-related risks and opportunities over time. To construct the variable, we multiply the climate change exposure by 1000 and take the natural logarithm. The measure is the share of the conversation in the conference call devoted to climate change, including physical threats, regulatory interventions, and technological opportunities. They develop a new approach that adapts the keyword discovery algorithm to construct related climate change bigrams in earnings calls. Next, the study uses the bigrams to construct firm-level measures of exposure to climate change. It captures how participants across the globe view firms' exposures to different facets of climate change. One of the benefits of the measures is that they reflect soft information perceived from communications between analysts and firm managers. Sautner *et al*. (2023)'s measure captures varying degrees of firms' climate change exposure over time. The data covers over 10,000 firms in 34 countries between 2002 and 2020. In addition to *CCExposure*, we use an alternative measure Δ*CCExposure* for robustness, which is the changes in the firm-level climate change exposure in the year relative to the previous year.

In addition to this broadly defined climate change, the study constructs three variables capturing firms' exposure to specific topics related to climate change: opportunities ($CCExposure^{opp}$), physical shocks ($CCExposure^{phy}$), and regulatory shocks ($CCExposure^{reg}$). The research starts with an initial set of bigrams related to each topic. These bigrams are used as seeds in an algorithm that searches through earnings call transcripts to identify additional bigrams that indicate discussions about climate change. The frequency of bigrams from these topic-specific sets is calculated. $CCExposure^{opp}$ is the climate change exposure in opportunity at the firm-year level, multiplied by 1000 and taking natural logarithm. $CCExposure^{reg}$ is the climate change exposure in regulation at the firm-year level, multiplied by 1000 and taking natural logarithm. $CCExposure^{phy}$ is the climate change exposure in physical risks at the firm-year level, multiplied by 1000 and taken by natural logarithm. Separately examining specific climate change exposures helps us to identify the key driver of the climate change exposure thus providing a broad pattern of the financial implications of climate change exposure.

3.3.2 Mutual Fund Ownership Data

Following prior literature (Gibson *et al.*, 2000), we employ a net growth in mutual fund ownership $\Delta Ownerhisp$. It is the changes in mutual fund ownership at the year-end relative to the previous year. We aggregate the fund holdings at the firm-year level and divide the market value of the shares held by mutual funds by the total market value of a firm at the year-end. Then we calculate the changes in the ratio in the year relative to the previous year. The data for mutual fund holdings are collected from the Thomson Reuters Mutual Fund database.

$$\Delta Ownerhsip_{i,t} = \sum_{m=1}^{M} \frac{market\ value\ of\ shares\ of\ firm\ i\ owned\ by\ mutual\ fund\ m\ in\ year\ t}{total\ market\ value\ of\ shares\ of\ firm\ i\ in\ year\ t} - \sum_{m=1}^{M} \frac{market\ value\ of\ shares\ of\ firm\ i\ owned\ by\ mutual\ fund\ m\ in\ year\ t-1}{total\ market\ value\ of\ shares\ of\ firm\ i\ in\ year\ t-1} \tag{3-1}$$

To further ensure the robustness of the results, we also employ two additional measures of mutual fund ownership. $\Delta Ownerhisp\#share$ is the change in the ratio of the number of shares held by mutual funds to the total shares of a firm outstanding at the year-end relative to the previous year.

3.3.3 Data on Control Variables

Following prior related research, we control firm characteristics and regional characteristics that can affect firms' mutual fund ownership (i.e. Sautner *et al*. (2023)). Firms' financial characteristics include the annual holding period return of the stock (*Recent Return*), the return on assets (ROA), size (*Size*), leverage ratio (*Leverage*), capital expenditure (*Capex*), cash ratio (*Cash*), z-score (*Z-Score*), R&D expenditure (*R&D*) and the book-to-market ratio (*Book-to-Market*) at the year-end. We also include firms' social responsibility score (*CSR*) and analysts' coverage (*Analyst Coverage*) at the year-end. To capture the state-level variation, we include states' Gross Domestic Product at the year-end (*GDP*).

3.3.4 Sample and Summary Statistics

We construct the sample by matching the sample firms covered by Sautner *et al*. (2023) with multiple data sources, such as Refinitiv Mutual Fund, Compustat, MSCI, I/B/E/S, etc. The sample period starts in 2002 and ends in 2020. After matching with other databases, our final sample includes 12,628 firm-year observations and 1,825 unique firms in 46 states of the U.S.

Table 3-1 presents the sample distributions. Table 3-1 Panel A reports the time distribution of our sample. The numbers of observations show a relatively balanced distribution in the years 2004 to 2020. The numbers of observations in the years 2002 and 2003 are smaller than in other years. We will remove the observations in these two years for robustness tests.

Table 3-1 Panel B and Figure 3-1 report the regional distribution of the firm headquarters in our sample. The sample firms are distributed in 46 states (including the District of Columbia). The numbers of firms in California, Texas, Massachusetts, and New York are top-ranked, while there are less than 10 in Mississippi and West Virginia. Given the small proportion of the firms, we will remove these states with the least number of firms for robustness tests.

Panel C reflects industry variations in climate change exposure. We report the top 10 industries with the highest mean value of climate change exposure. Statistics are reported at the firm-year level across various industries categorized by 2-digit SIC industry codes. The firm with the highest climate change exposure on average is the industry in “electric, gas & sanitary services”. Following that, the industry “transportation equipment” and “primary metal industries” also exhibit large mean values of climate change exposure. The mean values of climate change exposure in other industries range from 1.1140 to 1.6457. On the other side, the industries exhibiting small climate change exposure include “Insurance Carriers”, “Personal Services”, “Security & Commodity Brokers, Dealers, Exchanges & Services”, “Motion Pictures”, etc. The mean values of climate change exposure of the lowest 10 industries range from 0.0000 to 0.1951. Overall, climate change exposure shows substantial variations across industries, which is consistent with Sautner *et al*. (2023).

Table 3-1 Sample distribution

Panel A Time distribution of observations

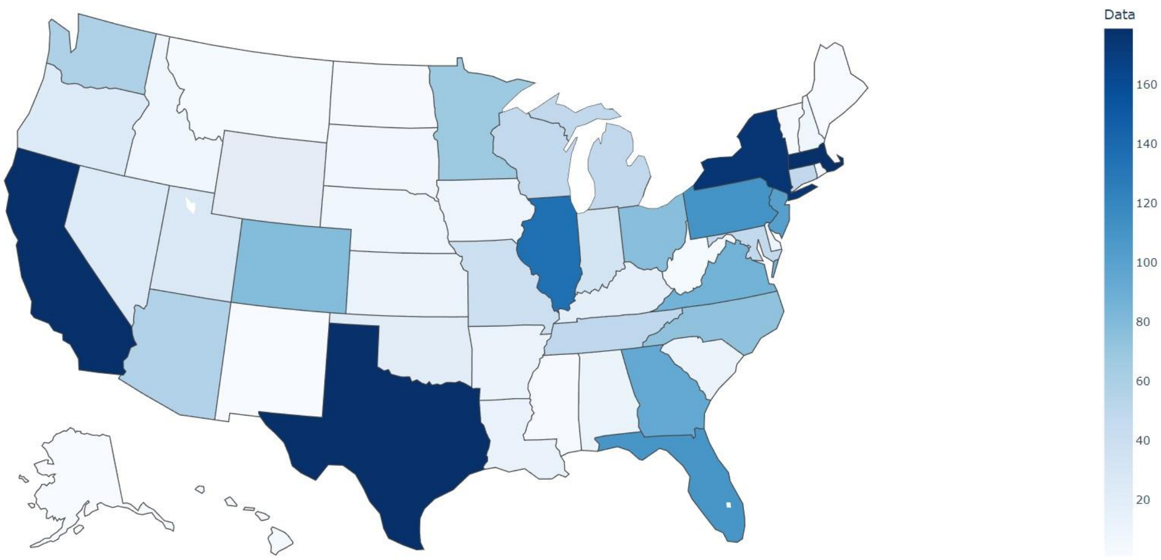
Table 3-1 Panel A reports the distribution of observations across different years.

Year	Observation	Year	Observation
2002	31	2012	454
2003	263	2013	771
2004	666	2014	767
2005	694	2015	727
2006	636	2016	772
2007	623	2017	801
2008	673	2018	808
2009	733	2019	868
2010	761	2020	840
2011	740		
Total Obs.			**12,628**

Panel B Geographic distribution of firms

Table 3-1 Panel B reports the geographic distribution of firms in our sample across various states. It includes the columns for the 2-digit state code, state name, and the number of firms.

State code	State	Firm Number	State code	State	Firm Number
AL	Alabama	42	MS	Mississippi	2
AR	Arkansas	14	MT	Montana	28
AZ	Arizona	215	NC	North Carolina	322
CA	California	2,853	ND	North Dakota	10
CO	Colorado	246	NE	Nebraska	57
CT	Connecticut	230	NH	New Hampshire	51
DC	DC	60	NJ	New Jersey	450
DE	Delaware	49	NV	Nevada	111
FL	Florida	361	NY	New York	672
GA	Georgia	344	OH	Ohio	440
IA	Iowa	62	OK	Oklahoma	33
ID	Idaho	33	OR	Oregon	101
IL	Illinois	549	PA	Pennsylvania	610
IN	Indiana	162	RI	Rhode Island	63
KS	Kansas	22	SC	South Carolina	89
KY	Kentucky	97	SD	South Dakota	32
LA	Louisiana	34	TN	Tennessee	229
MA	Massachusetts	1,041	TX	Texas	875
MD	Maryland	214	UT	Utah	128
ME	Maine	17	VA	Virginia	276
MI	Michigan	278	WA	Washington	258
MN	Minnesota	392	WI	Wisconsin	283
MO	Missouri	187	WV	West Virginia	6
Total					**12,628**



Notes: Figure 3-1 illustrates the geographic distribution of firms in our sample across various states. The color gradient, ranging from light to dark hues, represents a scale from 0 to over 160, denoting the number of firms.

Figure 3-1 Geographic distribution of firms

Panel C Industry distribution of firms

Table 3-1 Panel C reports the top 10 industries with the highest and 10 with the lowest average climate change exposure. It includes the columns for the 2-digit SIC industry code, industry name, the number of observations, and various statistics for climate change exposure: mean value, minimum value, and maximum value.

SIC2	Industry	Obs.	Mean	Min	Max
Highest					
49	Electric, Gas, & Sanitary Services	7	2.7616	0.775	4.963
37	Transportation Equipment	518	1.9114	0.000	19.173
33	Primary Metal Industries	108	1.7238	0.000	10.136
36	Electronic & Other Electric Equipment	1,508	1.6457	0.000	27.857
10	Metal Mining	7	1.3773	0.275	4.127
12	Coal Mining	5	1.3569	0.694	3.312
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels	47	1.3016	0.148	3.436
32	Stone, Clay, Glass, and Concrete Products	78	1.2653	0.000	7.450
29	Petroleum Refining and Related Industries	72	1.1774	0.000	8.348
55	Automotive Dealers and Gasoline Service Stations	151	1.1140	0.000	21.980
Lowest					
63	Insurance Carriers	2	0.0000	0.000	0.000
72	Personal Services	6	0.0773	0.000	0.261
60	Depository Institutions	3	0.0865	0.000	0.172
83	Social Services	9	0.1278	0.000	0.451
23	Apparel, Finished Products from Fabrics & Similar Materials	33	0.1314	0.000	0.757
56	Apparel and Accessory Stores	331	0.1619	0.000	1.331
27	Printing, Publishing and Allied Industries	65	0.1653	0.000	0.903
59	Miscellaneous Retail	244	0.1700	0.000	0.854
78	Motion Pictures	16	0.1848	0.000	0.650
62	Security & Commodity Brokers, Dealers, Exchanges & Services	13	0.1951	0.000	1.355

Table 3-2 reports the summary statistics for the key dependent, independent, and control variables, including the number of observations, mean values, standard deviation, 25 percentile, 50 percentile, 75 percentile, minimum, and maximum values. We report both *CCExposure* and the before-logarithm *CCExposure*. The statistics for the latter are close to those presented in Sautner *et al.* (2023). The mean value for the variable Δ*CCExposure* is 0.243, indicating that the growth in climate change exposure is positive on average.

Table 3-2 Summary statistics

Table 3-2 reports the summary statistics for the dependent, independent, and control variables, including the number of observations, mean values, standard deviation, 25 percentile, 50 percentile, 75 percentile, minimum, and maximum values.

Variable	N	Mean	SD	p25	p50	p75	Min	Max
Independent								
CCExposure	12,628	0.458	0.534	0.119	0.273	0.581	0.000	2.596
CCExposure (before-log)	12,628	1.000	2.370	0.127	0.314	0.788	0.000	40.500
ΔCCExposure	12,628	0.243	1.234	-0.516	-0.078	0.569	-1.000	6.164
Dependent								
ΔOwnership	12,628	0.074	0.383	-0.121	0.006	0.172	-0.652	2.045
ΔOwnership#share	12,628	0.059	0.298	-0.100	0.007	0.143	-0.545	1.451
Control								
Recent Return	12,628	0.138	0.485	-0.146	0.086	0.332	-0.931	3.074
ROA	12,628	0.026	0.145	0.011	0.047	0.085	-3.072	0.340
Size	12,628	7.366	1.643	6.159	7.242	8.411	2.174	11.910
Leverage	12,628	0.210	0.203	0.013	0.183	0.320	0.000	1.116
Capex	12,628	0.048	0.050	0.017	0.033	0.060	0.000	0.343
Cash	12,628	0.132	0.141	0.032	0.087	0.183	0.000	0.907
Book-to-Market	12,628	0.453	0.397	0.220	0.381	0.602	-1.304	3.151
R&D	12,628	3.288	2.106	1.931	3.524	4.681	0.000	7.864
CSR	12,628	0.056	0.183	0.000	0.000	0.000	-0.750	1.000
Analyst Coverage	12,628	4.466	0.865	3.970	4.543	5.106	0.000	6.433
GDP	12,628	13.310	0.900	12.660	13.190	14.100	10.110	14.790

3.4 Empirical Results

3.4.1 Baseline Results

To test the hypothesis, we employ the following ordinary least square (OLS) regression model, estimating the impact of firms' climate change exposure on the net growth in mutual fund ownership.

$$\Delta Ownership_{i,t+1} = \beta_0 + \beta_1 CCExposure_{i,t} + \beta_2 Controls_{i,s,t} + T + I + \varepsilon_{i,s,t} \qquad (3-2)$$

Where $\Delta ownership_{i,t+1}$ is the net growth of mutual fund ownership of the firm *i* in year *t+1* relative to year *t*; $CCExposure_{i,t}$ is the logarithm of Sautner *et al*. (2023)'s climate change exposure of the firm *i* in year *t*; $Controls_{i,s,t}$ are control variables for the firm *i* located in the state *s* in year *t*, including the firm *i*'s holding period return (*Recent Return*), return-on-assets (*ROA*), size (*Size*), leverage ratio (*Leverage*), capital expenditure (*Capex*), cash ratio (*Cash*), book-to-market ratio (*Book-to-Market*), R&D expenditure (*R&D*), MSCI social responsibility score (*CSR*), analysts coverage (*Analyst Coverage*), and the GDP of the state *s* where the firm is located; *T*, and *I* are year fixed effects and firm fixed effects, respectively; β_0 is the constant term; β_1 and β_2 are regression coefficients; $\varepsilon_{i,s,t}$ is the error term.

Table 3-3 column (1) reports the univariate analysis. Climate change exposure is negatively correlated with the net growth in mutual fund ownership. Column (2) reports the baseline results of the regression model (2). In column (2), the regression coefficient of $CCExposure$ is negative and significant, supporting the notion that firms' climate change exposure significantly decreases the net growth in mutual fund ownership. The result exhibits a large economic magnitude. One standard deviation increase in the degree of climate change exposure reduces the net growth in mutual fund ownership by 0.021 (-0.040 × 0.534), which represents an increase of 12.2% from the sample mean of $\Delta Ownership$. The regression coefficient suggests a negative and significant relationship between the net growth in climate change exposure and mutual fund ownership. Overall, the empirical results support hypothesis $H1a$: Ceteris paribus, the firm's climate change exposure is negatively associated with the net growth in mutual fund ownership.

Table 3-3 Climate risk exposure and mutual fund ownership

This table reports the results for regression (3-2) examining the relationship between firms' climate change exposure and mutual fund ownership. Column (1) reports the baseline result with key independent variable *CCExposure* in year *t* and Δ*Ownership* in year *t+1*. *CCExposure* is the overall climate change exposure at the firm-year level, multiplied by 1000 and taken by natural logarithm. Δ*Ownership* is the net growth of the market value of shares held by the fund divided by the market value of the firm at the year-end. The control variables are consistent in all columns. Year fixed effects and firm fixed effects are included. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	ΔOwnership	ΔOwnership
	(1)	(2)
CCExposure	-0.042***	-0.040***
	(-3.110)	(-3.119)
Recent Return		0.022**
		(2.041)
ROA		-0.094**
		(-2.158)
Size		-0.034***
		(-2.699)
Leverage		0.382***
		(8.174)
Capex		-0.188
		(-1.000)
Cash		0.086**
		(2.127)
Book-to-Market		0.067**
		(2.091)
Z-Score		-0.000
		(-0.044)
Analyst Coverage		-0.092***
		(-7.483)
R&D		0.003
		(0.266)
CSR		0.001
		(0.152)
GDP		0.024
		(0.283)
Constant	0.058***	0.283
	(10.872)	(0.247)
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
N	12628	12628
adj R-sq	0.064	0.097

3.4.2 Additional Robustness Test

We conduct additional robustness tests to ensure that our baseline findings are not driven by sample bias. First, we adjust the sample by removing the observations in California (CA), Massachusetts (MA), Mississippi (MS), or West Virginia (WV), as the largest and smallest number of firms originate from these states. In Table 3-4 Panel A column (1), the sample size decreases to 8,726. The regression coefficient is still negative and significant. Overall, when we eliminate the concern of extreme values relating to firm locations, the baseline findings are unchanged. In Table 3-4 Panel A column (2), we adjust the sample by period. As discussed in Section 3.3.4, the numbers of observations in the years 2002 and 2003 are much smaller than in other years. We remove these observations and re-estimate the baseline model. The negative and significant correlation between climate change exposure and the net growth in mutual fund ownership still holds. In Table 3-4 Panel A column (3), we adjust the sample by industry. We eliminate the observations in the top-10 ranked industries shown in Table 3-1 Panel A. The regression coefficient is negative and statistically significant, indicating that the baseline findings are less likely driven by leading industries.

In Table 3-4 Panel B, we employ additional settings of the model. In Table 3-4 Panel B column (1), we use an alternative measure of the net growth in mutual fund ownership $\Delta Ownership\#share$. The variable is the number of shares held by the fund divided by the total shares outstanding at the year-end and then the net growth of the value over the current and previous year is calculated. The regression coefficient is negative and significant at a 10% significance level. In Table 3-4 Panel B columns (2), we use alternative measures of the dependent variable. $\Delta CCExposure$, which is the net growth in a firm's climate change exposure in the year relative to the previous year. The results are consistent.

Next, we replace the independent variable with the EGKLS Index. EGKLS is Engle's Climate Change Index, as estimated from news, based on textual analysis of news sources. First, researchers create a specialized vocabulary related to climate change by compiling terms from 74 authoritative texts, including reports and white papers from organizations such as the Intergovernmental Panel on Climate Change (IPCC), NASA, and the U.S. Environmental Protection Agency (EPA). These texts are treated as the foundational discourse on climate change. Then, articles from the Wall Street Journal (WSJ) are analyzed by comparing their content to the above vocabulary. This method quantifies how often terms appear in each article and adjusts for how common those terms are across the entire WSJ corpus. This index reflects the intensity of climate change discussions in the news, which is linked to climate risk. The variable *EGKLS* reflects to what extent the firm's exposure to climate change. As the variable is at the year level, we remove the year fixed effects. The regression coefficients are negative and statistically significant at a 1% significance level. The results indicate a consistent notion that mutual funds are averse to investment in firms with large climate change exposure.

Table 3-4 Additional robustness test

This table reports the results of additional robustness tests, examining the relationship between firms' climate change exposure and mutual fund ownership. The key independent variable *CCExposure* is the overall climate change exposure at the firm-year level, multiplied by 1000 and taken by natural logarithm. The key dependent variable Δ*Ownership* is the net growth of the market value of shares held by the fund divided by the market value of the firm at the year-end. Panel A reports the results of re-estimated baseline regression using alternative samples. In column (1), we exclude the states with the largest or smallest number of firms. In column (2), we exclude the year 2002 and the year 2003, since the numbers of observations in these years are much smaller than other years. In column (3), we exclude industries with a superior number of firms. Panel B reports the results of re-estimated baseline regression using an alternative model setting. In column (1), we use additional dependent variables which capture the mutual fund investment preferences. Δ*Ownership Alt* is an alternative measure of the net growth in mutual fund ownership, calculated by the number of shares held by the fund divided by the total shares outstanding at the year-end. In column (2), we use an alternative independent variable Δ*CCExposure*, which is the net growth in *CCExposure*. In column (3), we use an alternative variable EGKLS Index, which is Engle *et al*. (2020)'s climate change index. Control variables, year fixed effects and firm fixed effects are included, which are consistent with baseline regression. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

Panel A: Alternative sample

	Sample adjusted by state	*Sample adjusted by year*	*Sample adjusted by industry*
	ΔOwnership	ΔOwnership	ΔOwnership
	(1)	(2)	(3)
CCExposure	-0.031**	-0.041***	-0.037**
	(-2.031)	(-3.163)	(-2.538)
Recent Return	0.033**	0.023**	0.019
	(2.230)	(2.088)	(1.556)
ROA	-0.128*	-0.085*	-0.086*
	(-1.741)	(-1.905)	(-1.898)
Size	-0.037**	-0.033***	-0.028*
	(-2.353)	(-2.583)	(-1.708)
Leverage	0.463***	0.363***	0.311***
	(7.284)	(7.739)	(5.493)
Capex	-0.333*	-0.154	0.010
	(-1.691)	(-0.793)	(0.040)
Cash	0.090	0.095**	0.091**
	(1.608)	(2.330)	(2.090)
Book-to-Market	0.100***	0.060*	0.029
	(2.709)	(1.850)	(0.654)
Z-Score	0.002	-0.001	-0.003
	(0.446)	(-0.239)	(-0.856)
Analyst Coverage	-0.085***	-0.096***	-0.085***
	(-5.578)	(-7.566)	(-6.084)
R&D	0.010	-0.000	-0.022
	(0.711)	(-0.005)	(-1.508)
CSR	0.003	0.001	-0.002
	(0.374)	(0.198)	(-0.326)
GDP	-0.027	0.028	0.125
	(-0.266)	(0.312)	(1.164)
Constant	0.891	0.252	-1.019
	(0.675)	(0.209)	(-0.707)
Year Fixed Effect	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
N	8726	12334	8395
adj R-sq	0.106	0.096	0.100

Panel B: Alternative variable & fixed effect

	Alternative Dependent Variable	*Alternative Independent Variable*	
	ΔOwnership#share	ΔOwnership	ΔOwnership
	(1)	(2)	(3)
CCExposure	-0.016*		
	(-1.783)		
ΔCCExposure		-0.005***	
		(-2.656)	
EGKLS Index			-0.020***
			(-6.900)
Recent Return	0.029***	0.018	0.025**
	(3.446)	(1.439)	(2.410)
ROA	0.019	-0.130***	-0.099*
	(0.616)	(-2.682)	(-1.907)
Size	-0.033***	-0.023*	-0.066***
	(-3.410)	(-1.650)	(-4.805)
Leverage	0.024	0.375***	0.427***
	(0.756)	(6.891)	(8.421)
Capex	0.162	-0.309	-0.134
	(1.011)	(-1.536)	(-0.641)
Cash	0.080**	0.044	0.121***
	(2.225)	(0.915)	(2.711)
Book-to-Market	-0.029*	0.060*	0.147***
	(-1.803)	(1.692)	(4.350)
Z-Score	-0.004*	0.000	-0.001
	(-1.798)	(0.080)	(-0.448)
Analyst Coverage	-0.065***	-0.085***	-0.096***
	(-7.152)	(-6.379)	(-7.199)
R&D	-0.003	-0.004	0.021
	(-0.339)	(-0.324)	(1.620)
CSR	-0.002	0.001	0.001
	(-0.490)	(0.095)	(0.201)
GDP	0.085	0.042	-0.200***
	(1.372)	(0.471)	(-3.218)
Constant	-0.543	-0.042	0.025**
	(-0.659)	(-0.035)	(2.410)
Year Fixed Effect	Yes	Yes	No
Firm Fixed Effect	Yes	Yes	Yes
N	12628	10273	10920
adj R-sq	0.062	0.112	0.075

3.5 Economic Channels

Financial and nonfinancial motivations encourage fund managers to incorporate climate change into their investment decisions (Krueger *et al*., 2020). Our baseline results suggest a negative relationship between firms' climate change exposure and mutual fund investment, which is consistent with our hypothesis *H1a*. This section empirically investigates the economic channels through which firms' climate change exposure influences net growth in mutual fund ownership.

3.5.1 Climate Change Exposure by Topics

In addition to the overall exposure, Sautner *et al*. (2023) provide information on firms' climate change exposure in three detailed aspects: opportunity, regulation, and physical risks. Each of these aspects represents a unique facet of the challenges and prospects that firms face in the context of climate change. By disaggregating the overall exposure to these components, we aim to identify which aspect exerts the most significant influence on the observed negative impact on mutual fund ownership.

A firm's opportunity exposure is related to technical opportunities caused by climate change. For example, firms in traditional energy sectors face transition opportunities in renewable energy. These opportunities can create profits if successful and great losses if failure (Sautner *et al*., 2023). Firms that successfully navigate this transition can capitalize on emerging markets and technologies, potentially gaining competitive advantages and increasing profitability. However, the inherent uncertainties associated with these transitions, such as the pace of technological advancements and fluctuating market conditions, mean that these opportunities also carry substantial risks. The volatility and unpredictability of these opportunities may deter investors, leading to reduced mutual fund ownership as observed in our baseline regression.

The regulations, which range from international agreements like the Paris Agreement to national and local policies, often require firms to undertake significant changes in their operations, such as reducing emissions or increasing energy efficiency. While these regulations are designed to mitigate climate change, they also impose additional costs on firms, which may include investments in new technologies, changes in operational processes, and potential penalties for non-compliance. The financial burden and compliance risks associated with these regulations can negatively affect a firm's profitability and, consequently, its attractiveness to investors. Physical exposure refers to the risks caused by physical climate changes, such as sea level increases.

The physical risks can have immediate and severe consequences for firms, particularly those with assets or operations in vulnerable regions. The financial impact of these risks can be substantial, encompassing both direct costs, such as damage to infrastructure and increased insurance premiums, and indirect costs, such as supply chain disruptions and reduced productivity. As a result, firms with high physical exposure may be seen as higher-risk investments, leading to a reduction in mutual fund ownership as investors seek to minimize potential losses. In our baseline regression, we find that the overall climate change exposure negatively influences the net growth in mutual fund ownership. In this section, we separately examine the three aspects and explore the key drivers.

Using regression (3-2), we replace the independent variable with a firm's climate change exposure in opportunity ($CCExposure^{opp}$), regulation ($CCExposure^{reg}$), and physical risks ($CCExposure^{phy}$). $CCExposure^{opp}$ and $CCExposure^{reg}$ are positively correlated, while $CCExposure^{phy}$ shows an insignificant correlation with them. This finding is consistent with Sautner *et al*. (2023). Table 3-5 reports the regression results. In Table 3-5 column (1), the regression coefficient of $CCExposure^{opp}$ is negative and statistically significant at a 1% significance level. When separately examined, the economic magnitude of the impact is larger than the overall climate change exposure. In comparison, the regression coefficient of $CCExposure^{reg}$ is also negative in column (2). However, the impact is less significant than the overall climate change exposure and exposure in regulation. In column (3), the regression coefficient of $CCExposure^{phy}$ is insignificant. The results suggest that exposure to opportunity and regulation are very likely to drive the impact of overall climate change exposure, while exposure to physical risk is less likely to drive the baseline finding. Mutual fund investors incorporate the opportunity uncertainties and regulation risks related to climate change, and they might be less likely to incorporate the influence of physical risks.

Table 3-5 CCExposure by topics

This table reports the impact of climate change exposure in specific topics on the net growth of mutual fund ownership. The key independent variable *CCExposure* is the overall climate change exposure at the firm-year level, multiplied by 1000 and taking natural logarithm. $CCExposure^{opp}$ is the climate change exposure in opportunity at the firm-year level, multiplied by 1000 and taking natural logarithm. $CCExposure^{reg}$ is the climate change exposure in regulation at the firm-year level, multiplied by 1000 and taking natural logarithm. $CCExposure^{phy}$ is the climate change exposure in physical risks at the firm-year level, multiplied by 1000 and taking logarithm. Control variables, year fixed effects and firm fixed effects are included, which are consistent with baseline regression. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	ΔOwnership	ΔOwnership	ΔOwnership
	(1)	(2)	(3)
$CCExposure^{opp}$	-0.058***		
	(-3.178)		
$CCExposure^{reg}$		-0.093*	
		(-1.702)	
$CCExposure^{phy}$			-0.104
			(-0.824)
Recent Return	0.022**	0.022**	0.022**
	(2.054)	(2.062)	(2.051)
ROA	-0.095**	-0.094**	-0.094**
	(-2.172)	(-2.153)	(-2.155)
Size	-0.034***	-0.034***	-0.034***
	(-2.737)	(-2.695)	(-2.704)
Leverage	0.382***	0.383***	0.383***
	(8.193)	(8.202)	(8.196)
Capex	-0.192	-0.192	-0.194
	(-1.022)	(-1.022)	(-1.036)
Cash	0.085**	0.086**	0.085**
	(2.112)	(2.126)	(2.106)
Book-to-Market	0.068**	0.066**	0.066**
	(2.109)	(2.061)	(2.065)
Z-Score	-0.000	-0.000	-0.000
	(-0.034)	(-0.056)	(-0.059)
Analyst Coverage	-0.092***	-0.092***	-0.092***
	(-7.482)	(-7.464)	(-7.467)
R&D	0.003	0.002	0.003
	(0.263)	(0.219)	(0.237)
CSR	0.001	0.001	0.001
	(0.155)	(0.233)	(0.210)
GDP	0.019	0.025	0.026
	(0.218)	(0.289)	(0.298)
Constant	0.351	0.260	0.250
	(0.307)	(0.227)	(0.218)
Year Fixed Effect	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
N	12628	12628	12628
adj R-sq	0.101	0.100	0.100

3.5.2 Transition Risk and Stock Performance

Next, we explore why mutual fund investors incorporate climate change exposure, especially the exposure to opportunity uncertainties and regulation risks. Specifically, the transition risk channel and stock performance channel play critical roles in shaping how mutual fund investors respond to firms' climate change exposure.

We employ multiple approaches to examine the transition risk channel. First, following Ilhan *et al*. (2021) and Ginglinger and Moreau (2023), we investigate the heterogeneous impact of climate change exposure on mutual fund ownership across different industries. Ilhan *et al*. (2021) identify the 10 largest carbon-emitting industries, which greatly suffered from transition risks, such as metal industries, electric & gas services, auto services, etc. We construct a variable *Carbon Industry* that equals one if the industry belongs to carbon-emitting industries, and zero otherwise. Using the baseline regression, we primarily focus on the interactive effects between *CCExposure* and *Carbon Industry* on Δ*Ownership*. The single-term *Carbon Industry* could be absorbed by the industry fixed effects; therefore, the single term is not included in the regression.

In Table 3-6 Panel A column (1), the regression coefficient is -0.059, which is negative and statistically significant. Firms in carbon-emitting industries strengthen the impact of climate change exposure on mutual fund ownership. We then replace the carbon-emitting industry with the innovative industry, which also exhibits great transition uncertainties due to climate change. According to Bhattacharya *et al*. (2017) and Li *et al*. (2023), innovation is severely impacted by climate risks which increase costs, risks, and uncertainties of R&D. For firms in industries requiring large R&D investment, the impact of climate change exposure on mutual fund ownership is amplified. To test the hypothesis, we construct two sub-samples: innovative industry and non-innovative industry. We first calculate the mean value of the R&D expense for the firms within an industry (coded by 2-digit SIC industry code) at a given year and then calculate the mean value of the R&D expense for all industries. We categorize the industry as an innovative industry if the R&D expense is larger than the mean value, and as a non-innovative industry if the R&D expense is smaller than the mean value. Next, we re-estimate the baseline regression in the sub-samples and compare the effect of firms' climate change exposures on mutual fund ownership. In Table 3-6 Panel A column (2), the regression coefficient of the interaction term between *CCExposure* and *Innovative Industry* is negative and statistically significant at a 10% significance level. Overall, the results indicate that mutual fund investors incorporate the transition risks faced by firms with greater climate change exposure.

Table 3-6 Transition risks

This table reports the results of tests of economic channels. Panel A reports the result of the heterogeneous impact of climate change exposure on mutual fund ownership across different industries. *CCExposure* is the overall climate change exposure at the firm-year level, multiplied by 1000 and taking natural logarithm. Δ*Ownership* is the net growth of the market value of shares held by the fund divided by the market value of the firm at the year-end. The *Carbon Industry* is a dummy variable that equals one if the industry is carbon-emitting, and zero-otherwise. *Innovative Industry* is a dummy variable that equals one if the industry is innovative, and zero otherwise. Panel B estimates the interactive effect of firms' stock performance and downside risk. *Recent Return* is the firm's holding period return during the past year. *Downside Risk* is firms' value at risk during the past year. Control variables, year fixed effects and firm fixed effects are included, which are consistent with baseline regression. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses. The variables are explained in Appendix Table A3-1.

Panel A: Transition industry

	ΔOwnership	ΔOwnership
	(1)	(2)
CCExposure	-0.025**	-0.025**
	(-1.973)	(-1.974)
CCExposure × Carbon Industry	-0.059*	
	(-1.679)	
CCExposure × Innovative Industry		-0.073*
		(-1.868)
Recent Return	0.022**	0.022**
	(2.026)	(2.037)
ROA	-0.095**	-0.095**
	(-2.166)	(-2.166)
Size	-0.034***	-0.034***
	(-2.710)	(-2.706)
Leverage	0.384***	0.384***
	(8.200)	(8.204)
Capex	-0.184	-0.182
	(-0.977)	(-0.965)
Cash	0.085**	0.085**
	(2.111)	(2.099)
Book-to-Market	0.067**	0.067**
	(2.105)	(2.099)
Z-Score	0.000	0.000
	(0.004)	(0.007)
Analyst Coverage	-0.092***	-0.092***
	(-7.457)	(-7.440)
R&D	0.003	0.003
	(0.282)	(0.263)
CSR	0.001	0.001
	(0.184)	(0.198)
GDP	0.022	0.021
	(0.254)	(0.247)
Constant	0.315	0.322
	(0.276)	(0.282)
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
N	12628	12628
adj R-sq	0.098	0.098

Panel B: Stock Performance

	ΔOwnership	ΔOwnership
	(1)	(2)
CCExposure	-0.072***	-0.077***
	(-5.858)	(-2.927)
CCExposure × Recent Return	0.233***	
	(10.055)	
CCExposure × Downside Risk		-0.550*
		(-1.694)
Downside Risk		0.997
		(0.053)
Recent Return	0.034***	0.023**
	(3.318)	(2.102)
ROA	-0.069*	-0.085*
	(-1.673)	(-1.938)
Size	-0.016	-0.033***
	(-1.299)	(-2.601)
Leverage	0.356***	0.362***
	(8.021)	(7.699)
Capex	-0.080	-0.164
	(-0.456)	(-0.847)
Cash	0.094**	0.096**
	(2.389)	(2.350)
Book-to-Market	0.037	0.060*
	(1.244)	(1.848)
Z-Score	0.001	-0.001
	(0.413)	(-0.281)
Analyst Coverage	-0.083***	-0.096***
	(-7.268)	(-7.537)
R&D	0.001	0.000
	(0.121)	(0.039)
CSR	-0.003	0.001
	(-0.442)	(0.222)
GDP	0.008	0.029
	(0.094)	(0.323)
Constant	0.338	0.301
	(0.316)	(0.180)
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
N	12628	12334
adj R-sq	0.144	0.096

The stock performance channel further suggests how opportunity and regulation exposures influence mutual fund ownership by considering a firm's recent financial performance and risk profile. Firms with weaker stock performance or greater downside risks are more vulnerable to the negative effects of climate change exposure. This is because investors may view these firms as already struggling to maintain profitability, making them less capable of absorbing the additional costs or uncertainties associated with climate change. In this context, high opportunity or regulation exposure exacerbates concerns about the firm's future financial stability, leading mutual fund investors to reduce their holdings.

In Table 3-6 Panel B column (1), we include the interaction term between *CCExposure* and *Recent Return*. *Recent Return* measures the recent stock performance of a firm, a larger value of which indicates a lower pressure on mutual funds to improve their performance. We observe that the impact of climate change exposure on firms with robust recent stock performance is comparatively mitigated. This suggests that mutual fund investors face reduced pressure when investing in firms that have demonstrated strong recent stock performance. Moving to column (2) of the same panel, we apply a specific downside risk metric, the Value at Risk (VaR) of a stock, to further our understanding. The findings reveal that a larger *Downside Risk* intensifies the negative impact of climate change exposure on investment decisions. This is a crucial insight, indicating that mutual fund investors are actively incorporating the stock performance when evaluating their investment choices.

In summary, our analysis provides evidence that mutual fund investors are adapting their strategies to mitigate transition risks and incorporating stock performance.

3.5.3 Other Potential Explanations

In the previous section, firms' climate change exposure is negatively associated with net growth in mutual fund ownership, as mutual fund investors incorporate climate change-related transition risks and stock performance. This section explores other potential explanations that explain the impact of climate change exposure on mutual fund ownership: i) heightened climate change-related information collection cost; ii) reputation risks; and iii) financial constraints. Our empirical tests suggest that these explanations are less likely to be the key economic channels.

3.5.3.1 Information cost

The information hypothesis indicates that mutual funds focus more on firms with lower climate change exposure to avoid climate-related information processing. Firms' higher information disclosure levels can mitigate the effect of climate change exposure on mutual fund ownership. We employ two measures for the information disclosure level of a firm, analyst coverage (*Analyst Coverage*) and Climate Action 100+ target (*Climate Action*). Analyst coverage refers to the attention and scrutiny given to a firm's financial and operational details by financial analysts. Analysts' work often leads to increased information disclosure and transparency for the firms they cover in several ways. For example, analysts dig deep into a firm's financial statements, events, and operational activities to extract information that might not be immediately obvious to common investors. The variable *Analyst Coverage* is the logarithm of the number of analysts following the firm at the year-end, a larger number of which suggests a better information disclosure.

The variable *Climate Action* indicates whether the firm is a target of Climate Action 100+, which equals one if yes and zero otherwise. Climate Action 100+ is an investor-led initiative aimed at ensuring the world's largest corporate greenhouse gas emitters take necessary action on climate change. Investors associated with Climate Action 100+ actively engage with companies, demanding enhanced transparency and action on climate change. Companies are urged to set and disclose clear targets for reducing greenhouse gas emissions across their value chains. Climate Action 100+ improves a firm's climate-related disclosures by facilitating engaged dialogue between investors and companies, offering tools and frameworks for assessment, and creating a platform where collective investor action can leverage significant influence. This initiative enables, supports, and tracks companies in revealing more about their climate-related risks. Mutual funds can better access the information of firms with larger analysts' coverage or being a target of Climate Action 100+.

If the information hypothesis is the case, we would observe a weakened effect of climate change disclosure on mutual fund ownership. Empirically, we include the interaction term between climate change exposure *CCExposure* and the information disclosure measures *Analyst Coverage* and *Climate Action* in the baseline equation, then we estimate the coefficients of the interaction terms. Table 3-7 columns (1) and (2) report the results. In column (1), the variables of interest are *Analyst Coverage* and the interaction term between *Analyst Coverage* and *CCExposure*. The control variables and fixed effects are included but not reported. In Table 3-7 column (2), the variables of interest are *Climate Action* and the interaction term between *Climate Action* and *CCExposure*. The regression coefficients of the interaction terms are insignificant. General information acquisition costs or climate-related information costs are less likely to be the key drivers of the decrease in firms' mutual fund ownership growth.

Table 3-7 Other potential explanations

This table presents the tests of other potential economic channels. *CCExposure* is the overall climate change exposure at the firm-year level, multiplied by 1000 and taking natural logarithm. Δ*Ownership* is the net growth of the market value of shares held by the fund divided by the market value of the firm at the year-end. *Analyst Coverage* is the logarithm of the number of analysts following the firm at the year-end. *Climate Action* is a dummy variable that equals one if the firm is a member of Climate Action 100+, and zero otherwise. *Credit Rating* is a firm's S&P quality rating. *Z-Score* measures the extent of financial constraints. Control variables, year fixed effects and firm fixed effects are included, which are consistent with baseline regression. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses. The variables are explained in Appendix Table A3-1.

	ΔOwnership	ΔOwnership	ΔOwnership	ΔOwnership
	(1)	(2)	(3)	(4)
CCExposure	-0.032	-0.040***	-0.016	-0.040***
	(-0.328)	(-3.107)	(-0.648)	(-3.095)
Analyst Coverage	-0.002			
	(-0.078)			
CCExposure × Analyst Coverage	-0.002			
	(-0.078)			
Climate Action		0.030		
		(0.897)		
CCExposure × Climate Action		-0.004		
		(-0.071)		
Credit Rating			0.001	
			(0.477)	
CCExposure × Credit Rating			-0.005	
			(-1.218)	
Z-Score				0.012**
				(2.400)
CCExposure × Z-Score				0.028
				(0.261)
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
N	12628	12628	12628	12619
adj R-sq	0.097	0.097	0.097	0.098

3.5.3.2 Reputation risks

Reputation plays in various contexts, particularly how individuals, organizations, and even products gain and maintain their status and credibility within society or a given community. Krueger *et al*. (2020)'s survey suggests that reputation is one of the considerations of institutional investors. By investing in firms with good reputations, mutual funds can reduce their reputation risks. Reputation theory (Diamond, 1991) suggests that firms, by borrowing repeatedly from banks, can build their reputation and use it to access the bond market under favorable terms. Climate exposure may have negative implications on a firm's reputation. Mutual fund investors incorporate the issue to protect their reputation.

To test the conjecture, we use a firm's S&P quality rating to measure its reputation. S&P quality rating is committed to providing information on firms' creditworthiness to the market. The stocks are ranked as A+, A, A-, B+, B, B-, C, and D, while some stocks are not rated due to their relatively lower quality. We construct a variable *Credit Rating* to identify a firm's S&P quality rating, the integer values of which range from 0 to 8 referring to the quality from no rating to A+. A larger value of *Credit Rating* indicates better creditworthiness of the firm. We include the variable *Credit Rating* and the interaction term between *Credit Rating* and *CCExposure* in the regression. Table 3-7 column (3) reports the results. The regression coefficient of the interaction term is insignificant. Climate change-related reputation risks are less likely to drive mutual fund investors' investment decisions.

3.5.3.3 Financial constraints

Firms with high exposure might face hefty costs to transition to cleaner operations, which could impact financial performance and shareholder returns. Firms that successfully manage and mitigate these financial risks are not only safeguarding their operations but are also potentially positioning themselves to capitalize on new opportunities emerging from the global transition towards a low-carbon economy. This is not only imperative for the firm’s sustainability but is also becoming increasingly crucial for attracting investments, especially from climate-aware investors and funds. Based on the firm financial constraint hypothesis, mutual funds are averse to firms with large climate change exposures, due to the increased financial burden caused by climate change.

If this is the case, firms’ financial constraints will amplify the impact of climate change exposure on mutual funds’ decisions. We include the measure of financial constraint (*Z-Score*) of the firms in the baseline regression and examine the regression coefficients of the interaction term between *Z-Score* and climate change exposure *CCExposure*. In Table 3-7 Column (4), the regression coefficient of the interaction term is insignificant, indicating that the financial constraint is less likely to be a key economic channel.

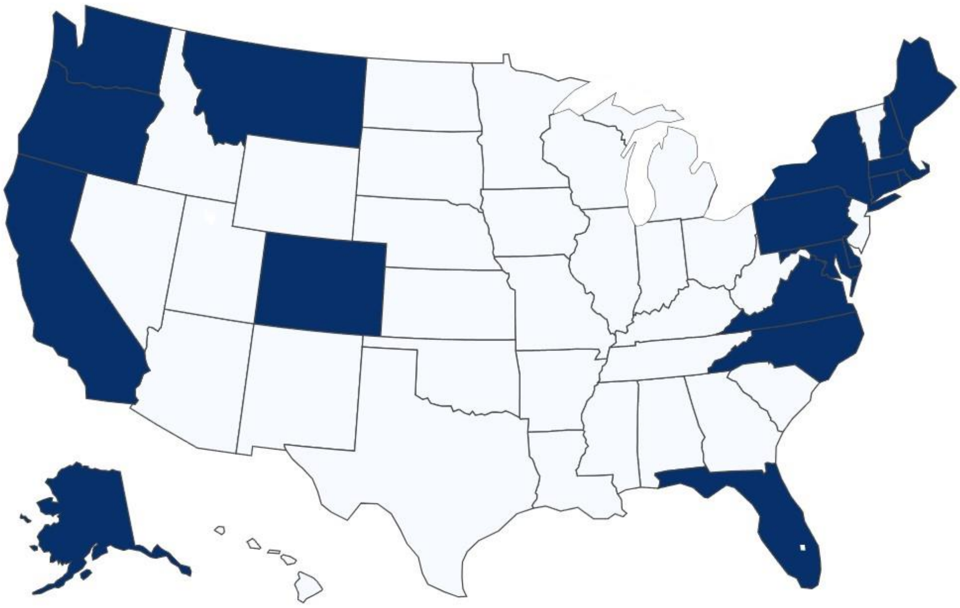
3.6 Additional Test

3.6.1 Endogeneity

We use a staggered difference-in-differences (DiD) model to alleviate the endogeneity concerns such as the omitted variables, although we have employed a set of control variables and fixed effects. First, we employ an exogenous shock on firms' climate change exposure. Following Heo (2021), the state-level climate change adaption plans reflect the effort of states to proactively adapt to the current and future impacts of climate change. Climate change adaptation plans are developed to address the impacts of climate change and to enhance the resilience of communities, infrastructure, and ecosystems. These plans focus on preparing for and mitigating the adverse effects of climate change, such as extreme weather events, rising sea levels, and shifting ecological patterns. As of 2021, 19 states have adopted the climate change adaption plan, the details of which can be found in Heo (2021), which are plotted in Figure 3-2. We predict that climate change adaption plans can mitigate the negative impact of climate change exposure by increasing the resilience of climate change.

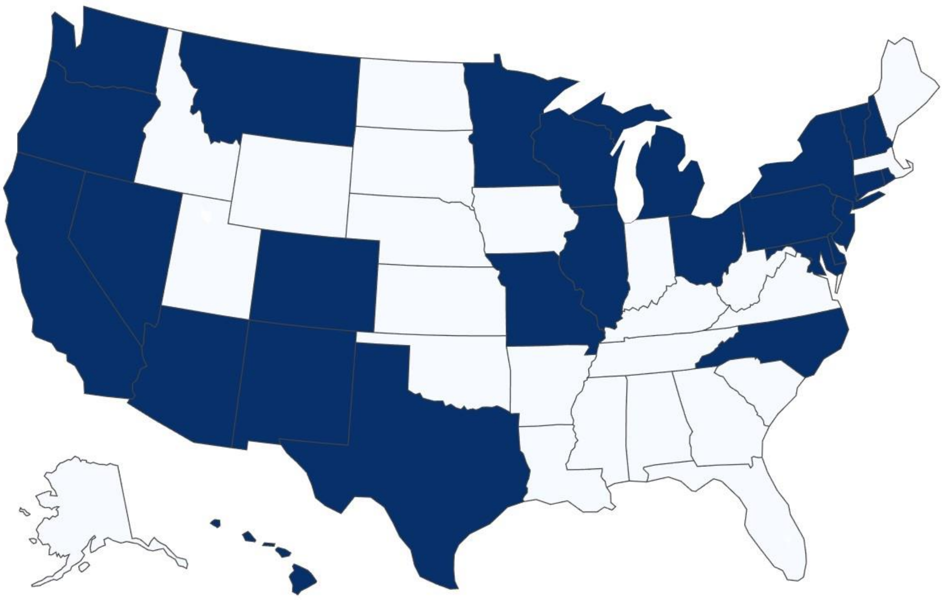
Second, we employ an exogenous shock primarily on firms' climate change exposure in opportunity and regulation. The exogenous shock is the implementation of Renewable portfolio standards (RPS) by the states. The policy requires electricity providers to use a certain percentage of renewable energy sources, the goal of which is to promote the use of renewable energy and reduce reliance on fossil fuels. The PRS is typically implemented at the state level in the United States. RPS policies can send a strong signal to the public and the business community that the government is committed to addressing climate change and promoting a clean energy future. The adoption of state-level RPS can strengthen public attention toward the benefits and costs of climate-related issues. To empirically investigate whether the implementation of RPS raises public attention to public change in the states, we rely on the Google Trend Index (GTI). Google Trends provides data on the search frequencies of terms on a weekly basis. Scholars used the index to proxy for individuals' attention (Da *et al*., 2011), a larger of which indicates a larger degree of attention. We obtain the *GTI* at the state-year level by searching "climate change". The index reflects the degree of the public's attention to climate change. The results of t-tests suggest that *GTI* after the adoption of RPS is significantly higher than before. The heightened public focus ensures that firms with RPS-adopting states are conspicuously exposed to climate change. As Sautner *et al*. (2023)'s *CCExposure* is based on the attention paid by earnings call participants to firms' climate change exposures, the RPS-increased attention can positively affect the firms' climate change exposure. By the end of 2022, there are 30 states adopting the RPS, which are plotted in Figure 3-3.[35]

[35] Source: The U.S. Energy Information Administration (EIA) (2022). Available at: https://www.eia.gov



Notes: Figure 3-2 displays the adoption status of Climate Change Adaption Plans by states as of the end of 2020. States that have adopted the plans are marked in black, whereas states that have not are shown in white.

Figure 3-2 The adoption status of climate change adaption plans by states



Notes: Figure 3-3 displays the adoption status of Renewable Portfolio Standards (RPS) by states as of the end of 2021. States that have adopted RPS are marked in black, whereas states that have not are shown in white.

Figure 3-3 The adoption status of Renewable Portfolio Standards (RPS) by states

To examine the impact of changes in climate change exposure, we identify a treatment group of states that adopted climate change adaption plans or RPS leading to a significant change in attention to climate change, and a control group of states that did not adopt the policies. The staggered DiD model is as follows.

$$\Delta Ownership_{i,t+1} = \beta_0 + \beta_1 Post_{i,t} + \beta_2 Controls_{i,s,t} + T + I + \varepsilon_{i,s,t} \quad (3-3)$$

Where $Post_{i,t}$ is a dummy variable that equals one if the state of the firm i in year t has adopted climate change adaption plans (*Climate Change Adaption*) or RPS (*Renewable Portfolio Standards*), and zero otherwise; $\Delta Ownership_{i,t+1}$ is the net growth of mutual fund ownership of the firm *i* in year *t+1* relative to year *t*; $Constrols_{i,s,t}$ are control variables for the firm *i* located in the state *s* in year *t*, consistent with the control variables in the baseline model; *T* and *I* are year fixed effects and firm fixed effects, respectively; β_0 is the constant term; β_1 and β_2 are regression coefficients; $\varepsilon_{i,s,t}$ is the error term.

Table 3-8 column (1) reports the result of the DiD regression. The regression coefficient of the variable *Climate Change Adaption* is positive and statistically significant at a 5% significance level. It suggests that the increased resilience to climate change reduces the difference between the control and treatment groups. In Table 3-8 column (2), the regression coefficient of the variable *Renewable Portfolio Standards* is negative and statistically significant at a 5% significance level. It suggests that the increased climate change exposure caused by the attention to climate change after the adoption of RPS can significantly decrease the firms' net growth in mutual fund ownership.

Table 3-8 Endogeneity Tests

This table reports the results of the endogeneity tests including the staggered difference-in-differences (DiD) tests. In column (1), the exogenous shock is the adoption of climate change adaption plans at the state-year level. In column (2), the exogenous shock is the adoption of the Renewable Portfolio Standards (RPS) at the state-year level. The variable *Climate Change Adaption* is a dummy variable that equals one if the state of the firm *i* in year *t* has adopted climate change adaption plans, and zero otherwise. The variable *Renewable Portfolio Standards* is a dummy variable that equals one if the state of the firm *i* in year *t* has adopted RPS, and zero otherwise. Δ*Ownership* is the net growth of the market value of shares held by the fund divided by the market value of the firm at the year-end. Control variables, year fixed effects and firm fixed effects are included, which are consistent with baseline regression. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Overall Exposure	*Opportunity & Regulation Exposure*
	ΔOwnership	ΔOwnership
	(1)	(2)
Climate Change Adaption	0.033**	
	(2.266)	
Renewable Portfolio Standards		-0.046**
		(-2.555)
Recent Return	0.022**	0.023**
	(2.033)	(2.090)
ROA	-0.097**	-0.096**
	(-2.210)	(-2.197)
Size	-0.034***	-0.034***
	(-2.693)	(-2.716)
Leverage	0.386***	0.383***
	(8.227)	(8.178)
Capex	-0.200	-0.185
	(-1.062)	(-0.991)
Cash	0.086**	0.085**
	(2.139)	(2.118)
Book-to-Market	0.067**	0.066**
	(2.078)	(2.042)
Z-Score	-0.000	-0.000
	(-0.010)	(-0.007)
Analyst Coverage	-0.091***	-0.091***
	(-7.365)	(-7.377)
R&D	0.001	0.002
	(0.063)	(0.168)
CSR	0.001	0.001
	(0.206)	(0.223)
GDP	-0.005	-0.029
	(-0.051)	(-0.321)
Constant	0.644	1.008
	(0.547)	(0.837)
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
N	12628	12628
adj R-sq	0.097	0.097

3.6.2 Political Uncertainty

We explore the fluctuations in public attention and their effects on investment decisions, particularly in relation to firms' climate change exposure. According to Sautner *et al*. (2023), we gauge firms' climate change exposure through the lens of public attention as reflected in earnings call discussions. This approach provides insights into the prominence of climate issues in the public discourse. When the public focus shifts towards other topics, mutual funds may adapt by integrating more information on these more prevalent issues, potentially diminishing the relative impact of firms' climate change exposure on investment decisions. To substantiate this hypothesis, we analyze the influence of political attention, particularly during significant events such as presidential elections. Political events, especially presidential elections, have a profound impact on investor sentiment, often overshadowing other concerns due to the uncertainties and policy implications associated with political changes. We hypothesize that in election years, the focus on political uncertainties and costs may eclipse climate concerns, thereby reducing the impact of climate change exposure on investment decisions.

To test this hypothesis, we segment our sample based on whether the data corresponds to a presidential election year or not. The years of presidential elections include the years 2004, 2008, 2012, 2016, and 2020. This setting allows us to conduct a comparative analysis of the influence of firms' climate change exposures on mutual fund ownership in different public attention contexts. We then re-estimate our baseline regression within these sub-samples, enabling a targeted examination of the effects of climate change exposure under varying degrees of political attention.

Table 3-9 reports the results. The impact of climate change exposure and climate change exposure in opportunity are insignificant when there is a presidential election, while significant when there is no presidential election. The results are consistent with our hypothesis. The impact of climate change exposure is mitigated by the public's attention in other areas. This analysis not only sheds light on the specific case of climate change exposure but also offers broader insights into how external factors shape market dynamics and investor behavior.

Table 3-9 Public attention

This table reports the results of the cross-sectional analysis. $\Delta Ownership$ is the net growth of the market value of shares held by the fund divided by the market value of the firm at the year-end. *CCExposure* is the overall climate change exposure at the firm-year level, multiplied by 1000 and taking natural logarithm. $CCExposure^{opp}$ is the climate change exposure in opportunity at the firm-year level, multiplied by 1000 and taking natural logarithm. The sample is divided into two subgroups in columns (1) and (3) with low public attention to climate change and in columns (2) and (4) with high public attention to climate change. The observation is categorized as low public attention in climate change if the year has a presidential election, and high otherwise. Control variables are consistent with baseline regression. Year fixed effects and firm fixed effects are included. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	Climate Attention Low	*Climate Attention High*	*Climate Attention Low*	*Climate Attention High*
	ΔOwnership	ΔOwnership	ΔOwnership	ΔOwnership
	(1)	(2)	(3)	(4)
CCExposure	-0.031	-0.047***		
	(-1.160)	(-3.144)		
$CCExposure^{opp}$			-0.054	-0.056**
			(-1.378)	(-2.544)
Recent Return	0.040	0.017	0.040	0.018
	(1.440)	(1.493)	(1.451)	(1.505)
ROA	0.060	-0.128**	0.056	-0.128**
	(0.652)	(-2.524)	(0.610)	(-2.515)
Size	-0.031	-0.032**	-0.030	-0.033**
	(-1.240)	(-2.142)	(-1.223)	(-2.194)
Leverage	0.080	0.466***	0.081	0.467***
	(0.959)	(7.851)	(0.964)	(7.862)
Capex	-0.568	0.072	-0.564	0.066
	(-1.264)	(0.332)	(-1.255)	(0.305)
Cash	0.175	0.062	0.173	0.062
	(1.584)	(1.282)	(1.566)	(1.280)
Book-to-Market	0.015	0.063*	0.016	0.063*
	(0.284)	(1.650)	(0.297)	(1.656)
Z-Score	-0.009*	0.002	-0.009*	0.002
	(-1.825)	(0.477)	(-1.794)	(0.464)
Analyst Coverage	-0.069***	-0.100***	-0.069***	-0.100***
	(-2.821)	(-7.286)	(-2.825)	(-7.280)
R&D	0.004	0.007	0.004	0.007
	(0.189)	(0.533)	(0.181)	(0.527)
CSR	0.016	0.003	0.016	0.004
	(1.119)	(0.503)	(1.110)	(0.518)
GDP	-0.144	0.105	-0.151	0.101
	(-1.006)	(1.067)	(-1.053)	(1.023)
Constant	2.489	-0.796	2.573	-0.750
	(1.296)	(-0.605)	(1.337)	(-0.567)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
N	3405	9223	3405	9223
adj R-sq	0.121	0.121	0.121	0.121

3.6.3 Global Evidence

The distinction between domestic and international mutual fund investors is primarily rooted in their differential exposure to risks and opportunities, influenced by geographic and economic boundaries. Domestic investors typically have a deeper understanding and closer ties to local markets, making them more susceptible to domestic economic conditions, regulatory changes, and political events. Conversely, international investors must navigate a broader spectrum of risks that extend beyond local markets. At the firm level, the impact of auditing and accounting standards on investment decisions is well-documented, as shown in studies by DeFond *et al.* (2011) and Chou *et al.* (2014). These standards play a crucial role in ensuring transparency and reliability of financial reporting, factors that are particularly important for international investors who may be less familiar with the local context and require standardized information to make informed decisions. However, there’s a limited understanding of how other firm-level characteristics influence the decisions of foreign mutual fund investors. For instance, climate change exposure could potentially sway international investment. The varying importance placed on the factor could significantly differentiate the investment strategies and preferences between domestic and international mutual funds.

We calculate the net growths in foreign mutual fund ownership $\Delta\mathrm{Ownership}^{Global}$. Then we re-estimate the baseline regression (3-2) by replacing the dependent variable with $\Delta\mathrm{Ownership}^{Global}$, and the independent variables of interest include overall climate change exposure and exposure in specific aspects: opportunity, regulation, and physical risks. Table 3-10 reports the regression results. The regression coefficients are insignificant, and also insignificant when we use alternative measures of dependent variables or independent variables. We find no evidence that global mutual fund investors are affected by firms’ climate change exposure.

Table 3-10 Global evidence

This table reports the results for regression (3-1) using a global sample. $CCExposure^{opp}$ is the climate change exposure in opportunity at the firm-year level, multiplied by 1000 and taking natural logarithm. $CCExposure^{reg}$ is the climate change exposure in regulation at the firm-year level, multiplied by 1000 and taking natural logarithm. $CCExposure^{phy}$ is the climate change exposure in physical risks at the firm-year level, multiplied by 1000 and taking natural logarithm. Δ*Ownership* is the net growth of the market value of shares held by the fund divided by the market value of the firm at the year-end. Control variables are consistent with baseline regression. Year fixed effects and firm fixed effects are included. Standard errors are clustered at the firm level. Significance at 10%, 5%, and 1% are indicated by *, **, and *** with t-statistics in parentheses.

	$\Delta \text{Ownership}^{Global}$	$\Delta \text{Ownership}^{Global}$	$\Delta \text{Ownership}^{Global}$	$\Delta \text{Ownership}^{Global}$
	(1)	(2)	(3)	(4)
CCExposure	-0.271			
	(-0.744)			
$CCExposure^{opp}$		-0.385		
		(-0.672)		
$CCExposure^{reg}$			1.101	
			(0.532)	
$CCExposure^{phy}$				0.343
				(0.109)
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
N	11142	11142	11142	11142
adj R-sq	0.084	0.089	0.089	0.089

3.7 Conclusion

In this paper, we use Sautner (2023)'s climate change measure to investigate the implication of firms' climate change exposure on their mutual fund ownership. Using a sample of firms in the United States between 2002 and 2020, we find strong evidence that firms' climate change exposure has a significantly negative and economically meaningful effect on the net growths in mutual fund ownership. The result is robust to a series of robustness tests. We employ alternative samples adjusted by state, year, or industry to avoid our results being driven by unbalanced distribution. Then we employ alternative variables or models. We find consistent results when we use various measures of the dependent variable or fixed effects.

Next, we identify the economic channels of the impact. The impact of climate change exposure on mutual fund ownership is more pronounced in firms within innovative sectors and carbon-emitting sectors. These industries suffer greater transition risks caused by climate change. Further, the negative impact is mitigated by firms' recent performance and lower downside risks. The results suggest that mutual funds incorporate firms' climate change exposure, driven by heightened transition risks and investment uncertainties. We find less evidence supporting other potential explanations such as climate information processing, increased reputation risks, or financial constraints.

In additional tests, we alleviate the endogeneity concern using a staggered difference-in-differences approach. We employ the state-level adoption of climate change adaption plans and Renewable portfolio standards as the exogenous shocks. Climate change adaption plans increase firms' resilience to climate change. The treated firms observe a larger net growth in mutual fund ownership than control firms after the adoption of climate change adaption plans. Renewable portfolio standards increase the pressure on firms and the public's attention to climate change. The treated firms observe a smaller net growth in mutual fund ownership than control firms after the adoption of the standards. The results support the causal inference of the relationship between climate change exposure and mutual fund ownership. Additionally, greater political uncertainties mitigate the impact of climate change exposure. Finally, we find no consistent evidence in a global setting.

Overall, this chapter highlights the negative role of climate change exposure in mutual fund investment allocation. This research contributes to the body of literature on the financial consequences of climate change and how mutual fund investors incorporate climate change in their investment decisions. Our findings may be more applicable to certain sectors or regions, depending on the level of exposure to climate-related risks and the regulatory environment. In the future, studies can expand the geographical scope of research to include a broader range of markets, especially emerging economies. This would enhance our understanding of how different regulatory environments and stages of economic development influence the relationship between climate change exposure and mutual fund ownership. In addition, the current findings suggest a dynamic consequence (net changes of mutual fund ownership). Further investigation on a stable outcome can help to understand investors' behavior.

Appendix

Table A3-1 Variable description

Variable	Definition	Source
Independent		
CCExposure	Firm-level climate change overall exposure, multiplied by 1000 and taken natural logarithm.	Sautner *et al*. (2023)
$\text{CCExposure}^{\text{opp}}$	Firm-level climate change exposure that captures opportunities, multiplied by 1000 and taken natural logarithm.	Sautner *et al*. (2023)
$\text{CCExposure}^{\text{reg}}$	Firm-level climate change exposure that captures regulatory shocks, multiplied by 1000 and taken natural logarithm.	Sautner *et al*. (2023)
$\text{CCExposure}^{\text{phy}}$	Firm-level climate change exposure that captures physical shocks, multiplied by 1000 and taken natural logarithm.	Sautner *et al*. (2023)
ΔCCExposure	The net growth of CCExposure over the current year and last year.	
EGKLS	Engle et al. (2020)'s climate change index, which is estimated from news at the year level.	Engle *et al*. (2020)
Dependent		
ΔOwnership	The market value of shares held by the fund is divided by the market value of the firm at the year-end. The market value of the firm is the sum of the market value of equity, long-term debt, and short-term debt at the year-end. Then calculate the net growth of the value over the current and previous year.	Refinitiv Mutual Fund
ΔOwnership #share	The number of shares held by the fund divided by the total shares outstanding at the year-end. Then calculate the net growth of the value over the current and previous year.	Refinitiv Mutual Fund
$\Delta\text{Ownership}^{Global}$	The market value of shares held by the foreign fund divided by the market value of the firm at the year-end. The market value of the firm is the sum of the market value of equity, long-term debt, and short-term debt at the year-end. Then calculate the net growth of the value over the current and previous year.	Refinitiv Mutual Fund
Control		
Recent Return	Holding period return of the stock during the year.	Compustat
ROA	The return on assets at the year-end.	Compustat
Size	The natural logarithm of the dollar value of total assets at the year-end.	Compustat
Leverage	The leverage ratio at the year-end.	Compustat
Capex	The capital expenditure at the year-end.	Compustat
Cash	The cash ratio at the year-end.	Compustat
Book-to-Market	The book-to-market ratio at the year-end.	Compustat

Z-Score	The financial constraints calculated by the following formula: Z-Score = 1.2*(working capital/total assets) + 1.4*(retained earnings/total assets) +3.3*(EBIT/total assets)+0.6*(market value of equity/total liabilities)+(sales/total assets)	Compustat
Analyst Coverage	The logarithm of the number of analysts covering the firm at the year-end	I/B/E/S
R&D	The logarithm of R&D expenditure at the year-end	Compustat
CSR	The CSR performance of the firm at the year-end	MSCI
GDP	The natural logarithm of the amount of Gross Domestic Product(GDP) of the state at the year-end.	U.S. BEA
Other Variables		
Carbon Industry	Dummy variable that equals one if the firm belongs to carbon-emitting industry, and zero otherwise.	Ilhan *et al*. (2021)
Innovative Industry	Dummy variable that equals one if the firm belongs to innovative industry, and zero otherwise.	
Downside Risk	The value at risk (VaR) of the firm's stock during the last year.	
Climate Action	Dummy variable that equals one if the firm is a target of Climate Action 100+, and zero otherwise.	Climate Action 100+
Credit Rating	Firms' S&P quality rating.	CRSP
Climate Change Adaption	Dummy variable that equals one if the state of the firm has adopted climate change adaption plans in the year, and zero otherwise.	Heo (2021)
Renewable Portfolio Standards	Dummy variable that equals one if the state of the firm has adopted renewable portfolio standards in the year, and zero otherwise.	National Renewable Energy Laboratory

Conclusion

This thesis, traversing the intricate landscapes of corporate finance in the digital age, concludes with significant findings and contributions from its three comprehensive chapters. It represents an in-depth exploration of the dynamic interplay between the digital age and traditional financial practices. This research has not only provided a comprehensive analysis of current trends and patterns within the realm of corporate finance but has also illuminated the pathways through which digital technologies are reshaping financial strategies, management behaviors, decision-making processes, and market dynamics. The findings offer both academic scholars and industry practitioners an understanding of how to adapt amidst these transformative changes.

Chapter 1 Social Connectedness and Cross-Border Mergers and Acquisitions provides a deep dive into the impact of between-countries' social connectedness on outcomes of cross-border M&As. The key finding underscores the importance of social connectedness's informational role in international business. This chapter not only enhances our understanding of the determinants of cross-border M&As but also sets a precedent for future research in linking sociological concepts to finance. Chapter 2 Remote or Face-to-Face: CEO Interviews and Investor Disagreement shifts the focus to the financial implications of CEOs' disclosure modalities: remote and face-to-face. The revelation that remote interviews are associated with a larger investor disagreement sheds light on the importance of CEOs' communication modalities and non-verbal behaviors. This insight offers a new perspective to both academics and practitioners in the field of corporate governance, behavior finance, and communications in reality. Chapter 3 Climate Change Exposure and Mutual Fund Ownership explores the financial consequences of climate change. The discovery that climate change exposure negatively affects mutual fund ownership highlights the growing importance of climate change-related issues. This chapter contributes significantly to the literature on how institutional investors react to climate change.

Collectively, these chapters contribute to a richer, more nuanced understanding of M&As, CEOs, and institutional investors. The findings across the chapters not only interlink but also independently stand to offer valuable insights into corporate finance. In the digital age, data is abundant and increasingly accessible. This work underscores the burgeoning potential of innovative methods in financial research, such as big data-based Facebook's Social Connectedness Index and textual-based Sautner *et al*. (2023)'s climate change exposure index. The digital age ushers in not only advancements but also new challenges, particularly with the integration of emerging technologies into daily life and the business sphere. Technologies such as virtual communication and artificial intelligence have become ubiquitous, fundamentally altering how we interact and conduct business. This thesis addresses a crucial debate in this context: the effectiveness of remote communication and its significant impact on the financial markets.

The findings from this thesis transcend the traditional boundaries of academic theory, providing actionable insights and strategic recommendations directly applicable to policymakers, investors, corporate managers, and firms. These implications are especially significant in the digital age, where the rapid evolution of technology continuously reshapes the financial landscape. The use of digital data sources and analytical methods highlighted in this research reflects the shift towards a more data-driven and technologically advanced approach in corporate finance. Furthermore, the research opens up several new pathways for future investigation. One such area, for example, is the exploration of CEOs' non-verbal behaviors, a relatively emerging territory that holds significant promise. Present research concentrates on analyzing CEOs' vocal and facial cues. However, there exists a myriad of other cues that remain largely unexplored. These could include body language and other forms of non-verbal cues, each potentially offering valuable insights into CEO behaviors and decision-making processes. Another burgeoning area of interest lies in the risks associated with artificial intelligence. AI technologies, such as ChatGPT, introduce novel uncertainties and challenges in the realm of firm operations. These technologies are not only reshaping the landscape of business processes but also posing unique risks and opportunities. How investors and managers adapt to and integrate these AI developments represents a relatively uncharted territory in research. Understanding their strategies for incorporating AI advancements and mitigating associated risks is crucial for navigating the future of corporate governance and strategy in an AI-influenced business environment.

In conclusion, this thesis stands as a testament to the intricate and dynamic nature of finance in the digital age, showcasing the potential of big data, advanced analytical tools, and financial innovations in unraveling the complexities of the corporate finance world.

Reference

Adra, S., Barbopoulos, L. G., & Saunders, A. (2020). The impact of monetary policy on M&A outcomes. *Journal of Corporate Finance, 62*, 101529. https://doi.org/10.1016/j.jcorpfin.2019.101529

Ahern, K. R., Daminelli, D., & Fracassi, C. (2015). Lost in translation? The effect of cultural values on mergers around the world. *Journal of Financial Economics, 117*(1), 165–189. https://doi.org/10.1016/j.jfineco.2012.08.006

Ahmad, M. F., Aktas, N., & Aziz, S. (2022). Does bilateral trust matter during mergers and acquisitions negotiations? *British Journal of Management, 0*, 1–22. https://doi.org/10.1111/1467-8551.12692

Aleksanyan, M., Hao, Z., Vagenas-Nanos, E., & Verwijmeren, P. (2021). Do state visits affect cross-border mergers and acquisitions? *Journal of Corporate Finance, 66*, 101800. https://doi.org/10.1016/j.jcorpfin.2020.101800

Allen, L., Peng, L., & Shan, Y. (2018). *Social interactions and peer-to-peer lending decisions*.

Alok, S., Kumar, N., & Wermers, R. (2020). Do fund managers misestimate climatic disaster risk? *Review of Financial Studies, 33*(3), 1146–1183. https://doi.org/10.1093/rfs/hhz143

Amiram, D., Owens, E., & Rozenbaum, O. (2016). Do information releases increase or decrease information asymmetry? New evidence from analyst forecast announcements. *Journal of Accounting and Economics, 62*(1), 121–138. https://doi.org/10.1016/j.jacceco.2016.06.001

Anand, A., Samadi, M., Sokobin, J., & Venkataraman, K. (2021). Institutional order handling and broker-affiliated trading venues. *Review of Financial Studies*, *34*(7), 3364–3402. https://doi.org/10.1093/rfs/hhab004

Au, S.-Y., Dong, M., & Zhou, X. (2024). Does social interaction spread fear among institutional investors? Evidence from Coronavirus disease 2019. *Management Science, 70*(4), 2406–2426. https://doi.org/10.1287/mnsc.2023.4814

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., & Wong, A. (2018a). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives, 32*(3), 259–280. https://doi.org/10.1257/jep.32.3.259

Bailey, M., Cao, R., Kuchler, T., & Stroebel, J. (2018b). The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy, 126*(6), 2224–2276. https://doi.org/10.1086/700073

Bailey, M., Gupta, A., Hillenbrand, S., Kuchler, T., Richmond, R., & Stroebel, J. (2021). International trade and social connectedness. *Journal of International Economics, 129*, 103418. https://doi.org/10.1016/j.jinteco.2020.103418

Bailey, M., Dávila, E., Kuchler, T., & Stroebel, J. (2019). House price beliefs and mortgage leverage choice. *Review of Economic Studies, 86*(6), 2403–2452. https://doi.org/10.1093/restud/rdy068

Bacidore, J. M., & Sofianos, G. (2002). Liquidity provision and specialist trading in NYSE-listed non-U.S. stocks. *Journal of Financial Economics, 63*(1), 133–158. https://doi.org/10.1016/S0304-405X(01)00092-7

Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does climate change affect real estate prices? Only if you believe in it. *Review of Financial Studies, 33*(3), 1256–1295. https://doi.org/10.1093/rfs/hhz073

Bali, T. G., Hirshleifer, D. A., Peng, L., & Tang, Y. (2021). Attention, social interaction, and investor attraction to lottery stocks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3978401

Bamber, L. S., Barron, O. E., & Stevens, D. E. (2011). Trading volume around earnings announcements and other financial reports: Theory, research design, empirical evidence, and directions for future research. *Contemporary Accounting Research*, *28*(2), 431–471. https://doi.org/10.1111/j.1911-3846.2010.01061.x

Banker, R. D., Ding, H., Huang, R., & Li, X. (2024). Market reaction to CEOs' dynamic hemifacial asymmetry of expressions. *Management Science, 70*(7), 4847–4874. https://doi.org/10.1287/mnsc.2023.4922

Barcellos, L. P., & Kadous, K. (2022). Do managers' nonnative accents influence investment decisions? *The Accounting Review, 97*(3), 51–75. https://doi.org/10.2308/tar-2020-0228

Bennett, J. A., Sias, R. W., & Starks, L. T. (2003). Greener pastures and the impact of dynamic institutional preferences. *Review of Financial Studies, 16*(4), 1203–1238. https://doi.org/10.1093/rfs/hhg040

Bertrand, O., Betschinger, M. A., & Settles, A. (2016). The relevance of political affinity for the initial acquisition premium in cross-border acquisitions. *Strategic Management Journal*, *37*(10), 2071–2091. https://doi.org/10.1002/smj.2438

Bhattacharya, U., Hsu, P. H., Tian, X., & Xu, Y. (2017). What affects innovation more: Policy or policy uncertainty? *Journal of Financial and Quantitative Analysis, 52*(5), 1869–1901. https://doi.org/10.1017/S0022109017000540

Birdwhistell, R. L. (1970). *Kinesics and context.*

Blankespoor, E., Hendricks, B. E., & Miller, G. S. (2017). Perceptions and price: Evidence from CEO presentations at IPO roadshows. *Journal of Accounting Research, 55*(2), 275–327. https://doi.org/10.1111/1475-679X.12164

Boeh, K. K. (2011). Contracting costs and information asymmetry reduction in cross-border M&A. *Journal of Management Studies, 48*(3), 568–590. https://doi.org/10.1111/j.1467-6486.2010.00938.x`

Brochet, F., Chychyla, R., & Ferri, F. (2023). Virtual Shareholder Meetings. *Management Science*. https://doi.org/10.1287/mnsc.2023.4946

Bruner, R. F., & Perella, J. R. (2004). *Applied mergers and acquisitions.* John Wiley & Sons.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature, 527*(7577), 235–239. https://doi.org/10.1038/nature15725

Busse, J. A., & Clifton Green, T. (2002). Market efficiency in real time. *Journal of Financial Economics*, *65*(3), 415–437. https://doi.org/10.1016/S0304-405X(02)00148-4

Butticè, V., Di Pietro, F., & Tenca, F. (2020). Is equity crowdfunding always good? Deal structure and the attraction of venture capital investors. *Journal of Corporate Finance*, *65*(October). https://doi.org/10.1016/j.jcorpfin.2020.101773

Byrne, D., Griffitt, W., & Stefaniak, D. (1967). Attraction and similarity of personality characteristics. *Journal of Personality and Social Psychology*, *5*(1), 82–90. https://doi.org/10.1037/h0021198

Cade, N. L., Koonce, L., & Mendoza, K. I. (2020). Using video to disclose forward-looking information: the effect of nonverbal cues on investors' judgments. *Review of Accounting Studies, 25*(4), 1444–1474. https://doi.org/10.1007/s11142-020-09539-8

Cai, X., Jiang, F., & Kang, J.-K. (2023). Remote board meetings and board monitoring effectiveness: Evidence from China. *The Review of Financial Studies*, *36*(11), 4318–4372. https://doi.org/10.1093/rfs/hhad026

Cai, Y., & Sevilir, M. (2012). Board connections and M&A transactions. *Journal of Financial Economics, 103*(2), 327–349. https://doi.org/10.1016/j.jfineco.2011.05.017

Cao, Y., Guan, F., Li, Z., & George Yang, Y. (2020). Analysts' beauty and performance. *Management Science*, *66*(9), 4315–4335. https://doi.org/10.1287/mnsc.2019.3336

Capron, L., & Shen, J. (2007). Acquisitions of private vs. public firms: Private information, target selection, and acquirer returns. *Strategic Management Journal, 28*(9), 891–911. https://doi.org/10.1002/smj.612

Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science, 353*(6304). https://doi.org/10.1126/science.aad9837

Ceccarelli, M., Ramelli, S., & Wagner, A. F. (2019). When investors call for climate responsibility, how do mutual funds respond? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3353239

Chaudhry, A. N., Kontonikas, A., & Vagenas-Nanos, E. (2022). Social networks and the informational role of financial advisory firms centrality in mergers and acquisitions. *British Journal of Management, 33*(2), 958–979. https://doi.org/10.1111/1467-8551.12477

Chen, C. R., Diltz, J. D., Huang, Y., & Lung, P. P. (2011). Stock and option market divergence in the presence of noisy information. *Journal of Banking and Finance, 35*(8), 2001–2020. https://doi.org/10.1016/j.jbankfin.2011.01.020

Choudhury, P., Wang, D., Carlson, N. A., & Khanna, T. (2019). Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles. *Strategic Management Journal, 40*(11), 1705–1732. https://doi.org/10.1002/smj.3067

Chou, J., Zaiats, N., & Zhang, B. (2014). Does auditor choice matter to foreign investors? Evidence from foreign mutual funds worldwide. *Journal of Banking & Finance, 46*(1), 1–20. https://doi.org/10.1016/j.jbankfin.2014.04.005

Cohen, L., Frazzini, A., & Malloy, C. (2008). The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy, 116*(5), 951–979. https://doi.org/10.1086/592415

Cookson, J. A., & Niessner, M. (2020). Why don't we agree? Evidence from a social network of investors. *Journal of Finance, 75*(1), 173–228. https://doi.org/10.1111/jofi.12852

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *Journal of Finance, 66*(5), 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science, 32*(5), 554–571.

Dávila, A., & Guasch, M. (2022). Managers' Body Expansiveness, Investor Perceptions, and Firm Forecast Errors and Valuation. *Journal of Accounting Research, 60*(2), 517–563. https://doi.org/10.1111/1475-679X.12426

DeFond, M., Hu, X., Hung, M., & Li, S. (2011). The impact of mandatory IFRS adoption on foreign mutual fund ownership: The role of comparability. *Journal of Accounting and Economics*, *51*(3), 240–258. https://doi.org/10.1016/j.jacceco.2011.02.001

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature, 52*(3), 740–798. https://doi.org/10.1257/jel.52.3.740

Devos, E., Kadapakkam, P.-R., & Krishnamurthy, S. (2009). How do mergers create value? A comparison of taxes, market power, and efficiency improvements as explanations for synergies. *Review of Financial Studies, 22*(3), 1179–1211. https://doi.org/10.1093/rfs/hhn019

Diamond, D. W. (1991). Debt maturity structure and liquidity risk. *The Quarterly Journal of Economics, 106*(3), 709–737. https://doi.org/10.2307/2937924

Dikova, D., Sahib, P. R., & van Witteloostuijn, A. (2010). Cross-border acquisition abandonment and completion: The effect of institutional differences and organizational learning in the international business service industry, 1981-2001. *Journal of International Business Studies, 41*(2), 223–245. https://doi.org/10.1057/jibs.2009.10

Ding, R., & Hou, W. (2015). Retail investor attention and stock liquidity. *Journal of International Financial Markets, Institutions and Money, 37*, 12–26. https://doi.org/10.1016/j.intfin.2015.04.001

Doellman, T., Huseynov, F., Nasser, T., & Sardarli, S. (2020). Corporate tax avoidance and mutual fund ownership. *Accounting and Business Research, 50*(6), 608–635. https://doi.org/10.1080/00014788.2020.1731676

Dontoh, A., & Ronen, J. (1993). Information content of accounting announcements. *The Accounting Review, 68*(4), 857–869.

Duncan, Starkey, J. (1969). Nonverbal communication. *Psychological Bulletin*, *72*(2), 118–137. https://doi.org/10.1037/h0027795

Dyck, A., Lins, K. V., Roth, L., & Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics, 131*(3), 693–714. https://doi.org/10.1016/j.jfineco.2018.08.013

Elliott, W. B., Hodge, F. D., & Sedor, L. M. (2012). Using online video to announce a restatement: Influences on investment decisions and the mediating role of trust. *The Accounting Review, 87*(2), 513–535. https://doi.org/10.2308/accr-10202

El-Khatib, R., Fogel, K., & Jandik, T. (2015). CEO network centrality and merger performance. *Journal of Financial Economics, 116*(2), 349–382. https://doi.org/10.1016/j.jfineco.2015.01.001

Engelberg, J., Sasseville, C., & Williams, J. (2012). Market madness? the case of Mad Money. *Management Science, 58*(2), 351–364. https://doi.org/10.1287/mnsc.1100.1290

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies, 33*(3), 1184–1216. https://doi.org/10.1093/rfs/hhz072

Erel, I., Liao, R. C., & Weisbach, M. S. (2012). Determinants of cross-border mergers and acquisitions. *The Journal of Finance, 67*(3), 1045–1082. https://doi.org/10.1111/j.1540-6261.2012.01741.x

Ferreira, M. A., Massa, M., & Matos, P. (2010). Shareholders at the gate? Institutional investors and cross-border mergers and acquisitions. *Review of Financial Studies, 23*(2), 601–644. https://doi.org/10.1093/rfs/hhp070

Ferreira, M. A., & Matos, P. (2008). The colors of investors' money: The role of institutional investors around the world. *Journal of Financial Economics*, *88*(3), 499–533. https://doi.org/10.1016/j.jfineco.2007.07.003

Ferris, S. P., Javakhadze, D., & Rajkovic, T. (2017). CEO social capital, risk-taking and corporate policies. *Journal of Corporate Finance, 47*, 46–71. https://doi.org/10.1016/j.jcorpfin.2017.09.003

Flam, R., Green, J., & Sharp, N. Y. (2020). Do investors respond to CEO facial expressions of anger during television interviews? *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.3740755

Florackis, C., Louca, C., Michaely, R., & Weber, M. (2023). Cybersecurity risk. *Review of Financial Studies*, *36*(1), 351–407. https://doi.org/10.1093/rfs/hhac024

Garmaise, M. J., & Natividad, G. (2013). Cheap credit, lending operations, and international politics: The case of global microfinance. *The Journal of Finance, 68*(4), 1551–1576. https://doi.org/10.1111/jofi.12045

Gibson, S., Safieddine, A., & Titman, S. (2000). Tax-Motivated Trading and Price Pressure: An Analysis of Mutual Fund Holdings. *The Journal of Financial and Quantitative Analysis, 35*(3), 369. https://doi.org/10.2307/2676209

Giglio, S., Liao, Y., & Xiu, D. (2021). Thousands of alpha tests. *The Review of Financial Studies*, *34*(7), 3456–3496. https://doi.org/10.1093/rfs/hhaa111

Giglio, S., Maggiori, M., Rao, K., Stroebel, J., & Weber, A. (2021b). Climate change and long-run discount rates: Evidence from real estate. *Review of Financial Studies, 34*(8), 3527–3571. https://doi.org/10.1093/rfs/hhab032

Ginglinger, E., & Moreau, Q. (2023). Climate Risk and Capital Structure. *Management Science*. https://doi.org/10.1287/mnsc.2023.4952

Goldstein, I., Spatt, C. S., & Ye, M. (2021). Big data in finance. *The Review of Financial Studies, 34*(7), 3213–3225. https://doi.org/10.1093/rfs/hhab038

Guiso, L., Sapienza, P., & Zingales, L. (2006). Does culture affect economic outcomes? *Journal of Economic Perspectives, 20*(2), 23–48. https://doi.org/10.1257/jep.20.2.23

Guiso, L., Sapienza, P., & Zingales, L. (2009). Cultural biases in economic exchange? *Quarterly Journal of Economics, 124*(3), 1095–1131. https://doi.org/10.1162/qjec.2009.124.3.1095

Harrison, J. S., Thurgood, G. R., Boivie, S., & Pfarrer, M. D. (2020). Perception is reality: How CEOs' observed personality influences market perceptions of firm risk and shareholder returns. *Academy of Management Journal*, *63*(4), 1166–1195. https://doi.org/10.5465/amj.2018.0626

He, X., Yin, H., Zeng, Y., Zhang, H., & Zhao, H. (2019). Facial structure and achievement drive: Evidence from financial analysts. *Journal of Accounting Research, 57*(4), 1013–1057. https://doi.org/10.1111/1475-679X.12259

Heo, Y. (2021). Climate change exposure and firm cash holdings. *SSRN Electronic Journal,* July. https://doi.org/10.2139/ssrn.3795298

Hofstede, G. (2001). Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations. *Thousand Oaks*.

Hong, H., Kubik, J. D., & Stein, J. C. (2004). Social interaction and stock-market participation. *The Journal of Finance, 59*(1), 137–163. https://doi.org/10.1111/j.1540-6261.2004.00629.x

Hong, H., & Stein, J. C. (2007). Disagreement and the stock market. *Journal of Economic Perspectives, 21*(2), 109–128. https://doi.org/10.1257/jep.21.2.109

Howell, S. T., Niessner, M., & Yermack, D. (2020). Initial coin offerings: Financing growth with cryptocurrency token sales. *The Review of Financial Studies*, *33*(9), 3925–3974. https://doi.org/10.1093/rfs/hhz131

Hsieh, T. S., Kim, J. B., Wang, R. R., & Wang, Z. (2020). Seeing is believing? Executives' facial trustworthiness, auditor tenure, and audit fees. *Journal of Accounting and Economics, 69*(1), 101260. https://doi.org/10.1016/j.jacceco.2019.101260

Hsiang, S., & Kopp, R. E. (2018). An economist's guide to climate change science. *Journal of Economic Perspectives*, *32*(4), 3–32. https://doi.org/10.1257/jep.32.4.3

Hu, N., Li, L., Li, H., & Wang, X. (2020). Do mega-mergers create value? The acquisition experience and mega-deal outcomes. *Journal of Empirical Finance, 55*, 119–142. https://doi.org/10.1016/j.jempfin.2019.11.004

Huang, P., Officer, M. S., & Powell, R. (2016). Method of payment and risk mitigation in cross-border mergers and acquisitions. *Journal of Corporate Finance, 40*, 216–234. https://doi.org/10.1016/j.jcorpfin.2016.08.006

Huang, X., Ivković, Z., Jiang, J. X., & Wang, I. Y. (2023). Angel investment and first impressions. *Journal of Financial Economics, 149*(2), 161–178. https://doi.org/10.1016/j.jfineco.2023.05.001

Huberman, G. (2001). Familiarity breeds investment. *Review of Financial Studies, 14*(3), 659–680. https://doi.org/10.1093/rfs/14.3.659

Hwang, B. H., & Kim, S. (2009). It pays to have friends. *Journal of Financial Economics, 93*(1), 138–158. https://doi.org/10.1016/j.jfineco.2008.07.005

Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies, 34*(3), 1540–1571. https://doi.org/10.1093/rfs/hhaa071

Javakhadze, D., Ferris, S. P., & French, D. W. (2016). Social capital, investments, and external financing. *Journal of Corporate Finance, 37*, 38–55. https://doi.org/10.1016/j.jcorpfin.2015.12.001

Kamiya, S., Kim, Y. H., & Suh, J. (2019). The face of risk: CEO Testosterone and risk taking behavior. *European Financial Management, 25*(2), 239–270.

Kim, O., & Verrecchia, R. E. (1991). Trading volume and price reactions to public announcements. *Journal of Accounting Research, 29*(2), 302. https://doi.org/10.2307/2491051

Kim, Y. H. (Andy). (2013). Self attribution bias of the CEO: Evidence from CEO interviews on CNBC. *Journal of Banking & Finance, 37*(7), 2472–2489. https://doi.org/10.1016/j.jbankfin.2013.02.008

Kong, D., Pan, Y., Tian, G. G., & Zhang, P. (2020). CEOs' hometown connections and access to trade credit: Evidence from China. *Journal of Corporate Finance, 62*, 101574. https://doi.org/10.1016/j.jcorpfin.2020.101574

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *Review of Financial Studies, 33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Kuchler, T., Li, Y., Peng, L., Stroebel, J., & Zhou, D. (2022). Social proximity to capital: implications for investors and firms. *The Review of Financial Studies, 35*(6), 2743–2789. https://doi.org/10.1093/rfs/hhab111

Kuchler, T., & Stroebel, J. (2021). Social finance. *Annual Review of Financial Economics, 13*(1), 37–55. https://doi.org/10.1146/annurev-financial-101320-062446

Kuhnen, C. M., & Niessen, A. (2012). Public opinion and executive compensation. *Management Science*, *58*(7), 1249–1272. https://doi.org/10.1287/mnsc.1110.1490

Landsman, W. R., Maydew, E. L., & Thornock, J. R. (2012). The information content of annual earnings announcements and mandatory adoption of IFRS. *Journal of Accounting and Economics, 53*(1–2), 34–54. https://doi.org/10.1016/j.jacceco.2011.04.002

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1998). Law and finance. *Journal of Political Economy, 106*(6), 1113–1155. https://doi.org/10.1086/250042

Lee, R. M., & Robbins, S. B. (1998). The relationship between social connectedness and anxiety, self-esteem, and social identity. *Journal of Counseling Psychology*, *45*(3), 338–345. https://doi.org/10.1037/0022-0167.45.3.338

Levine, R., Lin, C., & Shen, B. (2020). Cross-border acquisitions: Do labor regulations affect acquirer returns? *Journal of International Business Studies*, *51*(2), 194–217. https://doi.org/10.1057/s41267-019-00281-1

Li, C., Lin, A. P., Lu, H., & Veenstra, K. (2020). Gender and beauty in the financial analyst profession: evidence from the United States and China. *Review of Accounting Studies, 25*(4), 1230–1262. https://doi.org/10.1007/s11142-020-09542-z

Li, F., Lin, C., & Lin, T.-C. (2023). A one-two punch to the economy: Climate vulnerability and corporate innovation strategies. *SSRN Electronic Journal,* February. https://doi.org/10.2139/ssrn.3777313

Li, J. (Jie), Massa, M., Zhang, H., & Zhang, J. (2021). Air pollution, behavioral bias, and the disposition effect in China. *Journal of Financial Economics, 142*(2), 641–673. https://doi.org/10.1016/j.jfineco.2019.09.003

Li, K., Mai, F., Shen, R., & Yan, X. (2021b). Measuring corporate culture using machine learning. *The Review of Financial Studies, 34*(7), 3265–3315. https://doi.org/10.1093/rfs/hhaa079

Li, Q., Shan, H., Tang, Y., & Yao, V. (2024). Corporate climate risk: Measurements and responses. *The Review of Financial Studies*, *37*(6), 1778–1830. https://doi.org/10.1093/rfs/hhad094

Li, L., & Tong, W. H. S. (2018). Information uncertainty and target valuation in mergers and acquisitions. *Journal of Empirical Finance, 45*, 84–107. https://doi.org/10.1016/j.jempfin.2017.09.009

Li, Z., & Wang, P. (2023). Cross-border mergers and acquisitions and corporate social responsibility: Evidence from Chinese listed firms. *Journal of Business Finance & Accounting*, *50*(1–2), 335–376. https://doi.org/10.1111/jbfa.12617

Lim, J., Makhija, A. K., & Shenkar, O. (2016). The asymmetric relationship between national cultural distance and target premiums in cross-border M&A. *Journal of Corporate Finance, 41*, 542–571. https://doi.org/10.1016/j.jcorpfin.2016.07.007

Loughran, T., & McDonald, B. (2011). When Is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance, 66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Luong, T. S., Qiu, B., & Wu, Y. (Ava). (2021). Does it pay to be socially connected with wall street brokerages? Evidence from cost of equity. *Journal of Corporate Finance, 68*, 101939. https://doi.org/10.1016/j.jcorpfin.2021.101939

Lyon, J. D., Barber, B. M., & Tsai, C. L. (1999). Improved methods for tests of long-run abnormal stock returns. *The Journal of Finance, 54*(1), 165–201. https://doi.org/10.1111/0022-1082.00101

Marra, A., Pettinicchio, A., & Shalev, R. (2024). Home sweet home: CEOs acquiring firms in their birth countries. *Journal of Accounting Research, 62*(4), 1363–1404. https://doi.org/10.1111/1475-679X.12533

Maskara, P. K., Kuvvet, E., & Chen, G. (2021). The role of P2P platforms in enhancing financial inclusion in the United States: An analysis of peer-to-peer lending across the rural–urban divide. *Financial Management*, *50*(3), 747–774. https://doi.org/10.1111/fima.12341

Mayew, W. J., & Venkatachalam, M. (2012). The power of voice: managerial affective states and future firm performance. *The Journal of Finance, 67*(1), 1–43. https://doi.org/10.1111/j.1540-6261.2011.01705.x

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in social networks. *Annual Review of Sociology, 27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Momtaz, P. P. (2021). CEO emotions and firm valuation in initial coin offerings: An artificial emotional intelligence approach. *Strategic Management Journal, 42*(3), 558–578. https://doi.org/10.1002/smj.3235

Nguyen, G., Nguyen, M., Pham, A. V., & Pham, M. D. (Marty). (2023). Navigating investment decisions with social connectedness: Implications for venture capital. *Journal of Banking and Finance, 155*(8), 106979. https://doi.org/10.1016/j.jbankfin.2023.106979

Obaid, K., & Pukthuanthong, K. (2022). A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news. *Journal of Financial Economics, 144*(1), 273–297. https://doi.org/10.1016/j.jfineco.2021.06.002

O'Neal, E. S. (1997). How many mutual funds constitute a diversified mutual fund portfolio? *Financial Analysts Journal*, *53*(2), 37–46. https://doi.org/10.2469/faj.v53.n2.2070

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics, 135*(2), 468–482. https://doi.org/10.1016/j.jfineco.2019.06.006

Pankratz, N., Bauer, R., & Derwall, J. (2023). Climate change, firm performance, and investor surprises. *Management Science.* https://doi.org/10.1287/mnsc.2023.4685

Peng, L., Teoh, S. H., Wang, Y., & Yan, J. (2022). Face value: Trait impressions, performance characteristics, and market outcomes for financial analysts. *Journal of Accounting Research, 60*(2), 653–705. https://doi.org/10.1111/1475-679X.12428

Raman, K., Shivakumar, L., & Tamayo, A. (2013). Target's earnings quality and bidders' takeover decisions. *Review of Accounting Studies, 18*(4), 1050–1087. https://doi.org/10.1007/s11142-013-9224-0

Rennekamp, K. M., Sethuraman, M., & Steenhoven, B. A. (2022). Engagement in earnings conference calls. *Journal of Accounting and Economics, 74*(1), 101498. https://doi.org/10.1016/j.jacceco.2022.101498

Renneboog, L., & Zhao, Y. (2014). Director networks and takeovers. *Journal of Corporate Finance, 28*, 218–234. https://doi.org/10.1016/j.jcorpfin.2013.11.012

Rohleder, M., Wilkens, M., & Zink, J. (2022). The effects of mutual fund decarbonization on stock prices and carbon emissions. *Journal of Banking and Finance, 134*, 106352. https://doi.org/10.1016/j.jbankfin.2021.106352

Rossi, S., & Volpin, P. F. (2004). Cross-country determinants of mergers and acquisitions. *Journal of Financial Economics, 74*(2), 277–304. https://doi.org/10.1016/j.jfineco.2003.10.001

Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance*, *78*(3), 1449–1498. https://doi.org/10.1111/jofi.13219

Siganos, A., & Tabner, I. T. (2020). Capturing the role of societal affinity in cross-border mergers with the Eurovision Song Contest. *Journal of International Business Studies, 51*(2), 263–273. https://doi.org/10.1057/s41267-019-00271-3

Sirri, E. R., & Tufano, P. (1998). Costly search and mutual fund flows. *Journal of Finance, 53*(5), 1589–1622. https://doi.org/10.1111/0022-1082.00066

Stein, E., & Daude, C. (2007). Longitude matters: Time zones and the location of foreign direct investment. *Journal of International Economics, 71*(1), 96–112. https://doi.org/10.1016/j.jinteco.2006.01.003

Stern, N., & Valero, A. (2021). Research policy, Chris Freeman special issue innovation, growth and the transition to net-zero emissions. *Research Policy, 50*(9). https://doi.org/10.1016/j.respol.2021.104293

Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics, 142*(2), 487–498. https://doi.org/10.1016/j.jfineco.2021.08.004

Uysal, V. B., Kedia, S., & Panchapagesan, V. (2008). Geography and acquirer returns. *Journal of Financial Intermediation, 17*(2), 256–275. https://doi.org/10.1016/j.jfi.2007.12.001

Voeten, E., & Merdzanovic, A. (2009). 'United Nations General Assembly voting data'. Available at: https://dataverse.harvard.edu/dataverse/Voeten (Accessed: 19 July 2021).

Wang, L., Dai, Y., & Kong, D. (2021). Air pollution and employee treatment. *Journal of Corporate Finance, 70*, 102067. https://doi.org/10.1016/J.JCORPFIN.2021.102067

Wang, Y., & Wu, S. (2024). Impact of mobile banking on small business lending after bank branch closures. *Journal of Corporate Finance*, *87*(5), 102593. https://doi.org/10.1016/j.jcorpfin.2024.102593

Woolcock, M. (1998). Social capital and economic development: Toward a theoretical synthesis and policy framework. *Theory and Society, 27*(2), 151–208. https://doi.org/10.1023/A:1006884930135

Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: A meta-analysis. *Psychological Bulletin, 139*(1), 53–80. https://doi.org/10.1037/a0028601

Wang, L., Dai, Y., & Kong, D. (2021). Air pollution and employee treatment. *Journal of Corporate Finance*, *70*, 102067. https://doi.org/10.1016/J.JCORPFIN.2021.102067

Wang, Y., & Wu, S. (2024). Impact of mobile banking on small business lending after bank branch closures. *Journal of Corporate Finance*, *87*(May), 102593. https://doi.org/10.1016/j.jcorpfin.2024.102593

Yang, J., Wu, Y., & Huang, B. (2023). Digital finance and financial literacy: Evidence from Chinese households. *Journal of Banking and Finance*, *156*(February 2021). https://doi.org/10.1016/j.jbankfin.2023.107005

Zhang, C., Kandilov, I. T., & Walker, M. D. (2021). Direct flights and cross-border mergers & acquisitions. *Journal of Corporate Finance, 70*, 102063. https://doi.org/10.1016/j.jcorpfin.2021.102063

Zhou, B., Guo, J. M., Hua, J., & Doukas, A. J. (2015). Does state ownership drive M&A performance? Evidence from China. *European Financial Management, 21*(1), 79–105. https://doi.org/10.1111/j.1468-036X.2012.00660.x

Zhu, H. (Susan), Ma, X., Sauerwald, S., & Peng, M. W. (2019). Home country institutions behind cross-border acquisition performance. *Journal of Management, 45*(4), 1315–1342. https://doi.org/10.1177/0149206317699520