Essays on M&As: The Effect of Political Ideology Divergence, Climate Change and Technology on M&As

By

Yongyi Xue

ICMA Centre
Henley Business School
University of Reading

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Supervisor: Dr Mohammad Shehub Bin Hasan

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To my dear family, with love

Declaration of Original Authorship

I confirm that this is my own work and that the use of all material from other sources has been properly and fully acknowledged.

Yongyi Xue

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Abstract

This thesis attempts to contribute to the strand of determinants of mergers and acquisitions (M&As) and the performance of acquisitions in the US and international markets, and it is composed of three main chapters.

The first main chapter examines the role of political ideology divergence (PID) between the CEO and board of directors in the context of mergers and acquisitions. Using a sample of 2,083 US-listed firms from 2000 to 2020, this study finds that firms with greater PID are positively associated with the likelihood of engaging in M&A activities. The results demonstrate that CEO risk-taking behaviours, proxied by CEO overconfidence, founder CEO, and pay for performance sensitivity, explain this positive relationship. Various identification strategies are employed to address endogeneity concerns and confirm the robustness of the findings. Furthermore, the research suggests that a higher level of PID has a positive effect on post-deal long-term stock return and operating performance. This study also finds that monitoring, through mechanisms such as board meeting frequency, institutional ownership, and independent directors, plays a moderating role in this long-term performance. Overall, these findings suggest that PID is a critical determinant of M&A decisions.

The second main chapter investigates the effect of firm-level climate change exposures on mergers and acquisitions with global evidence. Using the climate change exposures of Sautner et al. (2023), we find that firms facing higher climate change exposure exhibit a reduced propensity to initiate and finalise acquisitions while

allocating more resources to capital expenditures. The increased cost of external financing and low consumer confidence help explain the negative relationship between climate change exposure and acquisition likelihood. This negative effect of climate change exposure is more pronounced for acquirers of relatively small size, with steep growth potential, facing financial constraints, and those operating within pro-cyclical industries. When undertaking M&As, firms facing higher climate change exposure take a longer time to complete a deal and post poor announcement returns and operating performance. Several identification strategies address endogeneity concerns and ensure the robustness of the findings. Overall, this study emphasises the importance of considering climate change risks in M&A decision making.

The third main chapter investigates the post-merger short- and long-run performance of technology-related M&As using a global sample. Deals are classified according to the technological distance between acquirers and targets. Technologically distant pairs lead to higher announcement returns for acquirer shareholders, especially when targets are private. In contrast, pure technology deals gain significantly less and even adversely affect firm value. The positive wealth effect of technologically distant deals is more pronounced when the bidder is in a non-tech industry. Non-tech bidders acquiring tech targets have the highest positive change in operating performance among all acquisition types, suggesting better integration. Taken together, this study assesses the short- and long-term performance of technology-related M&As, emphasising that technologically distant firms yield higher returns for acquirers while similar technology deals are less beneficial and may even reduce value.

This thesis critically analyses the factors influencing the initiation and effectiveness of M&As in the US or international markets, encapsulated in three chapters. It identifies political ideology divergence (PID) between the CEO and board, the impact of climate change exposure, and the technological distance between acquirers and targets as key determinants impacting M&A propensity, completion time, stock returns, and post-deal performance.

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1. Introduction

Mergers and acquisitions (M&As) are one of the most critical corporate strategic decisions that have a significant impact on firms' operations and the economy around the world (Bruner and Perella, 2004; Campan and Hernando, 2004; Sudarsanam, 2010). The global M&A market spent more than $57.7 trillion on over 790,000 transactions during the last two decades (IMAA, 2020).[1] The number of deals and associated value have reached a historical high in 2021, with 65,162 deal announcements and a value of $5.72 trillion globally (KPMG, 2021).[2] All these showcase the scope and appetite for M&As worldwide. Firms employ M&As as a corporate strategy to achieve rapid growth, business transformation or restructuring, and to enhance profitability and competitiveness (Hitt et al., 2001, 2005; Cartwright and Schoenberg, 2006; Chandra, 2013). While the literature on M&A is elaborate (e.g., Travlos, 1987; Frank et al., 1991; Loughran and Vinjh, 1997; Moeller et al., 2004; Ferris et al., 2016; Malmendier et al., 2018), the three studies in this thesis are motivated by issues rarely been examined in depth in empirical research.

Chapter 2 presents the study of the relationship between political ideology divergence between the CEO and directors on board (*PID*) and M&As. Prior studies concentrate on political affiliations and alignment shaping the decision-making processes of CEOs, top management teams, and boards across various dimensions, including financial performance, corporate social responsibility, asset reallocation, and manager

[1] M&A Statistics, 2021, IMAA. Sourced from https://imaa-institute.org/mergers-and-acquisitions-statistics/.
[2] Global M&A review and forecast, 2021, KPMG. Sourced from https://kpmg.com/xx/en/home/insights/2021/12/global-m-and-a-review-and-forecast.html.

dismissal and compensation (Lee et al., 2014; Gupta et al., 2019; Park et al., 2019). However, very limited empirical research focuses on the divergence of political ideology between the CEO and board and its impact on corporate outcomes, particularly M&As, where acquisitions require an active engagement of both the CEO and board of directors. To this end, this study examines whether and how *PID*, specifically between the CEO and board of directors, affects the M&A likelihood and subsequent performance of these deals.

This study employs observations of US-listed firms from 1999 to 2019, with 18,830 announced deals during the 2000-2020 period. Following Hong and Kostovetsky (2012), the political ideology of CEOs and board members is computed as the ratio of the difference between one's entire political contributions to the Republican and Democratic Party over the total contribution to both two parties. Afterwards, the *PID* is measured as the equal-weighted average of the Euclidean distance of political ideology between the CEO and each director within a year.

The findings show a positive relationship between *PID* and the likelihood of M&A. Also, *PID* has a positive effect on post-deal long-run performance. This study demonstrates that the risk-taking nature of CEOs, proxied by CEO overconfidence, founder CEO, and higher pay for performance sensitivity, is the underlying mechanism through which *PID* positively influences firms' acquisition likelihood. Overconfident CEOs, who tend to overestimate their knowledge and abilities, are even more likely to engage in riskier endeavours such as M&As when *PID* increases. Founder CEOs, often deeply connected to their firm's legacy, exhibit more managerial optimism and overconfidence compared to non-founder CEOs. This intrinsic connection and emotional investment lead founder CEOs to be more inclined towards risk-taking behaviours, including M&As, especially when *PID* is high. Additionally, CEOs whose compensation is closely aligned with firm performance are more likely to pursue high-risk strategies like M&As for potential high rewards. This study finds a strong correlation between high *PID*, CEO compensation tied to performance, and a propensity for acquisitions.

In addition, to mitigate endogeneity concerns this study employs four identification strategies to reinforce the findings: propensity score-matching, an entropy-balancing approach, an instrumental variable approach using lagged values of political affiliations, and a difference-in-difference analysis leveraging the 2016 Trump election as an exogenous shock. These tests strengthen the argument that *PID* positively affects the likelihood of M&A activities. Also, the positive relationship between *PID* and M&As remains robust across alternative measures of individual political partisanship and different compositions of board members to construct CEO-board political divergence. Further, the study shows that the positive effect is more pronounced for firms with lower financial constraints, greater cash flow volatility, and higher Tobin's Q and sales growth.

The study further finds that the *PID* does not show a positive market reaction during the announcement period. A plausible explanation for such an unobservable effect of *PID* on short-term performance might be anchored in the market's awareness of the divergence between CEO and board. Any such misalignment would create potential impediments for future investments to enhance firm value, leading to a subdued market response. Hence, the influence of *PID* on immediate firm valuation may be subtle and not overtly perceptible.

Shifting to a longer horizon, this chapter then assesses the implications of *PID* on firms' stock and operating performance. Specifically, I examine the buy-and-hold abnormal returns (BHAR), change in return on assets (ΔROA), and earnings before interests and taxes (ΔEBIT). The results reveal a positive correlation between *PID* and post-deal long-term performance. This study finds that good corporate governance and enhanced monitoring, i.e., proxied by frequency of board meetings, proportion of institutional ownership, and independent directors, contribute to this long-term performance (Shleifer and Vishny, 1997; Vafeas, 1999; Nguyen and Nielsen, 2010).

This study contributes to our understanding of the effect of the intricate relationship between the CEO and board directors, particularly their political ideologies, on strategic investment decisions. It underscores the significance of the dynamic between the CEO and the board in determining a firm's success, highlighting the necessity of maintaining a balanced distribution of power. The findings emphasise the broader effect of political ideologies on organisational dynamics (Elnahas and Kim, 2017; Gupta et al., 2019; Park et al., 2019), suggesting that political divergence makes CEOs more inclined to M&As. Additionally, this research enriches the discourse on the influence of individual political ideologies of top executives and board members on corporate decision-making and outcomes (Lee et al., 2014; Gupta and Wowak, 2017; Rice, 2023). Furthermore, by identifying *PID* as a crucial determinant of M&A decisions, this study contributes novel insights into the factors influencing M&A activity. Overall, this research illuminates the critical role of ideological diversity in strategic decision-making within organisations.

Chapter 3 of this thesis aims to empirically examine the effect of climate change exposure on acquisition likelihood by employing a comprehensive dataset of listed firms from 34 countries, covering 39,336 acquisitions announced between 2002 and 2020. Climate change has drawn global attention during the past two decades as loss of life and large-scale property damage have become common phenomena due to frequent extreme weather events and natural disasters, such as heatwaves, droughts, floods, wildfires, etc. For example, extreme weather events caused more than 475,000 deaths and $2.56 trillion in economic losses during 2000-2019 (Eckstein et al., 2021). The Intergovernmental Panel on Climate Change (IPCC 2014, 2018) and the 2015 Paris Agreement highlight that governments and businesses need to take immediate action against the accelerated climate change issues to reduce their significant impacts on societies and economies. Prior literature finds that climate change uncertainties affect corporate valuation, investment, and financial decisions, including operating income, liquidity, cash holdings, and capital structure (Huang et al., 2018; Pankratz et al., 2023; Javadi et al., 2023; Ginglinger and Moreau, 2023). Moreover, Barnett et al. (2020) and Todaro et al. (2021) suggest that climate change is a great source of uncertainty for the business environment and such uncertainty is crucial when firms contemplate M&A decisions (Bloom, 2009; Bhagwat et al., 2016; Nguyen and Phan, 2017). For these reasons, climate change seems to be an essential factor in corporate acquisitions.

The extant literature on the role of climate change in acquisition activity is still in its infancy. The closest studies concentrate on target selection when acquirers face climate change risks. For example, Bose et al. (2021) and Li et al. (2022) underline that bidders with higher carbon emissions are likely to pursue cross-border acquisitions where the regions of targets have weaker environmental and climate protection regulations. Bai et al. (2021) explore that firms at risk from sea-level rise are associated with a propensity to acquire low sea-level rise targets and subsequently generate higher short-term cumulative abnormal returns (CARs). This chapter aims to fill this gap in the literature by utilising a holistic firm-level climate change exposure measure rather than focusing on a singular feature of climate risk, i.e., physical or regulatory, to understand the nexus between climate change and M&A decisions. The firm-level climate change exposure measure is obtained from Sautner et al. (2023). This measure employs a textual analysis approach to derive firm-level climate change exposure by computing the number of climate change exposure bigrams in the earnings conference calls of individual firms. The benefits of this firm-level climate change exposure are that it captures the opinion of managers and other main stakeholders, is more forward-looking than annual accounting reports, and covers both regulatory, physical, and technological climate shocks.

Chapter 3 documents a robust negative relationship between climate change exposure and firms' propensity to engage in M&As. This relationship persists even after addressing potential endogeneity concerns through entropy balancing, two-stage least squares, and difference-in-differences approaches. The results remain consistent when using long-term climate change exposure, adding further controls of macro and governance factors, and various compositions of fixed effects. A comparative analysis, comparing the likelihood of acquisition to capital expenditures (CAPEX) or research and development expenses (R&D) of firms, shows that firms exposed to high climate change exposure are more inclined to invest in CAPEX than acquisitions and R&D, indicating firms' willingness to avoid risky investments.

This chapter further explores that the negative effect is more pronounced for firms with higher external financing costs and when investor confidence is low. The results confirm that climate change exacerbates firms' financial constraints, increasing their cost of external financing, and investors adjust their expectations of the firm's future development according to firms' exposure to climate change; hence, firms become cautious when undertaking large and risky investment projects when facing such climate change uncertainty. Moreover, this research has also dissected the components of climate change exposure, highlighting the differential impact of physical, opportunity, and regulatory exposures on M&A activities.

This research further shows the consequences of climate change exposure on the M&A process and post-acquisition performance. Notably, firms with high climate change exposure tend to exhibit a reduced likelihood of deal completion, prolonged deal duration, weaker short-term stock, and long-term operating performance. These findings reflect that firms find it difficult to create value through M&As due to the high uncertainty induced by climate change. Overall, this study demonstrates the critical role of climate change exposure in shaping acquisition decisions in a global context.

Chapter 3 contributes by bridging a gap in understanding the interplay between firm-level climate change exposure and the likelihood of M&As. It contributes to the body of literature that underscores the impact of climate change on firm valuation and financial decision-making (Bansal et al., 2016; Barnett et al., 2020; Javadi et al., 2023), illustrating how climate change risks negatively affect various aspects of firm investment decisions and asset valuations. Also, this paper adds a novel dimension to the discourse on the nexus between climate risks and M&A activities. It offers new insights into how firms with higher climate change exposure adapt their M&A strategies, highlighting the influence of environmental factors on such corporate decisions. Further, the study enriches the understanding of the determinants of M&A activity by incorporating environmental uncertainties, specifically climate change exposure, as a significant factor. Overall, this study not only contributes to the academic discourse by linking climate change exposure to M&A likelihood but also underscores the increasing importance of environmental considerations in the strategic decision-making processes of corporations.

In addition to the determinants of M&A likelihood, Chapter 4 of this thesis documents the value creation of technology M&As using 79,455 deals for 52 countries announced during 1990-2018. During the last thirty years, there has been a boom in technology mergers and acquisitions with an increasing range of countries involved. The technology sector is one of the most attractive industries for M&As, with a surging trend in the past two decades and accelerated from 2012. For instance, it occupied the highest deal volume in the whole of the M&A market in 2018, amounting to 20% with a value of more than $570 billion, while it was only 6% in 2006 (Thomson One Banker, 2019). BCG

(2019) also reports that high-tech deals take up one-third of the M&As quantity and deal value, stating that tech deals still have further room to grow. Considering the influence of technology nowadays, firms view M&A as a key driver for acquiring technology assets.

Prior studies related to tech M&As have been predominantly focused on the US market and its niche technology sectors (i.e., computers, biotechnology, and pharmaceutical). In recent years, not only developed countries but emerging markets, such as China and India, have also actively participated in high-tech-driven mergers. They are now significant players, especially after the ‘Dotcom Bubble’ period. For example, technology deals make up one-third of the total volume of the Chinese M&A market, and 20% of Chinese M&A targets belong to the high-tech industry (BCG, 2019). This shifting dynamic highlights the increasing significance of tech M&As in shaping the future trajectory of the technology industry on a global scale rather than only in the European or North American markets. Unlike the period before 2002, when the acquirers and targets were both technology-intensive firms, participants in technology acquisitions have moved to non-tech-intensive firms. The number of high-tech firms acquiring non-tech and non-tech firms biding for high-tech firms has risen substantially. Because of the sheer size and importance of the technology M&A market in recent years and the lack of recent and aggregate industry studies on technology-related M&As, it is paramount to discuss the technology M&As. Using a global sample, this chapter aims to fill this gap by examining whether the technology-related M&As can create superior value for shareholders or if they are just a fad.

Categorising deals by the technological classification of acquirers and targets, this study differentiates deals based on the acquirer-target technology pair into four types: *High-tech* acquirer acquiring *High-tech* targets (*Hi-Hi*)*, High-tech* acquirer acquiring *Non-tech* targets (*Hi-Non*)*, Non-tech* acquirer acquiring *High-tech* targets (*Non-Hi*), and *Non-tech* acquirer acquiring *Non-tech* targets (*Non-Non*), then examines the characteristics, short-run and long-run performance of these four deal-types. The distribution of deal types confirms the surge in tech-distant (*Non-Hi* and *Hi-Non*) deal types since 2003. Also, tech deals are increasing both in terms of the number of mega-deals and cross-border deals. The average deal value of *Hi-Hi* and *Non-Hi* in 2015 reached the highest, \$10.6 billion and \$5.6 billion, respectively, from only \$3.2 billion and \$1.8 billion in 2010. The results demonstrate that technologically distant deals positively and statistically affect acquirers' 3-day cumulative abnormal returns (CARs), and this impact is more pronounced for *Non-Hi* deals when the target is not listed. In contrast, pure technology deals (*Hi-Hi*) earn significantly lower CARs than others.

This study further discusses the long-term operating performance of technology M&As by comparing changes in ROA before and after deal completion. Only *Non-Hi* deals show superior improvement in operating performance among all deal types. To address any potential concern about omitted variables affecting the findings, the propensity score matching approach (PSM) is employed which justifies that firm characteristics do not drive the findings. In addition, the results are robust to various specifications of firm technology. Overall, this study suggests that technologically distant deals generate significantly higher announcement returns than non-technology deals. The

Non-Hi technologically distant deals pay off handsomely, where they are associated with higher potential for synergies and growth opportunities, reaffirming the strategic advantage of disruptive technology assets in the corporate strategic landscape.

Chapter 4 represents a novel and significant contribution to the field of mergers and acquisitions literature, particularly in the realm of technology-related transactions. It uniquely categorises M&A deals based on the technological profiles of the acquirer and target companies, thereby distinguishing between technologically distant and similar pairing deals. This differentiation allows for a nuanced analysis of deal characteristics, wealth effects, and overall performance outcomes. This research contributes to the broader M&A discourse by providing comprehensive insights into the performance of technology-related deals (Fuller et al., 2002; Cartwright and Schoenberg, 2006; Bena and Li, 2014). It breaks new ground by classifying deals based on technological distance, a perspective previously unexplored, and sheds light on how this factor influences value creation and operational efficiency post-merger. The findings are particularly relevant for practitioners and scholars interested in the strategic implications of technology in M&As by demonstrating that technological distance can be a source of substantial gains. It also enriches the existing literature by complementing studies focused on specific technology segments and markets, offering a broader, more global perspective on the dynamics of technology M&As (Kohers and Kohers, 2000, 2001; Ahuja and Katila, 2001; Porrini, 2004; Lusyana and Sherif, 2016).

In summary, this thesis discusses under-explored areas of M&As through three distinctive chapters. Chapter 2 investigates a positive impact of *PID* between CEOs and board directors on M&As in US firms, attributing this to CEOs' risk-taking behaviours influenced by overconfidence, founder status, and performance-based compensation. Chapter 3 focuses on the influence of climate change exposure on M&A activities, analysing data from firms in 34 countries and finding a negative relationship between climate change exposure and firms' propensity to engage in M&As, particularly pronounced in firms with high external financing costs and low investor confidence. Chapter 4 explores the value creation of technology-related M&As by examining M&As across 52 countries. It categorises deals based on technological profiles and discovers that technologically distant mergers, particularly non-tech firms acquiring high-tech targets, yield higher returns and enhanced long-term performance.

The rest of this thesis is structured as follows: Chapter 2 investigates the relationship between political ideology divergence between CEO and board room and M&As; Chapter 3 examines the effect of firm-level climate change exposure on M&As; and Chapter 4 presents evidence on technology M&As around the world. Finally, Chapter 5 concludes.

2. Dressing in Red, Dancing with Blue: Political Ideology Divergence and M&As

2.1 Introduction

Does political ideology divergence matter for mergers and acquisitions (M&A)? M&A represent crucial strategic investment decisions for firms, having a significant impact on their valuation and growth (Hitt, Hoskisson, and Ireland, 2001, 2005; Cartwright and Schoenberg, 2006; Bena and Li, 2014). These decisions require active involvement from both CEOs and the board of directors. Extensive research has explored how different CEO characteristics such as gender, age, tenure, and board structure such as board size and independence, influence corporate decision-making and performance (Simsek, 2007; Cheng, 2008; Serfling, 2014; Armstrong, Core, and Guay, 2014; Faccio, Marchica, and Mura, 2016). Prior studies have examined how political affiliations shape the decision-making processes of CEOs, top management teams, and boards across various dimensions, including financial performance, corporate social responsibility, asset reallocation, and manager dismissal and compensation (Chin, Hambrick, and Trevino, 2013; Gupta and Wowak, 2017; Gupta, Nadkarni, and Mariam, 2019; Park, Boeker, and Gomulaya, 2019). However, extant literature provides very scant evidence regarding the impact of CEO and board cultural diversity on corporate performance, particularly concerning the decision-making and performance outcomes of M&As. In this paper, we aim to address this gap by investigating whether and how political ideology divergence (*PID*) between the CEO and board of directors, referring to the extent of differences in political affiliations between the CEO and each board member, affects firms' M&A likelihood and their subsequent deal performance.

Political ideology divergence, as one specific aspect of cultural diversity, recognises how the personal political beliefs of top management can influence decision-making, strategic preferences, and the interpersonal dynamics of a company. In an environment with high political ideology divergence, there may be diverse opinions on social responsibility, corporate ethics, and business strategies that align with different political ideologies. This diversity between the CEO and directors of a board can pave the way for robust discussions and flow of ideas that enhance firm value (Kim, Pantzalis, and Park, 2013), but it may also create difficulties in reaching a consensus on strategic decisions. This political ideology divergence between corporate leadership addresses an aspect that is different to agency conflicts. In fact, political divergence reduces agency costs and insiders' discretionary power (Kim et al., 2013; Lee, Lee, and Nagarajan, 2014). To this end, we expect the differences in political ideology between the CEO and board to facilitate objective evaluations of M&A initiatives.

One assumes, a priori, that the impact of political ideology divergence between CEOs and boards on the likelihood of M&As can either have a negative or positive effect. On the one hand, the homophily theory suggests that individuals with shared backgrounds, identities, and values are more likely to accept, trust, and commit to one another, thus reducing potential conflicts and enhancing communication (Earle and Cvetkovich, 1995; McPherson, Smith-Lovin, and Cook, 2001; Cohen, Frazzini, and

Malloy, 2008; Garcia-Retamero, Müller, and Rousseau, 2012; Cvetkovich and Lofstedt, 2013). In this context, when the CEO and board share a similar political ideology, i.e., a lower level of *PID*, they may have stronger interpersonal connections. This can result in smoother and more efficient communication, with reduced conflicts of interest and agency problems. Consequently, the board would be more effective and supportive of CEO decisions (Adams and Ferreira, 2007). This suggests that the politically homophily board and CEO would potentially be more involved in M&As and have better and timely decision-making with better acquisition performance. This perspective suggests a potential negative association between *PID* and the likelihood of M&As, as well as poor post-deal performance for high *PID* firms.

However, on the other hand, Jensen (1993) argues that when board members and management share similar values, it adversely affects board independence and efficiency. Associated with this idea, the "birds-of-a-feather-flock-together" effect may result in poor collaboration and unproductive investment decisions, as individuals within homogenous groups are more likely to have familiarity biases and are more inclined to conform than to express dissenting opinions (Barry and Friedman, 1998; Ang, Cheng, and Wu, 2015; Gompers, Mukharlyamov, and Xuan, 2016). In contrast, when the CEO and board of directors have greater *PID*, their connections and affinity would be lower, which may lead to increased scrutiny to identify better investment opportunities and improved decision-making. Hong and Page (2004) evidence that teams comprising individuals with diverse perspectives are more likely to explore a broader set of alternatives and identify novel solutions to complex problems. At this core, this assertion is premised on the idea that greater diversity in viewpoints, stemming from varied political beliefs, fosters a more rigorous and comprehensive evaluation of strategic opportunities, especially M&A decisions. Tjosvold (1985) also suggests that managed conflict, such as that arising from *PID*, can stimulate critical thinking and innovation, encouraging and making firms more proactive in pursuing strategic initiatives like M&A. In addition, a high *PID* may encourage CEOs to undertake more risky, innovative, and proactive actions to drive firm growth. Hence, CEOs in higher *PID* firms would potentially be more engaged in M&As as external growth through M&A is typically faster than internal development (Hitt et al., 2001; Chandra, 2013). These insights suggest that firms with higher levels of diversity in top management teams exhibit greater strategic dynamism and adaptability (Miller, Triana, and Trzebiatowski, 2014), lend credence to the hypothesis that *PID* could indeed incentivize firms to engage more actively in M&A activities as a means of external growth and value creation. Moreover, in high *PID* firms, the CEO and board may have lower trust encouraging directors to be more effective in monitoring, advising, and negotiating during the M&A deal process, and facilitating post-deal integration. In summary, it is highly plausible that greater *PID* is associated with better mutual monitoring between the CEO and board, leading to improved decision-making and ultimately enhancing firm value (Li, 2014).

In line with these arguments, we hypothesise that there is a positive relationship between the *PID* of CEOs and board of directors and the likelihood of M&As. Specifically, firms with a higher level of *PID* are more likely to engage in M&A activities. To measure *PID*, we adopt a quantitative approach (Hong and Kostovetsky, 2012; Hutton, Jiang, and Kumar, 2014. 2015; Lee et al., 2014). We construct this measure by calculating the equal-weighted average of the Euclidean distance between the political affiliation of the CEO and that of each director within the firm for each year. The political affiliation is determined based on an individual's net contribution to the Republican party, scaled by the sum of their contributions to both the Republican and Democratic parties. This computation takes into account an individual's total contribution from 1989 to 2020, providing a comprehensive assessment of the political affiliation dynamics within the board of a firm.

Using a dataset of 2,083 US-listed firms' accounting information from 1999 to 2019 and corresponding M&A deals from 2000 to 2020, we examine the relationship between CEO-board *PID* and the likelihood of M&As. To examine this relationship, we employ a probit regression controlling for various firm-level, CEO, and board characteristics. We find a robust and statistically significant positive relation between *PID* and the likelihood of M&As at a 1% significance level. In economic terms, a one standard deviation increase in *PID* is associated with a 1.2% increase in acquisition likelihood. In other words, a one standard deviation rise in *PID* corresponds to a 3.33% rise in acquisition likelihood relative to the sample average unconditional acquisition likelihood. Our finding emphasises the significance of CEO-board political polarisation in shaping strategically important M&A decisions.

We then examine the economic mechanisms through which *PID* affects M&As. Specifically, we explore the potential influence of risk-taking behaviours of CEOs as an underlying factor through which *PID* impacts M&A likelihood. Previous studies highlight the influential role CEOs' risk-taking appetite plays in shaping major organisational decisions, i.e., about mergers and acquisitions (Hagendorff and Vallascas, 2011; Ferris, Jayaraman, and Sabherwal, 2013; Croci and Petmezas, 2015; Cain and McKeon, 2016). CEOs with a higher risk preference are often more open to challenging and innovative opportunities that promise substantial rewards (Hirshleifer, Low, and Teoh, 2012). This behaviour gets amplified by external pressures or internal dynamics, such as market complexity, executive pay-performance sensitivity, CEO duality on board, and CEO managerial discretion (Coles, Daniel, and Naveen, 2006; Li and Tang, 2010). We conjecture that a diverse political ideology within top management may present itself as a challenge or an opportunity for CEOs, and how a CEO perceives this—as a threat or a chance to innovate—can be strongly moderated by their inherent risk-taking nature. Consequently, it becomes essential to explore how the risk-taking inclinations of CEOs interact with *PID* to influence M&A decisions.

We measure CEO risk-taking nature using three proxies – CEO overconfidence, CEO founder status, and pay-for-performance sensitivity. First, CEO overconfidence, often linked with managerial optimism, can significantly shape a firm's investment decisions (Malmendier and Tate, 2005, Hirshleifer, Low, and Teoh, 2012). Overconfident CEOs tend to believe they have superior information or ability compared to their peers (Malmendier and Tate, 2008), leading them to make riskier choices (Hirshleifer, Low, and Teoh, 2012; Ho et al., 2016). Prior studies (e.g., Malmendier and Tate, 2008; Ferris et al., 2013) show that overconfident CEOs, who are inherently more inclined towards risk, tend to undertake more acquisitions compared to their counterparts. Following Malmendier and Tate (2005, 2008), we quantify CEO overconfidence utilising their stock option holdings. Our analysis reveals that the positive effect of *PID* on the likelihood of M&As is more pronounced for firms with overconfident CEOs. CEOs with a high-risk appetite may view situations of ambiguity, like those created by *PID*, as unique opportunities rather than threats because of high managerial optimism, reinforcing their preference for acquisitions (Heaton, 2002; Graham, Harvey, and Puri, 2013). In such cases, overconfident CEOs may perceive acquisitions as a means to innovate and drive firm growth.

Second, CEO-founder status may influence their corporate strategic decisions. Founder CEOs often have an intrinsic and emotional connection to the firm and its legacy, influencing their strategic choices differently than non-founder professional CEOs (Fahlenbrach, 2009). Also, founder CEOs show more managerial optimism and overconfidence in their decisions (Lee, Hwang, and Chen, 2017). Our results are consistent with these arguments as we find that the positive relationship between *PID* and M&A likelihood is stronger for founder CEOs. This finding indicates that the impact of *PID* on M&A likelihood is more prominent when CEOs are unlikely to be dismissed, i.e., overconfident, more powerful, influential, and less hesitant in making risky acquisition decisions.

Third, we examine the role of pay-for-performance sensitivity of CEOs. The alignment of CEO compensation with firm performance can greatly impact CEOs' willingness to take risks. A CEO whose compensation is closely tied to firm performance may have a greater incentive to pursue high-risk high-reward strategies, such as M&As, which promise short-term rewards for CEOs (Hall and Liebman, 1998). Empirical evidence suggests that CEOs with greater pay-for-performance sensitivity are more likely to make acquisition decisions (Grinstein and Hribar, 2004; Hagendorff and Vallascas, 2011; Minnick, Unal, and Yang, 2011). In our analysis, we find that firms with higher *PID* and stronger pay-for-performance sensitive CEOs are more prone to make acquisitions. This highlights that the alignment between CEO incentives and firm performance, coupled with ideological differences, can play a significant role in shaping M&A decisions. Moreover, by using the three proxies to assess a powerful CEO, the CEO is a chairman, proportion of insiders on board, and CEO pay slice, we alleviate the concerns regarding the possibility that the observed positive relationship between PID and the likelihood of acquisitions is a consequence of decision-making centralisation among powerful CEOs. Overall, these findings highlight the interplay between political ideology and individual CEO risk-taking traits in initiating M&A decisions.

To mitigate potential endogeneity concerns inherent to the relationship between CEO-board *PID* and M&A decisions, we employ three distinct identification strategies. First, we apply propensity score-matching and entropy-balancing approaches to reduce heterogeneities between high and low *PID* firms. Second, following Lee et al. (2014), we utilise 7-year lagged time-varying values of individual political affiliations in an instrumental variable (IV) setting to overcome any potential endogeneity and reverse causality issues. Finally, we leverage an exogenous shock, the 2016 Trump election, to conduct a difference-in-difference (DID) analysis. By comparing changes in M&A activities and *PID* before and after the shock, we further bolster the robustness of our findings. In all cases, we find strong support in favour of our baseline results. Our results also survive when we use alternative measures of *PID*, and control for individual political affiliations, CEO and board average political affiliations.

Next, we extend our analysis to investigate the impact of *PID* on the time taken to complete M&A deals and post-deal performance. To understand the dynamics of the deal process, following Lawrence, Raithatha, and Rodriguez (2021) we compute the time to complete deals as the natural logarithm of days between the announcement and deal completion date. Our motivation for testing the effect of *PID* on time to complete deals is informed by evidence suggesting that an increase in CEO-board political divergence may make the decision-making process lengthy and elongate deal duration (Dikova, Sahib, and Van Witteloostuijn, 2010; Duchin et al., 2021). In line with our conjecture, we find that heightened *PID* increases the time to complete M&A deals.

To discern the impact of *PID* on deal performance, we first analyse acquirer firm announcement returns during the deal announcement period, then discuss long-term performance. Consistent with Elnahas and Kim (2017), where they find CEO political ideology significantly affect deal performance in long run but not short run, we find that, in the short term, *PID* does not necessarily have a positive market reaction. One possible explanation is that investors are already aware of the CEO-board political ideology differences based on publicly available voting information. Consequently, investors may view that individuals who share similar political ideologies are more likely to collaborate and establish trust (Malloy, 2008; Newton, Stolle, and Zmerli, 2018; Swigart et al., 2020; Dasgupta et al., 2021), which could potentially lead to better decision-making and performance. On the other hand, with a higher *PID,* the market may suspect a lack of coordination, misalignment in strategic decisions, and a compromised ability to enhance firm value, leading to a muted market response. Thus, the effect of *PID* on short-term firm valuation may not be readily observable.

Next, we shift our focus to assess the impact of *PID* on long-term stock and operating performance, i.e., the buy-and-hold abnormal returns (BHAR), change in return on assets (ΔROA), and change in earnings before interests and taxes (ΔEBIT). Our findings, in contrast to the short-term market response, reveal a positive relationship between *PID* and long-term performance. In the long run, firms with higher *PID* are more likely to enhance firm valuation as they post better stock returns and improved operating performance. These results underscore the potential benefits of having diverse perspectives in decision-making processes within the top management team (Kim et al., 2013), where heterogeneous groups often outperform homogenous ones as they can bring distinct problem-solving approaches (Page, 2007). To this end, firms with higher *PID* can plausibly leverage this diversity in decision-making to enhance firm value in the long term.

Associated with this, we investigate the underlying mechanisms of such enhanced long-term performance. Prior literature points to effective monitoring and corporate governance, including board independence, board meetings, and institutional shareholders' activism, as determinants of superior long-term firm performance (Vafeas, 1999; Davis, 2002; Brown and Caylor, 2004). Shleifer and Vishny (1997) argue that effective monitoring acts as a check against potential managerial entrenchment and can guide firms towards optimal decision-making. In environments characterised by heightened *PID*, the divergence of views and perspectives between the CEO and board highlights the importance of robust monitoring mechanisms. We examine board meeting frequency as an indicator of the board's active role in oversight and decision-making (Vafeas, 1999). Following Vafeas (1999) and Brick and Chidambaran (2010), we use board meeting frequency as a proxy for monitoring and find that in firms with high *PID* there is an increase in board meeting frequency when firms engage in M&As. This implies a collaborative effort between the CEO and the board to ensure optimal deal negotiations, scrutiny, due diligence, and commitment to enhance firm value.

Furthermore, we employ two other proxies for corporate governance: institutional ownership and the proportion of independent directors. Prior studies posit that a higher level of institutional ownership and board independence serves as a safeguard, ensuring managerial decisions resonate with shareholder interests (Shleifer and Vishny, 1997; Velury and Jenkins, 2006; Nguyen and Nielsen, 2010; Souther, 2021). We measure institutional ownership as the percentage of shares owned by institutions from Thomson Reuters institutional holdings (Form 13F) and calculate the proportion of independent directors as the number of independent directors to the total number of directors on a board. We find better long-term performance for firms with higher *PID* when monitoring is strong. In sum, increased board engagement and a higher proportion of institutional ownership and independent directors suggest a concerted effort to ensure long-term M&A performance.

Additionally, we explore cross-sectional analysis across different subsamples of firms to identify the ability to absorb higher levels of risk to facilitate M&A activities in the presence of ideological differences. We find that firms with lower financial constraints and higher cash flow volatility are more likely to engage in acquisitions when faced with higher levels of *PID*. This suggests that the availability of resources and capacity to engage in M&A activities when *PID* is high. In summary, the diversity in political beliefs can help identify and mitigate potential risks and capitalise on opportunities that might be overlooked by a more ideologically homogenous group.

Our study makes several important contributions to the existing literature. First, our study contributes to the literature by examining the relationship between the board of directors and CEOs. The dynamic of this relationship is crucial for firms' success, necessitating a balance of power between the CEO and board (e.g., Borokhovich, Parrino, and Trapni, 1996; Hermalin and Weisbach, 1998). Also, Lee et al. (2014) find that political homophily between the CEO and independent board weakens monitoring; thus, firms significantly underperform. We contribute by indicating the need for differences of opinion among the board and CEO to improve firm performance.

Second, we add to the literature on the effect of individual political ideology, particularly among top executives and board members, on corporate decision-making and firm outcomes. For instance, Elnahas and Kim (2017) find that Republican CEOs are less likely to engage in M&As. Likewise, Gupta and Wowak (2017) find that board members' ideologies influence CEO pay, demonstrating the impact of political ideologies on other organisational actors and their interactions with the firm. Our study complements it by focusing on political ideological differences.

Finally, our study adds to the literature on the determinants of M&A activity. Prior studies identify factors such as acquirer stock mis-valuation (e.g., Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004), policy uncertainties (e.g., Bhagwat, Dam, and Harford, 2016; Bonaime, Gulen, and Ion, 2018); product market complementarity (e.g., Rhodes-Kropf and Robinson, 2008; Hoberg and Philips, 2010), and CEO and board characteristics such as overconfidence, age, gender, partisanship, etc. (e.g., Billett and Qian, 2008; Malmendier and Tate, 2008; Yim, 2013; Levi, Li, and Zhang, 2014; Elnahas and Kim, 2017). We suggest that *PID* is an important determinant of M&A decisions. Overall, our study explores the complex interplay between the political ideology of the CEO and board and its impact on strategic decision-making in organizations. We attempt to show that, although ideological divergence represents less similarity and sharing, it is valuable.

The rest of the paper is organised as follows. Section 2.2 describes the data, sample, and measures of *PID* between the CEO and board of directors. Section 2.3 presents the empirical results, and Section 2.4 concludes the paper.

2.2 Data

2.2.1 Sample Selection

Our initial sample consists of all US listed firms with available CEO and board of director characteristics such as age, gender, full name, position, start and end date on the role, from the Compustat, ExecuComp, and BoardEx databases covering the period between 1999 and 2019.[3] We exclude financial firms (SIC code 6000-6999) and regulated utilities (SIC code 4900-4999) to control for the effects of regulation, which varies according to the political party in power, on decision-making. Firm-level financial and stock data come from Compustat and CRSP databases. This sample covers 26,434 firm-year observations corresponding to 2,083 unique firms, 4,676 unique CEOs, and 26,494 unique directors, and each firm-year has an average of 9.9 board of directors (261,929 director-year observations). We then merge this sample with the M&A sample.

Our M&A data are deals announced between 2000 and 2020, drawn from the Securities Data Company (SDC) database. We require that the acquirer is a US public firm, and the acquirer owns less than 10% shares of the target prior and holds more than 50% after the acquisition to eliminate the distraction of the less visible change in control where the acquirer already held a large portion of target's share before the deal. We exclude deals classified as minority stake purchases, recapitalisations, acquisitions of remaining interests, self-tenders, spin-offs, privatisations, reverse leverage buyouts, exchange offers, and repurchases. The M&A sample includes 18,830 deals with 1,666 unique acquirers; approximately 80% of our sample firms made at least one acquisition

[3] The sample period starts in 1999 due to data availability issues. Some key director characteristics are available since 1999 on BoardEx, such as name, age, position on the board, start and end date of each position, so our sample period begins in 1999.

during the study window.

2.2.2 Measuring Political Ideology Divergence (*PID*)

The key variable of interest in this study is the *PID*, measured as the difference in political ideology between the CEO and board of directors of a given firm in a given year. To detect an individual's political ideology, we use full names of CEOs and board of directors to identify individuals' direct political campaign donations to Republican and Democratic parties (senate, house, presidency, and committees), where extant literature evidence that political contributions reflect individual's views on politics and party affiliation (Poole and Rosenthal, 1984; Bonica, 2014; Hutton et al., 2014; Chirstensen et al., 2015). Individual contributions between 1989 and 2020[4] are gathered from two data sources: the Database on Ideology, Money, and Elections (DIME) (Bonica, 2014, 2016)[5] and the Federal Election Commission (FEC).[6]

The DIME database contains not only the same information as the FEC but also the unique contributor IDs based on the individual's name, employer, and occupation. Once the information of an individual as a contributor is clearly identified with the unique contributor ID, it is easy to find the individual's other contributions, which could alleviate the time spent matching the CEO and directors with each contribution information reported in the FEC database. DIME covers contribution records during 1989-2014. For

[4] The contribution period starts in 1989 because with 10-year window, which includes at least 2 presidential elections and 5 donation cycles, prior the CEO and director sample period starts, it would deliver greater coverage and interpretation of the contribution behaviours of individuals. Bonica (2016) also builds a measure of individual ideology using 1979-2014 contributions, named as Campaign Finance score (CFscore). This measure generates consistent results with our calculations. The results of CFscore are available if requests.
[5] DIME Source: https://data.stanford.edu/dime.
[6] Federal Election Commission (FEC) source: www.fec.gov/data.

the rest of the time spanning 2015 to 2020, we first use the committee ID in the committee master file from the FEC, which includes information for each campaign committee/candidate, such as name and party identification, to merge with the contribution records in FEC to find which political party the donation goes to. We then use a custom algorithm to match first and last names, occupations, and employer names in the FEC contribution file with data of CEOs and board of directors.[7] The sample includes individual contributions to local/state/federal election candidates, party committees, PACs, and super PACs. After verifying the accuracy of this matching process, the sample contains 97,598 and 674,785 individual political contributions made by CEOs and directors, respectively.

Using total individual political contributions, first, we measure political ideology of each CEO and director called Republican inclination index (Rep index in following sections), ranging from -1 (Democrat) to 1 (Republican), constructed as the ratio of the net political contribution made to Republican Party over the summation of donations made to both Republican and Democratic Parties (in Equation 2.1) following Hong and Kostovetsky (2012), Lee et al. (2014), Hutton et al. (2014, 2015) and Elnahas and Kim (2017):

$$REP_P = \frac{R_P - D_P}{R_P + D_P} \qquad (2.1.)$$

where REP_P, denotes the Republican inclination index (or Rep index), capturing

[7] Under the federal law disclosure requirements, once the amount of an individual's donations exceeds \$200 in a particular year for 1989-present, the recipient must disclose the donor's full name, contribution amount/date, occupation, employer, and address. We only use the compulsory disclosure contributions in the sample to evade any selection bias caused by voluntary disclosure contributions.

the time-invariant political orientation and the higher value of REP_P, the more the person is Republican inclined; where R_P (D_P) denotes the total dollar amount of contributions made by individual p to the Republican (Democratic) Party over the 16 election cycles from 1989 to 2020. If not specified, we classified one as politically neutral with the value of the Republican inclination index as zero if one's contributions could not be exactly identified[8], assuming who contributes the same amount to both parties.

For each CEO and director, we use the individual's entire contribution history to calculate their political ideology under the assumption that one's political ideology is stable over time as an individual's party ideology is established in their earlier formative years and remains consistent in adulthood (Burris, 2001; Jost, 2006; Green, Palmquist, and Schickler, 2004; Gupta and Wowak, 2017).[9] Moreover, this stable measure is more likely to represent one's actual political orientation, which could minimise potential distortion caused by occasional donations or opportunistic contributions to another party where contributors aim to earn special political benefits in a particular election cycle (Hong and Kostovetsky, 2012; Chin et al., 2013; Lee et al., 2014; Hutton et al., 2015; Christensen et al., 2015; Rice, 2023).

Next, in line with Kim et al. (2013) and Lee et al. (2014)[10], we use the following

[8] We include directors and CEOs who have not identified with contributions (non-donors) throughout our analysis if not specified. In the following empirical analysis, the CEO-board *PID*s with inclusion and exclusion of CEOs and directors without available contribution records generate similar results.
[9] Time-varying political orientation of the CEOs and directors is used as an alternative measure in robustness check, the results are similar.
[10] Lee et al. (2014) argue that group average of directors' ideology method does not catch the individual ideology within the group of each independent directors. The group average of directors' ideology is likely to missing variations at certain extent, thus this study mainly uses the difference between CEO and each director.

equation (in Equation 2.2)[11] to construct the PID between the CEO and board of directors as the equal-weighted average of the Euclidean distance between CEO REP index and each director's REP index in the firm for each year:

$$PID_{i,t} = \frac{1}{J}\sum_{j=1}^{J} |REP_{i,t}^{CEO} - REP_{i,j,t}^{BoD}| \qquad (2.2.)$$

where $PID_{i,t}$ denotes the political ideology divergence between the CEO and directors of firm i in year t and could take any value between 0 (most politically similar) and 2 (most politically divergent), where $REP_{i,t}^{CEO}$ denotes the Republican index of the CEO, $REP_{i,j,t}^{BoD}$ denotes the Republican index of the board of directors for j = 1,2, …, j, in firm i at year t, and J is the number of directors on the board. We provide six different versions of the CEO-board PID, where PID is the political ideology divergence between CEO and all board of directors; $PID(excl. CEO\ on\ brd)$ is the divergence between CEO and directors excluding the CEO him/herself if the CEO holds a position on board; $PID(excl. nocontri)$ is the divergence between CEO and directors excluding CEO holds a dual position on board and excluding individuals who have not contribution records; $PID(independent)$ is the divergence between CEO and independent directors; $PID(inside)$ is the divergence between CEO and inside directors; and $PID(outside)$ is the divergence between CEO and outside directors.

2.2.3 Summary Statistics

Table 2.1 Panel A presents descriptive statistics of CEO-board PID measures and other

[11] The study of Lee et al. (2014) focuses on the political ideology alignment between CEO and independent directors. Thus, they use the inverse of the distance. We use the absolute value of difference measure directly, as our study concentrates on the divergence of political ideology. They also measure political ideology between CEOs and independent directors as the difference of CEO political ideology and the group average of all independent directors.

variables used in our full sample. The definitions of all variables are provided in the Appendix A. To remove outliers, all dependent and control variables are winsorised at the 1% and 99% levels. The summary statistics for the M&A sample are in Appendix A Table A2.1. We first use the entire sample to test the effect of the PID on the probability of M&As. The dependent variable, *Deal dummy*, has a mean of 0.361. The key independent variable of interest, PID, has a mean of 0.55 and a standard deviation of 0.23. Then we discussed how PID affects the short-run and long-run performance of M&As, where the PID, with a mean of 0.58 in the M&A sample, is slightly higher than the full sample.

Following the extant studies (e.g., Lee et al., 2014; Elnahas and Kim, 2017; Bonaime et al., 2018), we construct a series of firm characteristics as control variables and verify that they are consistent with previous literature. These variables include CEO and board characteristics, such as CEO age, CEO tenure, CEO gender, and board size; firm financial characteristics, such as firm size, Tobin's Q, book leverage, cash to assets ratio, R&D expenditure, capital expenditure, sale growth, return on assets (ROA), and earnings before interests and taxes ratio ($EBIT$); deal-specific characteristics, such as deal value, target public status, diversify deal, friendly deal attitude, tender, payment method (including stock payment dummy and all cash payment dummy), relative size, acquirer's stock return volatility (*sigma*) and buy-and-hold return (*runup*) a week prior to the deal announcement date. Further, Table 2.1 Panel B shows the comparison of the mean of firm characteristics between high-*PID* and low-*PID* firms, where the high-*PID* subsample is firms with *PID* higher than the median *PID*, and others are low-*PID* firms. Columns (1) and (2) exhibit the mean of firm-characteristics for high-*PID* and low-*PID*, respectively.

Column (3) presents the t-test on the differences of the two groups. High-*PID* firms are associated with a higher average CEO age, tenure, and higher probability of female CEOs; larger board size, firm size, and leverage, but lower cash-to-assets ratio and less expenditures on R&D than low-*PID* ones.

2.3 Empirical Analysis

2.3.1 Baseline Regression

To examine the impact of *PID* between the CEO and board of directors on acquisition likelihood, we run the following probit regression:

$$Acquisition\ likelihood_{i,t+1} = \alpha + \beta * PID_{i,t} + C_{i,t} + \varphi_i + \gamma_t + \varepsilon_{i,t} \qquad (2.3.)$$

where $Acquisition\ likelihood_{i,t+1}$, the independent variable, is a dummy variable that equals one if firm i makes at least one acquisition announcement in year $t+1$, and zero otherwise. $PID_{i,t}$ is the political ideology divergence between the CEO and directors of the firm i at fiscal year t. $C_{i,t}$ is a vector of firm-level control variables constructed at year t, which have been evidenced explainable on the acquisitiveness of firms. The control variables included in the regressions are CEO age (Yim, 2013), CEO tenure (Malmendier and Tate, 2008), CEO gender (Tate and Yang, 2015), board size (Cheng, 2008), firm size, Tobin's Q, book leverage, cash to assets, R&D expenditures, capital expenditures, and sales growth.[12] We include year and industry fixed effects (SIC2, two-digit code of industrial classification) in the regressions as prior studies suggest year and

[12] For the control of firm size, Tobin's Q, book leverage, cash to assets, R&D expenditures, capital expenditures, and sales growth, see the example of Bena and Li (2014), Hoberg and Philips (2010), and Bonaime et al. (2018).

industry affect the level of acquisitions (Mitchell and Mulherin, 1996; Shleifer and Vishny, 1991, 2003), and cluster standard errors by firm and year (Bertrand, Duflo, and Mullainathan, 2004).

Table 2.2 presents probit regression results using six different measures of CEO-board *PID* (*PID*; *PID* (*excl. CEO on brd*); *PID* (*excl. nocontri*); *PID* (*independent*); *PID* (*inside*); *PID* (*outside*)). To facilitate a more direct interpretation, we report the marginal effects instead of regression coefficients. Our results present that *PID* between CEO and directors has a strong positive relation with firm acquisition likelihood. Across all specifications (1) to (6), *PID* consistently demonstrates a positive and statistically significant effect at the 1% level. Turning to the economic magnitude, taking Column (1) as an example, the estimate of *PID* suggests the probability for a firm to engage in at least one acquisition is 1.2% higher with one standard deviation increase in *PID*. In other words, a one standard deviation rise in *PID* corresponds to a 3.33% rise in acquisition likelihood relative to the sample average unconditional acquisition likelihood. The estimates of other control variables have consistent expected signs and statistical significance with prior studies (Yim, 2013; Huang and Kisgen, 2013; Bonaime et al., 2018).

2.3.2 Economic Mechanisms

In this subsection, we examine the factors contributing to the increased likelihood of firms engaging in acquisitions when faced with higher levels of *PID* between the CEO and the board. Specifically, we investigate the potential influence of CEO risk-taking behaviours[13] proxied by three measures through which *PID* affects the likelihood of M&As: CEO overconfidence, founder CEO, and pay for performance sensitivity.[14]

We measured CEO overconfidence proxied by the number of options held by the CEO (Malmendier and Tate, 2008, 2015; Campbell et al., 2011). Consistent with Campbell et al. (2011), we construct CEO overconfidence as a dummy variable that equals one if the CEO holds stock options that are more than 67% in the money; otherwise, zero.[15] Malmendier and Tate (2008), Billett and Qian (2008), and Ferris et al. (2013) examine that overconfident CEOs are more likely to be involved in acquisitions as they are more optimistic that they can enhance and maximise firm valuation through acquisitions. Table 2.3 Panel A shows that the *PID* is positive and significantly associated with CEO overconfidence. Then, we separate the sample into two groups: one is the sample of firms with overconfident CEOs, and the other is PSM-matched firms with non-overconfident CEOs.[16] We examine whether the *PID* has a different effect on the likelihood of M&As in these two subsamples and present results in Column (4) and Column (5). The estimate of *PID* with the overconfident CEOs is 0.298, which is statistically significant at 1% level, compared to 0.133, which is not statistically

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[13] We also find that monitoring may serve as a mechanism explaining the positive relationship between *PID* and M&A likelihood. Our analysis indicates that *PID* positively correlates with the proportion of institutional shareholders. The positive effect of *PID* on likelihood is more pronounced when monitoring is high, where the monitoring is proxied as proportion of institutional shareholdings. We observe that with an increase in the portion of institutional shareholders, *PID* exerts a more significant and positive influence on the likelihood of acquisitions. This finding suggests the crucial moderating role institutional shareholders play in enhancing the effect of *PID* on corporate M&A activities.

[14] Previous literature has evidenced that ideologically different CEO and board reduces agency costs and achieves better firm performance (Kim et al., 2013; Lee et al., 2014). This argument rules out that the increasing likelihood of M&A is potentially driven by agency conflicts between CEO and board members.

[15] Malmendier and Tate (2008) and Campbell et al. (2011) provide details on the calculation of the proportion of in the money option of total option amount.

[16] We use the propensity score matching nearest one approach to find the firms with non-overconfident CEOs who have identical characteristics of the firms with overconfident CEOs.

significant for the non-overconfident CEOs, confirming that the positive effect of *PID* on the likelihood of M&As exists only for firms with overconfident CEOs, who are more risk-loving and confident on their ability and decisions.

Next, we test whether the CEO as a firm founder could explain the relationship between *PID* and the likelihood of M&A. Most of the founder-CEOs are the owners or the entrepreneurs of the firm, typically have fewer concerns about their careers if they do not achieve firm growth and profit targets and are more powerful and influential in making decisions (Fahlenbrach, 2009). Besides, Lee et al. (2017) find that founder CEOs have more managerial optimism and overconfidence in firm performance. In other words, founder CEOs unlikely to be dismissed are more overconfident and likely to be involved in risk-taking behaviours, including acquisitions. Based on this idea, we report the results of the *PID* with the CEO as founders on the probability of M&As in Table 2.3 Panel B. Columns (1) to (3), with the dependent variable of the founder-CEO dummy, show that the *PID* is negatively associated with the firms with CEO as founder. We then run probit regressions on the likelihood of acquisitions with a separate sample of firms with founder-CEOs and PSM-matched firms without founder-CEOs[17] and present results in Column (4) and Column (5). The results show that the positive relationship between the *PID* and the likelihood of acquisition is only significant for firms with founder CEOs, where founder CEOs have more influence on board members and have more power in making M&A decisions.

[17] We use the propensity score matching nearest one approach to find the firms with non-founder CEOs who have identical characteristics of the firms with founder CEOs.

Third, as evidenced by Bliss and Rosen (2001) and Grinstein and Hribar (2004), CEOs obtain enormous compensations when they complete M&As successfully. We examine the pay for performance sensitivity of CEOs according to the assumption that CEOs will be more stimulated and desired to make risk-taking decisions, including M&A, to maximise firm profits when they are able to obtain better personal gains with better performance. Following Jenson and Murphy (1990) and Lee et al. (2014), we first conduct a regression on the relationship between *PID* and CEO pay for performance sensitivity (PPS), where we control *PID*, *board size*, *majority independent directors dummy*, *CEO age*, *CEO tenure*, *percentage of CEO stock owned*, *one-year stock volatility*, *one-year buy and hold stock returns*, and *lagged year Tobin's Q*, *ROA* and *natural logarithm of assets*. The dependent variable in Column (1) of Table 2.3 Panel C is the annual change in the sum of salary and bonus. The coefficient estimate is positive and statistically significant at 5% level, implying that a higher level of *PID* is associated with more substantial CEO compensation incentives. Consequently, CEOs are more prone to engaging in riskier strategies with higher compensation, including M&As, to enhance firm performance.

Further, we partition the sample into two groups based on the median of the PPS and assess their respective *PID* effects on the likelihood of acquisitions in Column (1) and Column (2) in Table 2.3. Comparing the coefficients of the two groups, the above median PPS group demonstrates an estimate of *PID* of 0.134 (significant at 5% level), while the below median PPS group's *PID* exhibits an estimated *PID* of 0.117 (significant at 10% level). The rejection of the assumption of equal coefficients, with a p-value of 0.000 (at the 0.000 percent level of significance) of the Chow-test in the bottom line of

Panel C, suggests that firms with a higher level of *PID* in the above-median PPS group are more inclined to engage in M&A activities.

Overall, our findings highlight that firm *PID* increases the likelihood of M&As through channels such as CEO overconfidence, succession CEOs, and pay for performance sensitivity.

2.3.3 Endogeneity

To overcome the concern that the relationship is reverse-causal or the firms' M&As likelihood could be affected by omitted variables associated with *PID* between CEO and board, we use three different identification methods to rule out potential endogeneity issues. First, we utilise propensity score-matched samples and entropy balancing techniques to reduce heterogeneity between firms with high and low *PID* between the CEO and the board. By creating balanced samples, we aim to alleviate potential biases and confounding factors that could influence the observed relationship. Second, in line with Lee et al. (2014), we use the 7-year lagged time variant values of individual political affiliation as an instrumental variable (IV) to construct firm-level *PID* to perform a two-stage analysis (*2SLS*) to ease the possibility of M&A decision and performance influence contribution patterns of the individual in the future period. Third, we leverage exogenous shocks as sources of identification. We utilise the 2016 Trump election as an exogenous shock to conduct a difference-in-differences (DID) analysis.

First, the propensity score matching (PSM) and entropy balancing approach are used to eliminate any correlated omitted variable biases, systematic differences between firm characteristics, and estimation of average treatment biases (Imbens and Wooldridge, 2009). Table 2.4 presents a one-to-one (the nearest neighbour) matching of PSM analysis. We match the probability of M&As for high *PID* firms (above median *PID* by each fiscal year) with low *PID* firms (below median *PID* by each fiscal year) and assign firms with high (low) *PID* into the treatment (control) group.

In Panel A of Table 2.4, we use the nearest neighbour matching approach to ensure that high *PID* firms (treatment) are identical to low *PID* firms (control) based on propensity scores. We compare the differences in means between the treatment and the control group. The *p*-values suggest no statistically significant difference in the mean of any firm characteristics between treatment and control groups. We then run a probit model to estimate the probability that a firm has a high *PID*,[18] according to the covariate matrix of CEO and firm characteristics used in Table 2.2 with control of year and industry fixed effects. In Column (1) of Panel B, we report pre-matching coefficients of the probit model. In Column (2) of Panel B, we repeat the probit model using a post-match sample and present the post-matching coefficients. None of the independent variables generate statistically significant effects, and the Pseudo R^2 drops from 0.034 to 0.002, indicating no differences in the probability of M&A exist between treatment and control groups. These results, observed in Panel A and the first two columns of Panel B, indicate that the propensity score matching process successfully removes sample selection biases. Then, we re-run Equation (2.3) using the sub-sample of matched observations and present the results in Column (3) of Panel B (Table 2.4). The estimate of *PID* between the CEO and

[18] If a firm's *PID* between CEO and board is above median, then it takes value of one, and zero otherwise.

board is still positive and statistically significant at the 1% level, implying that a firm's *PID* between the CEO and board has a positive effect on the probability of M&As after the removal of firm-specific characteristics.

As a robustness test, we also employ the entropy balancing approach to create a sample of treatment and control firms to address any potential biases due to differences in firm characteristics. Entropy balancing is a matching approach in re-weighting control variables of multiple moments to achieve post-weighted covariate distribution balance[19] and reduce the estimation of treatment biases (Hainmueller, 2012; McMullin and Schonberger, 2020). Following Ferri, Zhen, and Zou (2018), we choose the mean, variance, and skewness as moment properties and the same matching variables in the PSM method with control of firm and industry effects. The treatment (control) group is firms with high (low) *PID* (above (or below) median of *PID* by each fiscal year). The matching process assigns weights to observations in multiple iterations and ends until the moment properties of matching variables between treatment and post-weighted control groups are identical to satisfy the balance condition. The benefits of entropy balancing are that it matches the characteristics of firms on multiple moments (mean, variance, and skewness) and uses all the samples in the treatment and control groups in regressions based on the assigned weights. The results are provided in Appendix A Table A2.2. Panel A shows the differences in the means, variance, and skewness of variables in the treatment and control groups before entropy balancing. Then, in Panel B, Table A2.2, it presents the

[19] After weighting the control variables, the first, the second and even higher moment properties of these variables are identical in the treatment and control groups, thus the covariate distribution balance is achieved.

three dimensions of the matched variables across treatment and control groups that are identical after entropy balancing. As a last step, in Panel C of Table A2.2, we provide the result of the main regression with an entropy-weighed sample. The *PID* between the CEO and board still has a positive and significant (at 1% level) effect on the probability of M&As. To summarise, the results of baseline regression (without matching), the PSM, and the entropy balancing approach provide similar interpretations of the relationship of the likelihood of M&A and *PID* between CEO and board.

Second, we run a two-stage least squares (2SLS) instrumental variable (IV) regression to alleviate any endogenous changes that affect the individuals' donation patterns. In line with Lee et al. (2014), we use the 7-year lagged values of an individual's prior *REP* index as an instrument variable of *PID*,[20] which is correlated with CEO-board *PID* but does not affect the decision of M&As. This instrument eases the concern that the individual's political contribution is affected by the firm performance in the current and future years rather than when we use the entire donation history. Table 2.5 presents the results of the two-stage IV regressions. Column (1) reports the first stage model, where the dependent variable is the firm *PID* at year *t*. The coefficient of the *PID (prior lag 7)* suggests that the instrument is positively associated with the *PID* of the CEO and board at the 1% significance level, implying the validation of the instrument. The statistics of the Cragg-Donald weak identification test and the Kleibergen-Paap under identification

[20] The 7-year lagged value of individual's prior *REP* index is constructed using one's donation history from 1989 to 7-years prior to the fiscal year *t*. We then use this 7-year lagged *REP index* to calculate *PID* between CEO and board in the year t as we did before in Equation (2.2). Consistent with Lee et al. (2014), our sample CEOs have a median tenure of 6 years, and the directors have a median tenure of 7 years. Thus, we could use the same lagged interval of 7 years as Lee et al. (2014) did without worrying the change of the composition of the board or the CEO, and the future firm performance and decisions influence the political divergence.

test (5162.47 and 3516.63) are higher than the critical value of 2SLS and LIML size of nominal 5% Wald (both 16.38 in our sample), rejecting the null hypothesis of weak identification (Cragg and Donald, 1993; Stock and Yogo, 2002). Then, we re-run the Equation (2.3) using the estimated *PID* from the first stage. The second-stage result is presented in Column (2) of Table 2.5. The coefficient on the instrumented *PID* is positive and significant at the 1% level. This finding is robust in that *PID* positively affects the probability of acquisitions and alleviates endogeneity concerns.

Third, we use a Difference-in-Difference (DID) approach to stress the concern of endogeneity. Equation (2.4), as follows, is employed to estimate the causal relationship of *PID* on the likelihood of M&As:

$$M\&A\ likelihood_{i,t+1} = \alpha + \beta_1 * Post_{i,t} + \beta_2 * Treated_{i,t} + \beta_3 * Treated_{i,t} * Post_{i,t} + C_{i,t} + \varepsilon_{i,t} \qquad (2.4.)$$

We take the most recent US presidential election, the 2016 Trump election, as a natural experiment to repeat the above DID model process. The extant literature evidence that the partisan voting behaviours of individuals are clustering and concentrated at the geographic level using electoral supporting results to explain a new partisan alignment (Abramowitz, 2011), and people choose residences where they share similar lifestyles and values (Toal and Shelley, 2003; Bishop and Cushing, 2008). Motivated by Gupta and Wowak (2017), where they suggest the political ideology composition of the board room is influenced by the supply side, the position of the firm head-quartered, we assume that the presidential election, a highly partisan voting event, would cause the re-alignment and reflection of the regional partisan clustering. After the presidential election, the firm *PID* would decrease as within the firm, and employees are more likely to share identical political affiliations. Similar to our expectation, Column (1) in Table 2.6 reports that the post-event dummy (if the year after 2016 equals one) negatively affects the firm-level *PID*.[21] We define the treated firms as firms with the value of *PID* multiplied by a negative one below the median in a specific fiscal year t. In Column (2), the estimate of the interaction term $Treated_{i,t} \times Post_{i,t}$ is positive and statistically significant at 5% level, indicating that after the president election in 2016, firms with increased *PID* are more prone to engage in M&As. In summary, the results are in line with the events of exogenous shocks. These three analyses confirm that endogeneity was not a significant problem in our study.

2.3.4 Robustness Tests

Following Hong and Kostovetsky (2012), Lee et al. (2014), and Elnahas and Kim (2017), we use alternative measures of *PID* by considering different calculations based on individuals' political affiliations to conduct robustness tests. Specifically, we construct *PID* (*strong*) based on the idea that an individual's *Rep* equals one if he/she donates to the Republican $2,000 more than to the Democrat and otherwise equals zero. Next, we introduce *PID (extreme)*, which captures individuals with extremely strong partisanship. This measure is based on whether the individual exclusively donates to the Republican party. If an individual's donations are solely directed towards the Republican party, the Rep index takes a value of one; otherwise, it is set to zero. These two measures aim to

[21] In other words, post event dummy has a positive effect on the firm level of political ideology homophily. After the 2016 president election, the political ideology between CEO and the board are more similar. We then use the *PID* multiplied with negative one to construct the treated and control firms, where it represents political ideology homophily of CEO and board. We use this measure to make the result are more ease to interpret and consistent with the context of the acquisition likelihood.

minimise the disturbance of small and wavering contributors. The third alternative measure, *PID* (*cfscore)*, is the political ideology divergence where individual political ideology is defined by Bonica (2016) using one's total contribution from 1979 to 2014. We further use time-variant measures of individual political affiliation to construct *PID* (*prior*), *PID* (*strong prior*), and *PID* (*extreme prior*), intending to avoid forward-looking bias caused using future information. To construct time-variant measures, individual *REP index* is computed using historical contribution from 1989 to each year *t*. *PID* (*prior*) is the political ideology divergence constructed as individual total donations before each firm fiscal year *t*; *PID* (*strong prior*) is the political ideology divergence constructed as individual historical net donations of more than $2000 prior to each firm fiscal year *t*; *PID* (*extreme prior*) is the political ideology divergence constructed as individual historical donations only went to Republican prior to each firm fiscal year *t*.

We estimate the effect of the aforementioned six alternative measures of *PID* on the likelihood of M&As using the same regression model discussed earlier. The results of this robustness analysis are presented in Table 2.7, Panel A, which demonstrates the consistency and robustness of the previously identified significant and positive association between CEO-board *PID* and the likelihood of M&As. Taking the *PID strong* and *PID prior* as examples, the marginal effect coefficient of *PID strong* (*PID prior*) is 0.048 (0.045), suggesting a one standard deviation increase in the *PID strong* (*PID prior*) results in a 1.07% (1.06%) increase in the probability of making M&As, corresponding to 2.96% (2.94%) of the sample mean (0.361).

To eliminate the concern of the effect of CEO and directors' political affiliation on the likelihood of M&As, we repeat the same regression as in Equation (2.3) with further control of *CEO REP index* and average *directors REP index* and presented marginal effects of results. As shown in Table 2.7 Panel B, the magnitude and statistical significance of the estimates of CEO-directors *PID* remains intact, even after accounting for the CEO REP index and the average directors' REP index. The CEO REP index and average directors REP index coefficients are not statistically significant, further reinforcing the robustness of the positive association between the likelihood of M&As and the *PID* between the CEO and directors.

Furthermore, by addressing concerns regarding the possibility that the observed positive relationship between *PID* and the likelihood of acquisitions is a consequence of decision-making centralisation among influential CEOs, we aim to rule out the effects driven by powerful CEOs, who are responsible for the most significant decisions. This approach is crucial because, as highlighted by Adams et al. (2005), CEOs with significant power tend to resist collaboration with other top executives, opting instead for more unilateral and potentially more extreme decisions. Morse et al. (2011) further suggest that such CEOs may influence board decisions to skew and manipulate towards better performance reporting that enhances their incentive compensation, ultimately detrimentally affecting the firm's value and operational efficiency. Schopohl et al. (2021) also demonstrate that the presence of a powerful CEO significantly limits the capacity of female CFOs to decrease corporate leverage. By explicitly examining and controlling for the influence of CEO power, we ensure that the identified relationship between *PID* and acquisition likelihood is not confounded by the dominance of powerful CEOs in the decision-making process, thereby providing a more comprehensive and robust understanding of the *PID* and acquisition decisions.

Following Schopohl et al. (2021), we employ three proxies to assess a powerful CEO. The first one is the CEO as a chairman, a binary variable, which equals one if the CEO simultaneously holds a position as the chairman. This dual capacity of the CEO is indicative of a significant concentration of power, facilitating greater control over corporate decision-making processes (Adams et al., 2005). Our analysis first incorporates this variable as a control in the baseline regression model and further categorises the sample to evaluate the differential effects of *PID* on acquisition likelihood contingent on the CEO's dual role. The second measure involves the composition of the board, specifically the proportion of insiders. Drawing on the findings of Hermalin and Weisbach (1988), we posit that a board with a lower percentage of independent directors is more prone to acquiesce to the CEO's decisions, exhibiting less opposition or critical examination. This tendency is symptomatic of a CEO's heightened authority. We integrate the insider proportion as an additional control variable and proceed to divide the sample based on low, medium, and high insider presence, hypothesising that a greater insider ratio is indicative of more powerful CEOs. The CEO pay slice, which serves as our third proxy, is calculated as the CEO's total remuneration relative to the aggregate compensation of all board members. A larger pay slice ratio signals a CEO's dominant role in firm governance and is correlated with increased agency issues (Bebchuk et al., 2011). Following the inclusion of the CEO pay slice as a control in our baseline analysis, we segment the sample into categories of low, medium, and high CEO pay slice ratios to examine the correlation between CEO power and its influence on *PID* and firm acquisition decisions.

Appendix A Table A2.3 presents our results and indicates that the CEO's power does not underlie the positive relationship between *PID* and the likelihood of acquisitions. Our analysis reveals that the impact of *PID* on acquisition probability remains positive and consistent, irrespective of whether the CEO concurrently holds the chairman position. Furthermore, while the proportion of insiders on the board positively correlates with acquisition likelihood as a controlled variable, it fails to exhibit any significant variance in the relationship between *PID* and acquisition likelihood across different levels of insider presence. Notably, the results demonstrate a more pronounced positive effect of *PID* on acquisition likelihood for firms characterised by a medium level of CEO pay slice. Collectively, these outcomes robustly substantiate the assertion that the positive influence of *PID* on acquisition likelihood is not attributable to the power vested in the CEO.

2.3.5 *PID* and M&A Performance

2.3.5.1 Deal Duration

In this subsection, we test the effect of *PID* on the time to complete the deal. We compute the time to complete the deal as the deal announcement to deal completion, including the negotiation and recursive decision-making process with internal and external parties, is the critical part of the pre-deal process, where some of the post-merger integration problems are caused by the pre-deal period (Jemison and Sitkin, 1986; Haspeslagh and Jemison, 1991). Extant literature shows that boards and shareholders can negotiate with

CEOs via awarding options and influence the time of the completion (Fich, Cai, and Tran, 2011; Boyson, Gantchev, and Shivdasani, 2017; Jiang, Li, and Mei, 2018).

Table 2.8 presents the results of deal duration,[22] calculated as the natural log of the number of days from the deal announcement to the deal completion date (deal effective date). Similar to Lawrence et al. (2021), we exclude deals with the same date of announcement and completion. The results suggest that the *PID* has a positive and statistically significant effect on the deal duration at 1% level. Our findings indicate that with higher *PID* between CEO and boards, directors are monitoring and investing more time to incentivize CEOs to be more resistant in deal negotiations with targets, potentially aiming to improve the quality of deal closures.

2.3.5.2 Acquisition Performance

We first assess the relationship between *PID* and acquisition short-term stock performance, then the long-term and operating performance.

First, we analyse the announcement return of acquirers using the M&A sample described in Section 2.2.1. Our main independent variable is the three-day cumulative abnormal returns of the acquirers during the deal announcement, CAR (-1, +1). The CAR is constructed using the market model estimated with 241 trading days from the CRSP stock return data, and the end 41 days precede the announcement date. The acquirers experience a slightly average positive return of 0.6%. Besides the control of CEO and board characteristics and announcement year and acquirer industry fixed effects, we

[22] The duration is defined as the time of the deal transaction from announcement to complete.

further include several acquirer and deal characteristics that are known to affect acquirer short-run returns, including the *deal value* (Golubov, Petmezas, and Travlos, 2012), *public target* (Capron and Shen, 2007), *diversify* (Campa and Kedia, 2002), *friendly* (Servaes, 1991), *tender* (Jensen and Ruback, 1983), *including stock payment* (Travlos, 1987), *all cash payment* (Martin, 1996), *size* (Moeller et al., 2004), *relative size* (Fuller et al., 2002), *leverage* (Maloney, McCormick and Mitchell, 1993), *runup* (Rosen, 2006), *sigma* (Moeller, Schlingemann, and Stulz, 2007), *Tobin's Q* (Dong et al., 2006), and *cashflow* (Lang, Stulz, and Walkling, 1991). All variables are defined in the Appendix A.

In Table 2.9, Panel A, we present the results of the association between the *PID* and M&A announcement performance. In all Columns, the *PID* between the CEO and board is mildly negative but not significantly associated with abnormal announcement returns. The results imply that political divergence between CEO and directors might not have a positive effect on market response. It is possible to explain as the market investors are aware of the difference in political ideology between the CEO and directors from available public voting information. Investors might hold views that individuals are more friendly and efficient to keep more trust in others who share a similar political ideology. With the higher difference in political ideology between CEO and directors, the market does not deem the firm could make better investment decisions and enhance the firm value as the top manager and the boards are distinguished in their values, where they might not better incorporate and not have highly trusted ligament with each other. To conclude, the effect of the CEO and board directors' *PID* on the short-term firm valuation is not obvious.

Second, we investigate the effect of the *PID* between the CEO and board on acquirers' long-term stock return performance and operating performance, as the announcement return might not comprehensively capture the performance of acquisitions (Malmendier, Moretti, and Peter, 2018). We use buy-and-hold abnormal return (BHAR) to measure long-term stock return performance and change on return on assets (ΔROA) and change on earnings before interests and taxes (ΔEBIT) to measure long-run operating performance.

If the high *PID* firms indeed undertake better quality deals, then the long-term stock returns should reflect the outcome. Our dependent variable is the 1-, 2-, 3-, 4- and 5-year buy and hold abnormal returns (BHARs) after the deal completion dates. We calculate the BHAR as the end of monthly stock buy and hold stock return minus that of the matched firm according to size and book-to-market ratio, as suggested by Barber and Lyon (1997) and Barber, Lyon, and Tsai (1999). We perform OLS regressions and use the same control variables as in CARs. In Table 2.9 Panel B, the results report that the *PID* is associated with an increase in bidders' long-term stock performance by 3.7%, 8.2%, 12.3%, 13.5%, and 20.1% over one, two, three, four, and five years after the closure of acquisitions, indicating the *PID* is positively affect the M&A long-run performance.[23]

We next test whether the *PID* has a positive effect on operating performance. We repeat the analysis in BHARs, replacing the dependent variable as the change in operating performance of post-deal minus pre-deal. We use the return on assets (ROA) and

[23] The results of the effect of rest of measures of PID on BHARs are reported in Appendix A Table A2.6.

EBIT/Assets as proxies of acquirers' operating performance. The ROA is the acquirer's operating income before depreciation divided by total assets, and the EBIT/Assets is the ratio of the acquirer's earnings before interest and taxes divided by total assets. The change in operating performance is computed as the acquirer's operating performance one (or two, three, four, five) year post-deal announcement minus the operating performance one year before the deal announcement. Table 2.9 Panel C presents the results of ROAs, and Panel D presents the results of EBITs, where we use the same control variables as in BHARs but add the control of operating performance on the previous year.[24] The coefficient estimates are significantly positive in columns (3) (4) (5) of Panel C and Panel D. The *PID* has a positive effect on the change in ROA (EBIT/Assets) by 11.3%, 13.6% and 17.03% (0.8%, 1.3% and 1.8%) over three years, four years, and five years post-deal announcement.[25] In sum, the results in Panel B, Panel C, and Panel D in Table 2.9 suggest that the higher *PID* firms conduct deals with better long-run performance. With the existence of a higher *PID* between the CEO and board, they are more likely to make optimal investment decisions and ultimately enhance the valuation of the firm in the long term. Although the political affiliation of the CEO and board members is different, they are tied up and keep working together to generate better value for long-term firm development.

[24] We control the *ROA prior*, the return on assets in one year prior to the deal announcement, in the regressions of change in ROAs; and the *EBIT/Assets prior*, the EBIT to assets ratio in one year prior to the deal announcement, in the regressions of change in EBIT/Assets. For brevity, we report only the coefficient on the *PID* and omit all the control variables.
[25] The results of the effect of rest of measures of PID on operating performance (change in ROAs and change in EBITs) are reported in Appendix A Table A2.7.

2.3.5.3 The Role of Monitoring in the Acquisition of Long-term Performance

In this subsection, we address the importance of monitoring in moderating the deal performance for higher *PID* firms. First, we compare the effect of *PID* on the number of board meetings for firms after the deal announcement with those that have not been engaged in M&As. Then, we discuss the role of corporate governance, represented by the institutional investor and independent director, in improving the post-deal long-term performance of firms when *PID* is higher.

First, in Table 2.10, Panel A and Panel B, we provide results for the effect of the *PID* on the board meeting, separated by whether firms were involved in acquisitions or not. The frequency of board meetings is an essential proxy of board activity, reflecting the monitoring and advisory role of the board. Prior literature has argued that the number of board meetings increases with the firm poorer performance, growth opportunities, and important corporate decisions, specifically mergers and acquisitions, and board meetings are valuable and positively affect a firm operating performance in subsequent years (Vafeas, 1999; Brick and Chidambaran, 2010). We incorporated the *PID* with mergers and acquisitions on determinants of board meetings to stress that the *PID* is valuable for firm corporate events and corporate governance.

The data on the number of board meetings are obtained from Execucomp.[26] We first test the relationship between the $PID_{i,t}$ and the number of board meetings in year *t + 1* (the dependent variable), then test the $PID_{i,t}$ and the abnormal number of board

[26] The ExecuComp contains data of frequency of board meetings prior to 2007, thus we used the data of 1999-2006 to test.

meetings in year $t + 1$ (the dependent variable), which is defined as a firm's frequency of board meetings minus the average of industry in each fiscal year. Panel A in Table 2.12 presents the results of the *PID* on the number of board meetings. Column (1) are the firms that make at least one deal announcement at year *t*; Column (2) are those not involved in acquisitions. After the announcement of acquisitions, the board meeting frequency increased with the *PID*, suggesting that the boards' communication frequency and monitoring role strengthened in firms with higher *PID*. In Column (3), using the full sample, we include the $PID_{i,t}$, $Deal\ dummy_{i,t}$, and the interaction term of $PID_{i,t} \times Deal\ dummy_{i,t}$ in the left-hand side with control variables as same as the main regression and year and industry fixed effects. The *PID* solely has a negative effect on board meetings, indicating fewer communication channels and less trust between the CEO and board when their political affiliations are more different from each other. The positive and significant estimate of the deal dummy indicates that decisions of M&A promote the frequency of board meetings. And this effect is increased when the CEO and directors are more politically divergent, as shown in the interaction coefficient, which is 0.599, positive and statistically significant at 1% level. The magnitude of the interaction term, 0.599, is 1.8 times the deal dummy's estimates (0.299), implying that high *PID* further increases the frequency of board meetings following acquisition announcements. We repeated the process above in Panel B in Table 2.9 with the replacement of the dependent variable to the abnormal number of board meetings and presented similar results as in Panel A. The results suggest that the board of directors is advising, monitori ng more actively, and communicating more with CEOs. They are more likely to work together to ensure the performance of acquisitions and enhance firm value when the *PID* is higher.

In addition, we examine whether good corporate governance, proxying by the proportion of institutional investors and independent directors, which are monitoring mechanisms, plays an important role in enhancing the firm post-deal long-term performance in the higher *PID* firms. First, previous studies have discussed that institutional ownership improves stock price-earnings quality and operating performance through professional negotiating and monitoring activities on managers' behaviours (e.g., Bushee, 1998; Velury and Jenkins, 2006; Corenett et al., 2007). We measure institutional ownership as the percentage of shares owned by institutions from Thomson Reuters institutional holdings (Form 13F). Next, we calculate the proportion of independent directors as the number of independent directors to the total board of directors as the proportion of independent directors is a valuable aspect of board functions. Recent research suggests that a higher proportion of independent directors enhances the effectiveness of board advising and monitoring roles by increasing firm information transparency to ensure the profitability of shareholders (e.g., Petra, 2005; Nguyen and Nielsen, 2010; Armstrong et al., 2014).

As discussed above, we partition the deals by within-year sample median percentage of the institutional ownership (and by within-year sample median proportion of the independent directors). Then we conduct regressions for the two groups, above the median of percentage of the institutional ownership and below the median of portion of the institutional ownership (above or below median independent directors' ratio), on the BHARs, change in ROAs and change in EBITs, respectively. The results for the BHARs are reported in Table 2.9; other results for the ROAs and EBITs are presented in Appendix A Table A2.8 and Table A2.9. In Panel C of Table 2.9, we first investigate the relationship between the *PID* and the proportion of institutional ownership and independent directors. The results exhibit that the *PID* is positively related to the percentage of institutional ownership and independent directors. Firms with higher *PID* are associated with better monitoring and advisory from board functions and large institutional shareholders.

Then, in Table 2.9 Panel D, where the dependent variable is 3-year BHARs[27], we compare the coefficient estimates for the *PID* in Column (1) to that in Column (2) and in Column (3) to that in Column (4). The coefficients are both positive but only statistically significant in Columns (1) and(3), where the samples are above the median of institutional ownership or independent directors.[28] In summary, our findings indicate that the positive effect of *PID* on the long-term stock and operation performance is only present when the acquirer has a higher proportion of institutional ownership and independent directors, addressing the importance of negotiating, advising, and monitoring the role of professional large shareholders and board composition.

2.3.6 CEO Political Connection with Party in Power

This subsection investigates the relationship between *PID* and the CEO's political

[27] We present 3-year BHARs in Table 2.12 Panel D, the 1-, 2-, 4- and 5-years BHARs' results are presented in Appendix A Table A2.8 Panel A for institutional investors and Table A2.9 Panel A for independent directors. And the results of the ROAs and EBITs are also presented in Appendix A Table A2.8.

[28] In Appendix A Table A2.8 and Table A2.9, the dependent variable is 3-years change in post-deal ROAs in Panel B and the post 3-years change in EBITs in Panel C. The results are similar to the results of BHARs. When firms have higher proportion of institutional investors or independent directors, there is a positive effect of *PID* on the change in operating performance.

affiliation with the president and the gubernatorial party in power.

Specifically, we examine whether the positive effect of *PID* on the decision of M&A differs when the CEO's political affiliation is aligned with or not the president's party and the gubernatorial party in power.[29] The prior literature suggests that more homophily of political ideology between managers and the party in power would cause higher investment (e.g., Schwartz, 2019; Rice, 2023). Motivated by this idea, we test when the CEO's preferred party is in power how *PID* affects the investment decisions on M&As. We construct a binary variable that takes the value of one when the difference of gubernatorial (president) party in power (*Republican* = 1; *Democratic* = -1) and the CEO *REP index* is smaller than 1, otherwise zero. We first examine the relationship between party in power and firm-level *PID*. Next, we add the same CEO and party in power dummy into regression, and we then compare estimates of *PID* on the likelihood of acquisitions when splitting the sample into two groups: CEO with preferred party in power, CEO with non-preferred party in power, on both gubernatorial and president level. Table 2.11 reports the results, Panel A for the CEO and gubernatorial party, Panel B for the CEO and president party. The results suggest *PID* is negatively associated with the party in power on both gubernatorial and presidential levels. Further, when the preferred party of CEOs is in power, with higher *PID*, CEOs are more likely to make acquisitions, reflecting the investment optimism from partisan similarity.

[29] We also test the positive effect of *PID* on the decision of M&A differ when the average board of directors' political affiliation is aligned with the president party and the gubernatorial party in power or not. The results are provided in Appendix A Table A2.4. We have not found any difference effect of *PID* on M&A between the groups of alignment of partisan directors and party in power, and divergent of partisan of directors and party in power.

2.3.7 Additional Tests

In this part, we first analyse whether the *PID* affects the CEO's investment choices on internal and external investment and test whether the firm's financial condition affects the CEO's decision on M&As. We compare the effect of *PID* on M&As versus capital expenditure (CAPEX) or the research and development expenditure (R&D). Then, we discuss the *PID* on the likelihood of M&As when facing different conditions on financial constraint, cash flow volatility, and investment opportunity.

2.3.7.1 The PID on the Likelihood of M&A vs. CAPEX or R&D

We analyse whether the *PID* similarly affects the CEO's internal and external investment decisions. We use the Seemingly unrelated regression (SUR), where the residuals are correlated, to test the investment decision relatedness of M&A (external investment) and the amount spent on CAPEX or R&D (internal investment), similar to Elnahas and Kim (2017).[30] The results are shown in Appendix A Table A2.5. In Panel A, the dependent variables are the deal dummy and CAPEX scaled by total assets, and the dependent variables are the deal dummy and R&D normalised by total assets in Panel B. The results indicate that firms with higher levels of *PID* are more likely to make external investments and have no apparent influence on internal investment. The *PID* obviously affects external investment decisions rather than internal investments.

2.3.7.2 Cross-sectional Analysis of the PID on the Likelihood of M&As

In this subsection, we test whether the positive relation between *PID* and the propensity of M&A differ in firm operating conditions, specifically, the difference in financial

[30] As Elnahas and Kim (2017) explained, the SUR could simultaneously test the external investment and internal investment with the same control variables and the main explanatory variable.

constraints, cash flow volatility, and investment opportunity.

We first measure the firm external financial constraints as suggested by Whited and Wu (2006),[31] where firms with higher levels of financial constraints are associated with higher costs of external financing, and they would prefer internal and innovative investment (Fazzari, Hubbard, and Petersen, 1988). We then sort the sample into financial constraint firms and unconstraint firms by the sample within-year median of the *WW-index* (Whited and Wu financial constraints index). Next, as Minton and Schrand (1999) discussed that firms with lower cash flow volatility have higher levels of internal investment on CAPEX and R&D, we compute the cash flow volatility and then partition the sample into high cash flow volatility and low cash flow volatility groups according to the yearly median cash flow volatility. Third, firms with more investment opportunities are more likely to engage in M&A (Lang and Stulz, 1994), and we use Tobin's Q and sales growth as proxies of investment opportunities and repeat the process discussed above.

Table 2.12 presents the results of the mentioned discussion, where Panel A is for the firm financial constraints, Panel B for the cash flow volatility, and Panel C and Panel D for the investment opportunity. Our results suggest the *PID* has a more substantial positive and statistically significant effect on the likelihood of M&A when firms are associated with lower financial constraints, higher cash flow volatility, higher Tobin's Q and sales growth. The results evidence that higher level *PID* firms are making investment

[31] See Whited and Wu (2006) for the detail construction of financial constraints index.

decisions conform to the actual situation of firms' operating conditions.

2.4 Conclusion

In conclusion, our study suggests that when there is a greater difference in political ideology between the CEO and board, firms are more inclined to pursue M&A activities. This finding remains robust as we employ various identification strategies to address endogeneity concerns. The positive effect of *PID* on M&A propensity is more pronounced when the CEO is more risk-taking and firms with higher levels of *PID* exhibit better buy-and-hold abnormal returns and improvements in operating performance in the long run.

This study then examines through which mechanisms *PID* influences mergers and acquisitions (M&As), with a focus on CEO risk-taking behaviours. It identifies three key traits of CEOs that affect M&A decisions: overconfidence, founder status, and pay-for-performance sensitivity. Overconfident CEOs, who are inherently risk-takers, are more likely to pursue acquisitions, especially in ambiguous situations created by *PID*. Founder CEOs, deeply connected to their firms, tend to make more optimistic and overconfident decisions, amplifying the impact of *PID* on M&A likelihood. Lastly, CEOs whose compensation aligns closely with firm performance show a greater propensity for high-risk strategies like M&As when *PID* increases. The study underscores the complex interplay between *PID* and CEO characteristics in shaping major organizational decisions, particularly in mergers and acquisitions. The analysis further highlights the role of corporate governance factors in moderating the relationship between *PID* and M&A

outcomes. Specifically, increased board meeting frequency, proportion of institutional ownership and independent directors are identified to enhance the positive impact of *PID* on firm performance of M&A decisions. These findings emphasise the importance of effective monitoring, advising, and information transparency by institutional investors and independent directors' role of corporate in a heterogeneous management team.

This study has several implications for practitioners and policymakers. The findings suggest that firms should be aware of the potential influence of *PID* on strategic decision-making, particularly regarding M&A activities. Understanding the impact of CEO-board political dynamics can help firms navigate the complexities of corporate governance and board effectiveness. Future research could investigate the impact of other divergence measures between the board and CEO, the board and top management team, or connections among the management team itself.

2.5 Tables and Appendices

Table 2.1 Summary Statistics

This table presents the summary statistics for the baseline sample of US-listed firms with available CEO data from Execucomp, directors from BoardEx, and firm financial data from Compustat and CRSP during 1999-2019. Panel A reports the number of observations (N), mean, standard deviation (SD), minimum, 25th percentile, median, 75th percentile, and maximum for the entire sample. Summary statistics for the M&A sample are reported in the Appendix A Table A1. Panel B shows the comparison of the mean of firm characteristics between high-political ideology divergence (*PID*) and low-*PID* firms, where the high-*PID* subsample is firms with *PID* higher than the median *PID*, and others are low-*PID* firms. Columns (1) and (2) exhibit the mean of firm-characteristics for high-*PID* and low-*PID*, respectively. Column (3) presents the t-test on the differences of the two groups. Definitions of all variables are provided in the Appendix A.

Panel A: Summary statistics for the full sample								
	N	Mean	SD	Min	25th Pct	Median	75th Pct	Max
PID	26,434	0.549	0.230	0	0.390	0.525	0.677	1.997
Acquisition likelihood	26,434	0.361	0.480	0	0	0	1	1
CEO age (log)	26,434	4.013	0.131	3.664	3.932	4.025	4.094	4.331
CEO tenure (log)	26,434	1.724	0.885	0	1.099	1.792	2.398	3.555
CEO female	26,434	0.033	0.179	0	0	0	0	1
Board size (log)	26,434	2.251	0.279	1.609	2.079	2.303	2.398	2.996
Firm size (log)	26,434	7.366	1.580	3.788	6.251	7.274	8.398	11.560
Tobin's Q	26,434	2.138	1.448	0.717	1.248	1.675	2.460	9.136
Leverage	26,434	0.660	1.835	-7.360	0.035	0.389	0.846	11.800
Cash to assets	26,434	0.171	0.179	0.001	0.037	0.105	0.246	0.795
R&D	26,434	0.037	0.063	0	0	0.007	0.049	0.352
Capex	26,434	0.047	0.047	0.001	0.018	0.032	0.058	0.272
Sales growth	26,434	0.101	0.253	-0.506	-0.012	0.069	0.170	1.349

Panel B: Firm-characteristics for high-*PID* and low-*PID* firms			
	High *PID*	Low *PID*	Difference
	(1) Mean	(2) Mean	(3)
Acquisition likelihood	0.385	0.336	0.049***
CEO age (log)	4.018	4.007	0.011***
CEO tenure (log)	1.764	1.684	0.080***
CEO female	0.038	0.028	0.010***
Board size (log)	2.283	2.219	0.064***
Firm size (log)	7.609	7.125	0.484***
Tobin's Q	2.132	2.141	-0.009
Leverage	0.699	0.620	0.079***
Cash to assets	0.163	0.178	-0.015***
R&D	0.034	0.040	-0.006***
Capex	0.048	0.046	0.002

Sales growth	0.099	0.103	-0.004

Table 2.2 Political Ideology Divergence (PID) and Firm Acquisition Likelihood

This table presents the marginal effects from probit regressions for the effect of political ideology divergence (*PID*) between the CEO and board of directors on the likelihood of engaging acquisitions for all public firms listed in the U.S., excluding financial firms and regulated utilities, where we can obtain available financial data, CEO, and board of directors' data from 1999 to 2019 (when using OLS regressions instead of probit models, the OLS regressions generate similar results as probit ones). The dependent variable is *Acquisition likelihood*, taking the value of 1 if a firm makes at least one acquisition announcement in year $t+1$ (where M&A announcements from 2000 to 2020) and zero otherwise. *PID* used as a main explanatory variable, is measured as the equal-weighted average of the Euclidean distance between the CEO Republican inclination index (*REP*) and each director's *REP* in the firm for each year. The *REP* is the difference between one's political contributions to Republican and Democratic divided by one's total contributions to both parties. We classify individuals without contribution records as politically neutral and their *REP* measures as zero if not specified. All *PID* between the CEO and board and firm-level variables are calculated at the end of the prior fiscal year t. We measured the *PID* between CEO and all board members (Column 1), *PID* between CEO and board members who do not act as CEO (Column 2), *PID* between CEO and board members who do not serve as CEO and excluding individuals without contribution records (Column 3), *PID* between CEO and independent directors (Column 4), *PID* between CEO and inside directors (Column 5), and *PID* between CEO and outside directors (Column 6), respectively. In all models, we control year and two-digit SIC industry fixed effects. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: *Acquisition likelihood*					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PID	0.053***					
	(4.26)					
PID (excl. CEO on brd)		0.050***				
		(4.55)				
PID (excl. nocontri)			0.065***			
			(6.07)			
PID (independent)				0.035***		
				(3.46)		
PID (inside)					0.040***	
					(3.92)	
PID (outside)						0.031***
						(3.35)
CEO age	-0.112***	-0.112***	-0.114***	-0.112***	-0.114***	-0.055*
	(-4.83)	(-4.81)	(-3.83)	(-4.81)	(-4.88)	(-1.70)
CEO tenure	0.007**	0.007**	0.005	0.007*	0.007**	0.002
	(2.13)	(2.09)	(1.18)	(1.87)	(2.12)	(0.43)
CEO female	-0.090***	-0.091***	-0.092***	-0.093***	-0.092***	-0.085***
	(-5.20)	(-5.23)	(-4.04)	(-5.32)	(-5.27)	(-3.29)
Board size	-0.066***	-0.064***	-0.072***	-0.077***	-0.063***	-0.076***
	(-5.77)	(-5.58)	(-4.87)	(-6.37)	(-5.45)	(-4.91)
Firm size	0.065***	0.065***	0.066***	0.067***	0.065***	0.072***
	(30.09)	(30.14)	(23.09)	(30.46)	(30.06)	(23.87)

Tobin's Q	0.009***	0.009***	0.008***	0.009***	0.009***	0.011***
	(4.80)	(4.78)	(3.95)	(4.65)	(4.80)	(3.54)
Leverage	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000*
	(-0.20)	(-0.20)	(-0.53)	(-0.21)	(-0.19)	(-1.76)
Cash to assets	-0.083***	-0.083***	-0.093***	-0.080***	-0.086***	-0.105***
	(-3.99)	(-3.98)	(-3.31)	(-3.83)	(-4.15)	(-3.48)
R&D	-0.191***	-0.190***	-0.119*	-0.192***	-0.195***	-0.168**
	(-4.00)	(-3.98)	(-1.77)	(-3.99)	(-4.06)	(-2.21)
Capex	-0.261***	-0.262***	-0.159	-0.251***	-0.263***	-0.267***
	(-3.41)	(-3.42)	(-1.64)	(-3.26)	(-3.41)	(-2.65)
Sales growth	-0.000	-0.000	0.004	-0.000	-0.000	-0.000
	(-1.07)	(-1.06)	(0.67)	(-1.12)	(-1.06)	(-0.25)
Constant	-0.232	-0.256	-0.185	-0.072	-0.224	-1.554***
	(-0.71)	(-0.78)	(-0.47)	(-0.22)	(-0.69)	(-3.18)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,434	26,434	16,224	26,240	26,335	14,140
Pseudo R^2	0.084	0.084	0.089	0.084	0.084	0.083

Table 2.3 Channel Analysis

This table presents channels of proxies for CEO risk-taking behaviour through which *PID* affects the acquisition likelihood. The CEO's risk-taking behaviour is proxied by CEO overconfidence, founder CEO, and sensitivity of pay for performance. Panel A, Panel B, and Panel C report whether the overconfident CEOs, founder CEOs, and higher pay for performance sensitivity of CEOs in high *PID* firms are more likely to engage in acquisitions, respectively. In Panel A, CEO overconfidence, a binary variable, equals one if the CEO holds stock options of more than 67% in the money (Malmendier and Tate, 2005; Campbell et al., 2011), otherwise zero. In Panel B, the CEO as founder, an indicator variable, takes the value of one if the CEO is also the founder of the firm. In Panel C, pay for performance sensitivity (PPS) of CEOs, the annual change of the sum of salary and bonus. Columns (1) to (3) in Panel A, Panel B, and Panel C present regression results of different channels on the firm-level *PID*. Columns (4) and (5) of Panel A and Panel B report results of acquisition likelihood on *PID* between CEO and board for subsamples of firms with overconfident CEOs comparing propensity score matching (PSM) matched firms with non-overconfident CEOs; firms with founder CEOs comparing PSM matched firms with non-founder CEOs, respectively. The PSM approach is employed to find firms with identical characteristics of overconfident CEO and founder CEO firms. In Columns (4) and (5) of Panel C, the firms are separated by a median of PPS. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variables definitions are provided in the Appendix A.

Panel A: CEO Overconfidence					
	CEO Overconfidence dummy			*Acquisition likelihood*	
	(1)	(2)	(3)	(4)	(5)
Variables				Overconfident	Non-overconfident
PID	0.038***	0.034***	0.026*	0.298***	0.133
	(3.21)	(2.83)	(1.78)	(3.56)	(1.54)
Controls	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
N	27,319	26,434	26,434	4,996	4,846
Adjusted R^2	0.000	0.058	0.095		
Pseudo R^2				0.090	0.094

Panel B: CEO as founder					
	CEO as founder dummy			*Acquisition likelihood*	
	(1)	(2)	(3)	(4)	(5)
Variables				CEO Founder	CEO Non-Founder
PID	-0.026***	-0.025***	-0.012**	0.528**	0.188
	(-4.86)	(-4.54)	(-2.21)	(2.06)	(0.84)
Controls	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
N	27,319	26,434	26,434	830	835
Adjusted R^2	0.001	0.070	0.129		

Pseudo R^2				0.176	0.152

Panel C: Pay for performance sensitivity (PPS)

	PPS			*Acquisition likelihood*	
	(1)	(2)	(3)	(4)	(5)
Variables				High *PPS*	Low *PPS*
PID	1.313	9.351	24.455**	0.134**	0.117*
	(0.10)	(0.465)	(1.98)	(2.13)	(1.83)
Controls	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
N	22,214	22,214	17,479	8,669	8,846
Adjusted R^2	0.000	0.085	0.057		
Pseudo R^2				0.083	0.096
F-statistics (Prob > F)				16.22 (0.000)	

Table 2.4 Propensity Score Matching (PSM)

This table presents the results of the propensity score matching approach (PSM). First, we split the full sample into above and below the median *PID* within each year. The treatment group are firms with *PID* higher than the median, others in the control group. The matching variable matrix is based on the CEO, board, and firm characteristics used in Table 2 and the year and industry fixed effects. Panel A presents the results for the difference-in-means of control variables between the treatment and control groups with the *p*-values after matching to show that the PSM analysis removes sample selection biases. Panel B Columns 1 and 2 show the results of pre- and post-match regressions. Panel B Column 3 presents the probit regression results of acquisition likelihood based on the matched sample. We use the same control variables as the baseline regressions. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Comparison of means of matched sample after matching

Variables	Treated	Control	*P*-value
CEO age	4.018	4.017	0.612
CEO tenure	1.764	1.749	0.176
CEO female	0.038	0.039	0.658
Board size	2.277	2.279	0.403
Firm size	7.592	7.585	0.737
Tobin's Q	2.145	2.144	0.934
Leverage	0.679	0.702	0.125
Cash to assets	0.167	0.165	0.576
R&D	0.035	0.034	0.383
Capex	0.047	0.047	0.895
Sales growth	0.098	0.098	0.928

Panel B: Regressions with matched sample

Variables	Pre-match	Post-match	*Dependent variable: Acquisition likelihood*
	(1)	(2)	(3)
PID			0.152***
			(3.01)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	26,397	14,210	14,052
Pseudo R^2	0.034	0.002	0.092

Table 2.5 Two-stage Instrumental Variable (IV) Approach

This table presents the results of two-stage least square regressions. Column (1) reports the first-stage regression where *PID* is the dependent variable. The instrumental variable is the *PID* constructed by 7-year lagged values of the individual's prior *REP* index. Column (2) shows the second-stage regression where the dependent variable is the acquisition likelihood. The dependent variable in Column (1) is the firm level *PID* at year *t*, and in Column (2) is the acquisition likelihood at year *t+1*. We control the same variables as in Table 2. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	First Stage	Second Stage
Variables	(1) *PID*	(2) *Acquisition likelihood*
PID (*prior lag 7*)	0.390***	
	(59.30)	
Instrumented PID		0.063**
		(2.03)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Cragg-Donald F-statistic	5162.467***	
Kleibergen-Paap Wald F-statistic	3516.630***	
2SLS Size of Nominal 5% Wald	16.380	
LIML Size of Nominal 5% Wald	16.380	
N	26,434	26,434
Adjusted R^2	0.206	0.102

Table 2.6 Difference in Difference (DID) Approach

This table presents the results of difference-in-difference (DID) regressions using the Trump 2016 election as an exogenous shock. The treated firms are defined as firms with *PID* multiplied by a negative one below the median in a specific fiscal year t. *Post* is an indicator variable taking the value of one after 2016 and otherwise zero. The dependent variable in Column (1) is the firm level *PID* at year *t*, and in Column (2) is the acquisition likelihood at year *t+1*. We control the same variables as in Table 2. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

DID		
	2016 Trump Election	
Variables	(1) *PID*	(2) *Acquisition likelihood*
Post-event	-0.091***	-0.815***
	(-9.46)	(-12.32)
Treated		-0.059***
		(-3.23)
Treated × Post event		0.115***
		(2.64)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	26,434	26,434
Adjusted R^2	0.051	
Pseudo R^2		0.084

Table 2.7 Robustness Checks

This table presents the robustness results for the effect of *PID* between CEO and board members on the likelihood of engaging acquisitions for all public firms listed in the U.S., excluding financial firms and regulated utilities, where we can obtain available financial data, CEO, and board of directors' data from 1999 to 2019. *PID* is used as a main explanatory variable. See Section 2 and the Appendix A for the definition of *PID*, *PID strong*, *PID extreme*, and *PID prior*. Panel A and Panel B present marginal effects from probit regressions. The dependent variable, Acquisition likelihood, takes the value of 1 if a firm makes at least one acquisition announcement in year t+1 (where M&A announcements from 2000 to 2020) and zero otherwise. All *PID* between CEO and board room measures and firm-level variables are calculated at the end of the prior fiscal year t. Panel A shows the results of alternative measures of *PID*. Panel B reports results with additional control of the CEO's political affiliation and the average political affiliation of board members. In all models, we control year and industry-fixed effects. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: With alternative measures of *PID*						
	Dependent variable: *Acquisition likelihood*					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PID strong	0.048***					
	(3.64)					
PID extreme		0.029***				
		(2.58)				
PID cfscore			0.039***			
			(3.46)			
PID prior				0.045***		
				(3.71)		
PID strong prior					0.028**	
					(2.51)	
PID extreme prior						0.044***
						(3.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,434	26,434	26,434	26,339	26,339	26,339
Pseudo R^2	0.084	0.084	0.084	0.084	0.084	0.084

Panel B: With additional control of *CEO REP index* and *directors REP index*						
	Dependent variable: *Acquisition likelihood*					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PID	0.056***					
	(4.49)					
PID (excl. CEO on brd)		0.053***				
		(4.75)				
PID (excl. CEO on brd & nocontri)			0.067***			
			(6.09)			
PID (independent)				0.037***		
				(3.66)		
PID (inside)					0.040***	
					(3.88)	

PID (outside)						0.033***
						(3.49)
CEO REP index	-0.007	-0.006	-0.005	-0.005	-0.003	0.000
	(-1.35)	(-1.14)	(-0.73)	(-0.92)	(-0.56)	(0.03)
Directors REP	0.018	0.015	0.010	0.013	-0.002	0.011
index	(1.50)	(1.29)	(0.87)	(1.26)	(-0.17)	(1.31)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,434	26,434	16,224	26,240	26,335	14,140
Pseudo R^2	0.084	0.084	0.089	0.084	0.084	0.083

Table 2.8 Time to Complete the Acquisition

This table provides Tobit model results of the effect of *PID* on the duration of deal completion for the M&As sample from the SDC Database of US-listed firms between 2000 and 2020. M&A deals are applied for the selection as follows: i) excluding the minority stake purchases, recapitalizations, acquisitions of remaining interests, self-tenders, spin-offs, privatizations, reverse leverage buyouts, exchange offers, and repurchases; ii) requiring the bidder owned less than 10% shares of the target prior and to hold more than 50% after the acquisition. The dependent variable, denoted by *time to complete (log)*, is the natural logarithm of the number of days between announcement data and completion date. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variables definitions are provided in the Appendix A.

	Dependent variable: *time to complete (log)*					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PID	0.149***					
	(2.63)					
PID (excl. CEO on brd)		0.121**				
		(2.45)				
PID (excl. CEO on brd & no contri)			0.170***			
			(3.53)			
PID (independent)				0.064		
				(1.41)		
PID (inside)					0.074*	
					(1.70)	
PID (outside)						0.117***
						(3.09)
CEO age	0.161	0.162	0.129	0.149	0.153	0.184
	(1.48)	(1.48)	(0.94)	(1.35)	(1.39)	(1.32)
CEO tenure	-0.016	-0.016	-0.022	-0.014	-0.016	-0.011
	(-1.02)	(-1.03)	(-1.15)	(-0.90)	(-1.04)	(-0.58)
CEO female	0.085	0.085	-0.029	0.090	0.084	0.212*
	(0.99)	(0.99)	(-0.28)	(1.05)	(0.98)	(1.78)
Board size	0.062	0.069	0.059	0.084*	0.072	0.107*
	(1.35)	(1.50)	(1.09)	(1.66)	(1.49)	(1.85)
Deal value	0.167***	0.167***	0.174***	0.168***	0.168***	0.150***
	(16.65)	(16.65)	(15.10)	(16.55)	(16.66)	(11.84)
Public target	0.537***	0.537***	0.514***	0.539***	0.534***	0.536***
	(21.29)	(21.30)	(17.18)	(21.24)	(21.08)	(16.67)
Diversify	-0.046*	-0.046*	-0.019	-0.047*	-0.047*	-0.048
	(-1.72)	(-1.73)	(-0.59)	(-1.76)	(-1.74)	(-1.39)
Incl. stock payment	0.095**	0.094**	0.083*	0.094**	0.093**	0.107**
	(2.48)	(2.47)	(1.85)	(2.45)	(2.42)	(2.35)
All cash payment	-0.047*	-0.047*	-0.027	-0.047*	-0.046*	-0.069**
	(-1.77)	(-1.75)	(-0.84)	(-1.77)	(-1.73)	(-2.09)
Friendly	-0.167**	-0.167**	-0.135	-0.162**	-0.166**	-0.180
	(-2.09)	(-2.09)	(-1.45)	(-2.02)	(-2.09)	(-1.64)
Size	-0.005	-0.005	-0.012	-0.006	-0.004	0.009
	(-0.51)	(-0.47)	(-1.00)	(-0.60)	(-0.38)	(0.67)
Relative size	0.001	0.001	-0.000	0.001	0.001	0.043***
	(0.44)	(0.46)	(-0.07)	(0.44)	(0.54)	(2.73)

Constant	2.427***	2.412***	2.941***	2.479***	2.481***	2.198***
	(4.90)	(4.87)	(5.09)	(5.00)	(5.00)	(3.67)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,213	5,213	3,538	5,178	5,187	3,171
Pseudo R^2	0.115	0.115	0.129	0.115	0.115	0.131

Table 2.9 Acquirers Performance

This table presents the results of OLS regressions for the effect of *PID* on acquirer short-run stock returns, long-term stock returns, and operating performance. The M&A sample consists of all deal announcements reported in the SDC database between 2000 and 2020 that were described previously. In Panel A, the dependent variable is a three-day (-1, +1) cumulative abnormal return (CAR) for acquirers around the deal announcement date, calculated using a market model where the market return is the CRSP value-weighted index return, with the parameters estimated over the period starting 241 days and ending 41 days precede the announcement date. Control variables include CEO age, CEO tenure, CEO female, board size, deal value, public target, diversify, friendly, tender, including stock payment, all cash payment, firm size, relative size, leverage, runup, sigma, Tobin's Q, cashflow, and industry and year fixed effects. Panel B reports the results of the acquirer's long-run stock performance. The dependent variables are 1-, 2-, 3-, 4-, and 5-year buy-and-hold abnormal returns (BHARs) after the deal completion date. The BHARs are computed using the matched firm-adjusted method suggested by Barber and Lyon (1997) and Lyon, Barber, and Tsai (1999), details of calculation are provided in Appendix A. We include the same control variables as in Panel A. Panel C and Panel D report the results of change in ROAs and EBITs, respectively. Panel C shows the change in return on assets (ROA), where the ROA is the bidder's operating income before depreciation divided by total assets. The change in ROA is defined as the ROA in years $t + 1$, $t + 2$, $t + 3$, $t + 4$, and $t + 5$ minus its ROA in year $t – 1$, where t is the year of the deal announcement. Panel D shows the change in earnings before interests and taxes ratio (EBIT/Total assets), defined as the bidder's EBIT divided by total assets in years $t + 1$, $t + 2$, $t + 3$, $t + 4$, and $t + 5$ minus its EBIT ratio in year $t – 1$, where t is the year of the deal announcement. We add the last fiscal year's ROA or EBIT ratio prior to the deal announcement to control variables, and other controls are the same as Panel A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variables definitions are provided in the Appendix A.

Panel A: CARs (-1, +1)						
	Dependent variable: *3-day acquirer CARs*					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PID	-0.006					
	(-1.41)					
PID (excl. CEO on brd)		-0.005				
		(-1.34)				
PID (excl. nocontri)			-0.001			
			(-0.36)			
PID (independent)				-0.004		
				(-1.12)		
PID (inside)					-0.004	
					(-1.06)	
PID (outside)						-0.001
						(-0.37)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7,449	7,449	4,891	7,420	7,416	4,355

Adjusted R^2	0.076	0.076	0.084	0.076	0.076	0.113

Panel B: BHARs

	Dependent variable: *acquirer BHARs*				
	(1)	(2)	(3)	(4)	(5)
Variables	1-year	2-year	3-year	4-year	5-year
PID	0.037*	0.082**	0.123***	0.135**	0.201***
	(1.65)	(2.29)	(2.59)	(2.21)	(2.71)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	6,320	6,322	6,292	6,088	5,838
Adjusted R^2	0.083	0.104	0.112	0.124	0.139

Panel C: Change in ROAs

	Dependent variable: *change in ROAs*				
	(1)	(2)	(3)	(4)	(5)
Variables	1-year	2-year	3-year	4-year	5-year
PID	0.245	0.271	1.128*	1.358**	1.703***
	(0.37)	(0.41)	(1.90)	(2.08)	(2.61)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	7,075	6,665	6,195	5,705	5,171
Adjusted R^2	0.308	0.335	0.333	0.326	0.340

Panel D: Change in EBITs

	Dependent variable: *change in EBITs*				
	(1)	(2)	(3)	(4)	(5)
Variables	1-year	2-year	3-year	4-year	5-year
PID	0.001	0.005	0.008*	0.013***	0.018***
	(0.26)	(1.10)	(1.82)	(2.71)	(3.49)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	7,139	6,826	6,476	6,019	5,527
Adjusted R^2	0.359	0.388	0.408	0.382	0.399

Table 2.10 The Role of Monitoring in Long-term Acquisition Performance

This table shows the role of monitoring and corporate governance in affecting the long-term performance of acquisitions. The Table first reports the effect of *PID* on board meetings at year *t+1* distinguished by whether the firm was involved in acquisitions at year *t* in Panel A and Panel B. The dependent variable in Panel A is the number of annual board meetings at year *t+1* obtained from Execucomp. The dependent variable in Panel B is the abnormal number of annual board meetings, defined as a firm's number of board meetings minus the average board meetings within the industry in each year *t+1*. Column (1) represents firms who engaged in acquisitions at year *t*, Column (2) represents firms who are not involved in acquisitions at year *t*, and Column (3) represents all firms with additional control of *acquisition likelihood* and the interaction term of *PID* multiply with *acquisition likelihood*. Then, in Panel C and Panel D, the table presents the role of corporate governance, represented by the institutional ownership and proportion of independent directors, in improving the firm post-deal long-term performance in higher *PID* firms. In Panel C, it shows the relationship between the *PID* and the proxies of corporate governance. The dependent variable in Column (1) is institutional ownership, denoted as the percentage of shares owned by institutions from Thomson Reuters institutional holdings-Form 13F. The dependent variable in Column (2) is the proportion of independent directors, computed as the number of independent directors scaled by the total number of board members. Then, we partition the sample into firms with high or low institutional ownership based on the median of institutional ownership with each fiscal year and firms with a high proportion of independent directors or low independent directors based on the median of independent directors with each fiscal year. Finally, in Panel D, we compare the coefficients of the main explanatory variable, *PID*, on the effect of long-term performance for the high corporate governance level to the low corporate governance level. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variables definitions are provided in the Appendix A.

Panel A: Number of board meeting			
	Dependent variable: *Number of board meeting*		
	Acquisition likelihood = 1	*Acquisition likelihood = 0*	*All*
Variables	(1)	(2)	(3)
PID	0.680**	-0.414*	-0.241**
	(2.56)	(-1.94)	(-2.08)
Acquisition likelihood			0.299***
			(4.13)
PID×Acquisition likelihood			0.558***
			(3.06)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	2,541	3,891	6,432
Adjusted R^2	0.063	0.082	0.077
Panel B: Abnormal number of board meeting			
	Dependent variable: *Abnormal number of board meeting*		

Variables	*Acquisition likelihood = 1* (1)	*Acquisition likelihood = 0* (2)	*All* (3)
PID	0.653**	-0.439**	-0.254**
	(2.46)	(-2.07)	(-2.19)
Acquisition likelihood			0.300***
			(4.12)
PID×Acquisition likelihood			0.559***
			(3.06)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	2,541	3,891	6,432
Adjusted R^2	0.028	0.035	0.031

Panel C: *PID* and institutional ownership or independent directors

Variables	Institutional ownership (1)	Proportion of independent directors (2)
PID	0.064**	0.140***
	(1.99)	(4.07)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	7,270	7,466
Adjusted R^2	0.185	0.126

Panel D: BHAR 3 year

	Above or below median of institutional ownership		Above or below median of proportion of independent directors	
Variables	(1) Above	(2) Below	(3) Above	(4) Below
PID	0.212***	0.022	0.143**	0.090
	(3.32)	(0.29)	(2.01)	(1.38)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3,483	2,692	2,889	3,403
Adjusted R^2	0.087	0.123	0.088	0.092

Table 2.11 Political Connections of CEO Partisanship and Party in Power

This table explores whether the effect of *PID* on acquisition likelihood is differentiated by the connections of CEO partisanship and party in power. In Columns (1) to (3) of both Panel A and Panel B, we show the relationship between *PID* and the connections of CEO partisanship and party in power. The dependent variable, *CEO & Guber same party* in Panel A (or *CEO & President same party* in Panel B), is the partisan similarity between a firm's CEO and the gubernatorial party (or the president party). The partisan similarity takes the value of 1 when the CEO and the gubernatorial party (or the president party) are the same, where the absolute difference between the CEO REP index and the gubernatorial party (or the president party) REP is less than one, otherwise zero. Column (4) of both Panel A and Panel B examines the influence of *PID* on the acquisition likelihood with additional control of the connection between the CEO and the party in power. In Columns (5) and (6), we split the sample into two groups to test the effect of *PID* on acquisition likelihood, where Column (5) are firms with CEO's partisanship same as the party in power, and Column (6) are firms with CEO's partisanship different as the party in power. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: ***CEO partisanship & Gubernatorial party in power***						
	CEO & gubernatorial same party			*Acquisition likelihood*		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables				All	Same Party	Different Party
PID	-0.515***	-0.492***	-0.467***	0.109***	0.134***	0.082
	(-43.30)	(-39.75)	(-37.17)	(2.89)	(2.90)	(1.19)
CEO & Guber same party				-0.099***		
				(-5.22)		
Controls	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
N	27,319	26,434	26,434	26,434	18,738	7,696
Adjusted R^2	0.068	0.085	0.105			
Pseudo R^2				0.085	0.081	0.093

Panel B: ***CEO partisanship & President party in power***						
	CEO & president same party			*Acquisition likelihood*		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables				All	Same Party	Different Party
PID	-0.541***	-0.525***	-0.491***	0.128***	0.214***	-0.016
	(-46.74)	(-43.64)	(-40.39)	(3.38)	(4.71)	(-0.22)
CEO & Pres same party				-0.056***		
				(-2.79)		
Controls	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
N	27,319	26,434	26,434	26,666	19,154	7,280

Adjusted R^2	0.077	0.088	0.182	0.084		
Pseudo R^2					0.083	0.099

Table 2.12 Additional Analysis

This table presents the *PID* on the likelihood of M&As on different firm operating conditions regarding financial constraint, cash flow volatility, and investment opportunity. Panel A reports the effect of *PID* on the acquisition likelihood distinguished by the firm financial constraints. We measure firm external financial constraints as suggested by the Whited and Wu index (2006). Panel B presents the effect of *PID* on the acquisition likelihood differentiated by the firm cash flow volatility, where the cash flow volatility is calculated as the standard deviation of operating cash flows since the prior seven years scaled by the mean of operating cash flows followed by Minton and Schrand (1999). Panel C and Panel D report the relationship of *PID* and the acquisition likelihood on the different conditions of investment opportunities as proxied by Tobin's Q and sales growth. Columns (1) and (2) in Panel A and Panel B, and Columns (1) to (4) in Panel C report results of acquisition likelihood on *PID* between CEO and board for subsamples of firms partitioned by median of financial constraints, cash flow volatility, Tobin's Q, and sales growth within a year. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Firm financial constraints		
Dependent variable: Acquisition likelihood	*Financial constraints*	
	(1)	(2)
Variables	*High*	*Low*
PID	0.056	0.215***
	(1.04)	(3.87)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	11,861	12,446
Pseudo R^2	0.081	0.078

Panel B: Cash flow volatility		
Dependent variable: Acquisition likelihood	*Cash flow volatility*	
	(1)	(2)
Variables	*High*	*Low*
PID	0.198***	0.036
	(3.68)	(0.65)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	11,836	11,983
Pseudo R^2	0.077	0.093

Panel C: Investment opportunity				
Dependent variable: Acquisition likelihood				
	Tobin's Q		*Sales growth*	
	(1)	(2)	(3)	(4)
Variables	*High*	*Low*	*High*	*Low*
PID	0.238***	0.099	0.229***	0.085
	(3.68)	(1.64)	(4.52)	(0.59)
Controls	Yes	Yes	Yes	Yes

Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	13,025	13,409	11,836	11,983
Pseudo R^2	0.105	0.084	0.077	0.093

Appendix A. Definitions of Variables and Complementary Tables (Essay One)

Appendix A1. Definitions of Variables (Essay One)

Variable	Definition
Dependent variables	
Acquisition likelihood	Binary variable takes the value of 1 where the firm makes at least one acquisition bid in year *t+1*.
Time to complete (log)	Natural logarithm of days between the deal announced date and effective date.
CAR (-1, +1)	Acquirers' cumulative abnormal return (CAR) in the 3-day event window (-1, +1), where 0 is the announcement day. The returns are computed using the market model with the market model parameters estimated over the period starting 241 days and ending 41 days prior to the announcement. The market index is the CRSP value-weighted index.
BHAR (completion, +t)	Buy and hold abnormal returns (BHAR) are calculated using the matched firm by size and market-to-book ratio method suggested by Barber and Lyon (1997) and Barber et al. (1999) for 1-, 2-, 3-, 4-, and 5- year period after the deal completion.
ROA change (-1, +t)	Acquirer's operating income before depreciation divided by total assets 1-, 2-, 3-, 4-, and 5-years after the deal announcement, minus the value in the year before the deal announcement.
EBIT change (-1, +t)	Acquirer's earnings before interest and tax divided by total assets 1-, 2-, 3-, 4-, and 5-years after the deal announcement, minus the value in the year prior to the deal announcement.
Key independent variables	
PID	Political ideology divergence between the CEO and all board members, using individual REP index.
PID (excl. CEO on brd)	Political ideology divergence between the CEO and board members excludes the CEO who also holds a role on the board, using individual REP index.
PID (excl nocontri)	Political ideology divergence between the CEO and board members excluding the individual without contribution records, using individual REP index.
PID (independent)	Political ideology divergence between the CEO and independent directors, using individual REP index.
PID (inside)	Political ideology divergence between the CEO and inside directors, using individual REP index.
PID (outside)	Political ideology divergence between the CEO and outside directors, using individual REP index.
PID (strong)	Political ideology divergence between the CEO and all board members, based on the individual's political ideology equals one if he/she donates to Republicans $2,000 more than to Democrats and otherwise equals zero.
PID (extreme)	Political ideology divergence between the CEO and all board members, based on whether the individual exclusively donates to the Republican party. If an individual's donations are solely directed towards the Republican party, his/her political ideology takes a value of one, otherwise zero.
PID (cfs)	Political ideology divergence between the CEO and all board members, where individual political ideology defined by Bonica (2016) using one's total contribution from 1979 to 2014. See Bonica (2016) for more details on the *cfscore*.
PID (prior)	Political ideology divergence between the CEO and all board members, a time-variant measure, where individual political ideology is constructed on individual total donations prior to each firm fiscal year *t*.
PID (strong prior)	Political ideology divergence between the CEO and all board members, a time-variant measure, where individual political ideology is constructed on that individual historical net donations of more than $2000 prior to each firm fiscal year t is one, otherwise zero.
PID (extreme prior)	Political ideology divergence between the CEO and all board members, a time-variant measure, where individual political ideology is constructed on that individual political ideology equals to one if his/her

	historical donations only went to Republicans prior to each firm fiscal year t, otherwise zero.
PID (prior lag7)	Political ideology divergence between the CEO and all board members, a time-variant measure, where individual political ideology is constructed as the 7-year lagged values of the individual's prior REP index.
CEO REP index	CEO political ideology, ranging from -1 (Democrat) to 1 (Republican), computed as the ratio of the net political contribution made to the Republican Party over the summation of donations made to both Republican and Democratic Parties.
Director REP index	The average political ideology of board members, ranging from -1 (Democrat) to 1 (Republican), computed as an equal average of the individual REP index, where the individual REP index is the ratio of the net political contribution made to Republican Party over the summation of contributions made to both Republican and Democratic Parties.
Control variables	
CEO age (log)	Natural logarithm of CEO age in the given year.
CEO tenure (log)	Natural logarithm of the number of years the CEO had held his/her chief executive officer position in the given year of the given firm.
CEO female	Binary variable takes the value of 1 where the gender of the CEO is female.
CEO founder	Binary variable takes the value of 1 where the CEO is a founder of the firm.
Board size (log)	Natural logarithm of the number of directors on the board.
Firm size (log)	Natural logarithm of total assets.
Tobin's Q	Market value of total assets over book value of total assets.
Leverage	Long-term debt and current liabilities divided by the market value of total assets.
Cash to assets	Cash and short-term investments divided by total assets.
R&D	Research and development expenses divided by total assets.
CAPEX	Capital expenditures divided by total assets.
Sales growth	Sales minus prior year sales, divided by prior year sales.
Overconfidence CEO	A binary variable takes the value of one if the CEO's stock options are more than 67% in the money, otherwise zero.
CEO as founder	A binary variable takes the value of one if the CEO is also the founder of the firm, otherwise zero.
Pay for performance sensitivity (PPS)	Annual change of the amount of salary and bonus.
Financial constraints	Firm financial constraints index, defined by Whited and Wu (2006). See Whited and Wu (2006) Equation (13) for details.
Cash flow volatility	Standard deviation of operating cashflows since the prior seven years scaled by the mean of these operating cashflows.
CEO as chairman	A binary variable takes the value of one if the CEO also holds a position as a chairman on the board in the specific year at a specific firm.
% of insiders	The percentage of the non-independent directors on board.
CEO pay slice	The CEO's total annual compensation divided by the sum of the board of directors' compensations.
CEO & gubernatorial same party	A binary variable takes the value of one it the difference between the CEO Rep index and the gubernatorial party in power is smaller than one, otherwise zero.
CEO & president same party	A binary variable takes the value of one it the difference between the CEO Rep index and the president party in power is smaller than one, otherwise zero.
Number of board meeting	The number of annual board meetings.
Abnormal number of board meeting	The difference between a firm's number of annual board meetings and the average of board meetings within the industry-year.
Deal value (log)	Natural logarithm of value of the transaction from SDC.
Public target	A binary variable where 1 signifies that the target is listed.
Diversify	A binary variable where 1 signifies that the first 2 digits of SICs of the acquirer and the target are different.
Payment incl. stock	A binary variable takes the value of 1, where the payment of acquisitions includes a percentage of stock payment.
All cash payment	A binary variable takes the value of 1, where the payment of acquisitions is 100% cash.
Friendly	A binary variable where 1 signifies that the deal attitude is friendly.
Tender	A binary variable where 1 signifies that the deal is a tender offer.

Size (log)	Natural logarithm of acquirer market value one month prior to the announcement.
Relative Size	The ratio of deal value to acquirer market value one month prior to the deal announcement.
Runup	Market-adjusted buy-and-hold return of the acquirer's stock over the period beginning 205 days and ending 6 days prior to the announcement date.
Sigma	Standard deviation of the acquirer's market-adjusted daily returns over the period starting 205 and ending 6 days before the deal announcement
Cashflow	Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the number of shares outstanding multiplied by the closing stock price at the fiscal year-end prior to the announcement.
ROA prior	Ratio of operating income before depreciation to the book value of total assets the year prior to the deal announcement.
EBIT prior	Acquirer's earnings before interest and tax divided by total assets the year prior to the deal announcement.
Institutional ownership	Percentage of stocks owned by institutional holders from Thomson Reuters institutional holdings.
Independent directors	Proportion of independent directors on the board, the number of independent directors scaled by the total number of board members.

Appendix A2. Complementary Tables (Essay One)

Table A2.1 Summary Statistics

This table presents the complementary summary statistics for the baseline sample of US-listed firms with available data of CEO from Execucomp, directors from BoardEx, and firm financial data from Compustat and CRSP during 1999-2019, and summary statistics for the M&A sample of deals announced by US public acquirers from SDC during 2000-2020. The table reports the number of observations (N), mean, standard deviation (SD), 25th percentile, median, and 75th percentile for the full sample in Panel A and the M&As sample in Panel B. Definitions of all variables are provided in the Appendix A.

	N	Mean	SD	25th Pct	Median	75th Pct
Panel A: Full Sample						
PID (excl. CEO on brd)	26,434	0.604	0.259	0.427	0.570	0.744
PID (excl nocontri)	16,223	0.518	0.344	0.265	0.536	0.738
PID (independent)	26,240	0.610	0.284	0.416	0.579	0.769
PID (inside)	26,335	0.602	0.277	0.416	0.567	0.752
PID (outside)	14,140	0.625	0.416	0.333	0.586	0.918
PID (strong)	26,434	0.351	0.223	0.167	0.333	0.500
PID (extreme)	26,434	0.205	0.248	0	0.125	0.250
PID (cfs)	26,434	0.552	0.254	0.381	0.519	0.680
PID (prior)	26,339	0.524	0.235	0.360	0.497	0.660
PID (strong prior)	26,339	0.322	0.230	0.143	0.286	0.500
PID (extreme prior)	26,339	0.213	0.250	0	0.125	0.267
PID (lag7)	26,434	0.440	0.251	0.259	0.407	0.579
CEO REP index	26,434	0.196	0.563	0	0	0.779
Director REP index	26,434	0.126	0.274	-0.052	0.131	0.315
Panel B: M&As Sample						
PID	7,449	0.578	0.229	0.419	0.558	0.711
PID (excl. CEO on brd)	7,449	0.637	0.260	0.457	0.604	0.785
PID (excl nocontri)	4,891	0.568	0.321	0.373	0.582	0.772
PID (independent)	7,420	0.643	0.286	0.444	0.614	0.818
PID (inside)	7,416	0.629	0.282	0.437	0.601	0.792
PID (outside)	4,355	0.672	0.433	0.382	0.617	0.949
Time to complete (log)	5,213	3.878	0.962	3.367	3.892	4.466
CAR (-1, +1)	7,449	0.006	0.083	-0.019	0.003	0.029
BHAR (completion, +1)	6,305	-0.013	0.333	-0.224	-0.028	0.173
BHAR (completion, +2)	6,307	-0.011	0.513	-0.343	-0.054	0.244
BHAR (completion, +3)	6,277	-0.001	0.681	-0.442	-0.072	0.317
BHAR (completion, +4)	6,073	0.012	0.856	-0.545	-0.092	0.402
BHAR (completion, +5)	5,823	0.032	1.044	-0.636	-0.110	0.493
ROA change (-1, +1)	7,075	-2.171	9.511	-3.945	-0.795	1.470
ROA change (-1, +2)	6,651	-2.164	9.605	-4.446	-0.828	1.702
ROA change (-1, +3)	6,174	-1.764	8.605	-4.574	-0.888	2.041
ROA change (-1, +4)	5,685	-1.736	8.971	-4.953	-0.861	2.035
ROA change (-1, +5)	5,154	-1.792	8.960	-4.599	-1.073	1.899
EBIT change (-1, +1)	7,139	-0.016	0.068	-0.038	-0.009	0.014
EBIT change (-1, +2)	6,817	-0.017	0.073	-0.044	-0.011	0.016
EBIT change (-1, +3)	6,469	-0.015	0.073	-0.047	-0.011	0.020
EBIT change (-1, +4)	6,012	-0.016	0.074	-0.051	-0.013	0.021
EBIT change (-1, +5)	5,519	-0.019	0.077	-0.054	-0.016	0.019
CEO age (log)	7,449	4	0.135	3.912	4.007	4.094
CEO tenure (log)	7,449	1.728	0.870	1.099	1.792	2.303
CEO female	7,449	0.020	0.141	0	0	0
Board size (log)	7,449	2.259	0.289	2.079	2.303	2.485
Deal value (log)	7,449	4.610	1.860	3.314	4.575	5.858
Public target	7,449	0.168	0.374	0	0	0
Diversify	7,449	0.416	0.493	0	0	1
Friendly	7,449	0.977	0.151	1	1	1
Tender	7,449	0.046	0.210	0	0	0
Incl. stock payment	7,449	0.100	0.301	0	0	0

All cash payment	7,449	0.422	0.494	0	0	1
Size (log)	7,449	8.086	1.745	6.866	7.897	9.188
Relative size	7,449	0.137	0.439	0.010	0.034	0.110
Leverage	7,449	0.207	0.178	0.049	0.193	0.309
Runup	7,449	-0.022	0.466	-0.206	-0.014	0.167
Sigma	7,449	0.105	0.681	0.016	0.021	0.029
Tobin's Q	7,449	2.311	1.480	1.403	1.856	2.633
Cashflow	7,449	0.059	0.131	0.037	0.059	0.089
ROA	7,075	5.840	7.178	3.109	6.005	9.312
EBIT	7,139	0.104	0.075	0.065	0.101	0.145

Table A2.2 Endogeneity Test: Entropy Balancing

This table presents the results of the entropy approach to the effect of *PID* on acquisition likelihood. First, we split the full sample into above and below the median *PID* within each year. The treatment group are firms with *PID* higher than the median, others in the control group. Following Ferri et al. (2018), we choose the mean, variance, and skewness as moment properties and the same matching variables in the propensity score matching (PSM) method with control of firm and industry effects to re-weight observations in control groups. After weighting the control variables from three-moment properties, these control variables should be identical in the treatment and control groups, thus, the covariate distribution balance is achieved. Panel A presents the differences in the means, variance, and skewness of variables in the treatment and control groups before entropy balancing. Panel B represents the three dimensions of the matched variables across treatment and control groups after entropy balancing. Panel C shows the results of *PID* on acquisition likelihood with entropy-weighted sample. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Before entropy balancing (without weighting)						
	Above or below median *PID*					
	Treat (N: 13233)			Control (N:13201)		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
CEO age	4.018	0.017	-0.237	4.008	0.018	-0.180
CEO tenure	1.760	0.768	-0.221	1.688	0.797	-0.112
CEO female	0.039	0.037	4.794	0.028	0.027	5.711
Board size	2.284	0.074	-0.048	2.218	0.080	0.105
Firm size	7.631	2.541	0.293	7.102	2.313	0.235
Tobin's Q	2.140	2.138	2.476	2.135	2.055	2.441
Leverage	0.712	3.689	1.908	0.609	3.040	2.108
Cash to assets	0.163	0.030	1.573	0.179	0.034	1.414
R&D	0.034	0.004	2.744	0.040	0.004	2.501
Capex	0.047	0.002	2.427	0.047	0.002	2.432
Sales growth	0.097	0.059	1.920	0.106	0.069	1.762

Panel B: After entropy balancing (with weighting)						
	Above or below median *PID*					
	Treat (N: 13233)			Control (N:13201)		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
CEO age	4.018	0.017	-0.237	4.018	0.017	-0.237
CEO tenure	1.760	0.768	-0.221	1.760	0.768	-0.221
CEO female	0.039	0.037	4.794	0.039	0.037	4.794
Board size	2.284	0.074	-0.048	2.284	0.074	-0.048
Firm size	7.631	2.541	0.293	7.631	2.541	0.293
Tobin's Q	2.140	2.138	2.476	2.140	2.138	2.476
Leverage	0.712	3.689	1.908	0.712	3.689	1.908
Cash to assets	0.163	0.030	1.573	0.163	0.030	1.573

R&D	0.034	0.004	2.744	0.034	0.004	2.744
Capex	0.047	0.002	2.427	0.047	0.002	2.427
Sales growth	0.097	0.059	1.920	0.097	0.059	1.920

Panel C: Regressions after entropy balancing

Variables	*Acquisition likelihood*
PID	0.150***
Controls	Yes
Industry FE	Yes
Year FE	Yes
N	26,434
Pseudo R^2	0.089

Table A2.3 Powerful CEO

This table displays the results of regression analysis examining how *PID* influences the acquisition likelihood across varying degrees of CEO power. CEO power is proxied as three measures, whether the CEO is also a chairman on the board in Panel A, the percentage of insiders on the board in Panel B, and the CEO pay slice in Panel C. In Panel A, Panel B, and Panel C, Column (1) adds the CEO power proxy as a control variable for all observations. Columns (2) and (3) in Panel A show results of acquisition likelihood on *PID* between CEO and board for subsamples of firms separated by CEO as chairman dummy. Columns (2) to (4) in Panel B report results for sample of firms separated into deciles by low, medium, and high percentage of insiders on board. And Columns (2) to (4) in Panel C present results for firms divided into deciles representing low, medium, and high level of CEO pay slice. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5% and 10% levels, respectively. Variables definitions are provided in the Appendix.

Panel A: CEO as chairman			
	Dependent variable: Acquisition likelihood		
	(1) All	(2) Yes	(3) No
Variables			
PID	0.155***	0.119**	0.177***
	(4.26)	(2.23)	(3.51)
CEO chairman	-0.005		
	(-0.28)		
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	26,434	13,225	13,209
Pseudo R^2	0.084	0.083	0.091

Panel B: % of insiders				
	Dependent variable: Acquisition likelihood			
	(1) All	(2) Low	(3) Medium	(4) High
Variables				
PID	0.142***	0.152**	0.147**	0.171***
	(3.90)			
% of insider	0.367***			
	(5.96)			
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	26,434	9,736	8,668	8,013
Pseudo R^2	0.085	0.100	0.091	0.090

Panel C: CEO pay slice				
	Dependent variable: Acquisition likelihood			
	(1) All	(2) Low	(3) Medium	(4) High

Variables				
PID	0.138***	0.026	0.247***	0.122
	(3.12)	(0.33)	(3.22)	(1.55)
CEO pay slice	-0.001			
	(-0.65)			
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	18,272	6,100	6,130	6,038
Pseudo R^2	0.095	0.092	0.102	0.108

Table A2.4 Board Partisanship and Party in Power

This table explores whether the effect of *PID* on acquisition likelihood is differentiated by the connections of board members' partisanship and party in power. In Columns (1) to (3) of both Panel A and Panel B, we show the relationship between *PID* and the connections of average board partisanship and party in power. The dependent variable, *board & gubernatorial same party* in Panel A (or *board & president same party* in Panel B), is the partisan similarity between a firm's average political REP index of board members and the gubernatorial party (or the president party). The partisan similarity takes the value of 1 when the average board political affiliation and the gubernatorial party (or the president party) are the same, where the absolute difference between the average board REP index and the gubernatorial party (or the president party) REP is less than on. Column (4) of both Panel A and Panel B examines the influence of *PID* on the acquisition likelihood with additional control of connection of board and party in power. In Columns (5) and (6), we split the sample into two groups to test the effect of *PID* on acquisition likelihood, where Column (5) are firms with board's partisanship same as the party in power, and Column (6) are firms with board's partisanship different as the party in power. All variables' definitions are provided in Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: ***Board partisanship & Gubernatorial party in power***						
	Board & gubernatorial same party			*Acquisition likelihood*		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PID	0.027**	0.028**	0.026*	0.156***	0.158***	0.154***
	(2.02)	(2.03)	(1.93)	(4.29)	(3.00)	(3.04)
Board & President same party				-0.075***		
				(-4.49)		
Controls	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
N	27,319	26,434	26,434	26,434	12,146	14,288
Adjusted R^2	0.000	0.003	0.021			
Pseudo R^2				0.085	0.084	0.090

Panel B: ***Board partisanship & President party in power***						
	Board & president same party			*Acquisition likelihood*		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PID	-0.018	-0.016	-0.008	0.155***	0.141***	0.164***
	(-1.38)	(-1.15)	(-0.60)	(4.25)	(2.75)	(3.15)
Board & President same party				-0.007		
				(-0.39)		
Controls	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
N	27,319	26,434	26,434	26,434	13,142	13,292
Adjusted R^2	0.000	0.001	0.138			

Pseudo R^2	0.084	0.086	0.086

Table A2.5 Additional Analysis: PID on the Likelihood of M&A vs. Capital Expenditure or R&D Expenditure

This table presents the estimated relations of alternative measures of *PID* on M&A decisions and capital expenditures (*CAPEX*) or research and development expenses (*R&D*) using seemingly unrelated regressions (SUR). In Panel A Columns (1) (3) (5) (7) (9) (11), the dependent variable takes the value of 1 if a firm makes at least one acquisition announcement in year $t+1$ and zero otherwise; in Column (2) (4) (6) (8) (10) (12), the dependent variable is the *CAPEX* divided by total assets in year $t+1$. And in Panel B Columns (1) (3) (5) (7) (9) (11), the dependent variable takes the value of 1 if a firm makes at least one acquisition announcement in year $t+1$ and zero otherwise; in Column (2) (4) (6) (8) (10) (12), the dependent variable is the *R&D* divided by total assets in year $t+1$. All variables' definitions are provided in the Appendix A. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: M&A vs CAPEX

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	*Acquisition likelihood*	*CAPEX*	*Acquisition likelihood*	*CAPEX*	*Acquisition likelihood*	*CAPEX*	*Acquisition likelihood*	*CAPEX*	*Acquisition likelihood*	*CAPEX*	*Acquisition likelihood*	*CAPEX*
PID	0.062***	0.001										
	(4.88)	(0.59)										
PID (excl. CEO on brd)			0.058***	0.001								
			(5.17)	(0.93)								
PID (excl. nocontri)					0.068***	-0.002**						
					(6.14)	(-2.25)						
PID (independent)							0.040***	0.001				
							(3.93)	(1.22)				
PID (inside)									0.048***	-0.001		
									(4.58)	(-1.30)		
PID (outside)											0.033***	0.004***
											(3.45)	(5.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	25,649	25,649	25,649	25,649	15,780	15,780	25,467	25,467	25,553	25,553	13,759	13,759
Adjusted R^2	0.101	0.411	0.101	0.411	0.109	0.456	0.102	0.414	0.101	0.413	0.102	0.422

Panel B: M&A vs R&D

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	*Acquisition likelihood*	*R&D*	*Acquisition likelihood*	*R&D*	*Acquisition likelihood*	*R&D*	*Acquisition likelihood*	*R&D*	*Acquisition likelihood*	*R&D*	*Acquisition likelihood*	*R&D*
PID	0.062***	0.003										
	(4.88)	(0.79)										
PID (excl. CEO on brd)			0.058***	0.001								
			(5.18)	(0.21)								
PID (excl. nocontri)					0.067***	0.006***						
					(6.09)	(3.06)						
PID (independent)							0.040***	0.001				
							(3.93)	(0.42)				
PID (inside)									0.048***	-0.000		
									(4.55)	(-0.17)		
PID (outside)											0.034***	0.004
											(3.54)	(1.27)
Controls			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	25,649	25,649	25,649	25,649	15,780	15,780	25,467	25,467	25,553	25,553	13,759	13,759
Adjusted R^2	0.102	0.139	0.102	0.139	0.109	0.185	0.102	0.139	0.102	0.139	0.102	0.082

Table A2.6 BHARs

This table reports the results of OLS regression analysis for the effect of alternative measures of *PID* on acquirer long-run stock performance. The sample consists of all mergers and acquisitions in 2000-2020 described previously. The dependent variables are 1-, 2-, 3-, 4-, and 5-year buy-and-hold abnormal returns (BHARs) after the deal completion date. The BHARs are computed using the matched firm-adjusted method suggested by Barber and Lyon (1997) and Lyon, Barber, and Tsai (1999). We include the same control variables as in Table 2.12. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variables definitions are provided in Appendix A.

BHARs															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Variables	1-year	3-year	5-year	1-year	3-year	5-year	1-year	3-year	5-year	1-year	3-year	5-year	1-year	3-year	5-year
PID (excl. CEO on brd)	0.035*	0.113***	0.176***												
	(1.78)	(2.70)	(2.70)												
PID (excl. nocontri)				0.015	0.104**	0.236***									
				(0.72)	(2.43)	(3.61)									
PID (independent)							0.035*	0.095**	0.164***						
							(1.91)	(2.49)	(2.68)						
PID (inside)										0.034*	0.084**	0.134**			
										(1.84)	(2.20)	(2.22)			
PID (outside)													0.020	0.047	0.072
													(1.29)	(1.47)	(1.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,320	6,292	5,838	4,142	4,134	3,912	6,295	6,267	5,813	6,292	6,264	5,810	3,678	3,679	3,579
R^2	0.083	0.112	0.139	0.096	0.132	0.174	0.083	0.110	0.138	0.081	0.110	0.137	0.115	0.152	0.171

Table A2.7 Operating Performance

This table presents the effects of alternative measures of *PID* on change in the operating performance of acquirers following acquisitions. Panel A shows the change in return on assets (ROA, which is operating income before depreciation scaled by total assets), defined as the bidder's ROA in year *t + 1, t + 3,* and *t + 5* minus its ROA in year *t – 1*, where *t* is the year of the deal announcement. Panel B shows the change in earnings before interests and taxes ratio (EBIT/Total assets), defined as the bidder's EBIT divided by total assets in year *t + 1, t + 3,* and *t + 5* minus its EBIT ratio in year *t – 1*, where *t* is the year of the deal announcement. We add the last fiscal year's ROA or EBIT ratio prior to the deal announcement to control variables, and other controls are the same as in Table 2.13. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variables definitions are provided in Appendix A.

Panel A: Change in ROAs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Variables	1-year	3-year	5-year	1-year	3-year	5-year	1-year	3-year	5-year	1-year	3-year	5-year	1-year	3-year	5-year
PID (excl. CEO on	0.250	1.089**	1.616***												
brd)	(0.43)	(2.10)	(2.80)												
PID (excl.				-0.190	1.229**	1.091**									
nocontri)				(-0.35)	(2.45)	(2.00)									
PID (independent)							0.515	0.990**	1.642***						
							(0.97)	(2.12)	(2.82)						
PID (inside)										0.260	0.823*	1.126**			
										(0.49)	(1.71)	(2.09)			
PID (outside)													0.535	1.107***	1.609***
													(1.09)	(2.83)	(3.71)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,075	6,195	5,171	4,674	4,147	3,521	7,054	6,175	5,149	7,044	6,167	5,146	4,149	3,776	3,337
R^2	0.308	0.333	0.340	0.374	0.384	0.363	0.311	0.337	0.343	0.308	0.332	0.346	0.351	0.362	0.349

Panel B: Change in EBITs

Variables	(1) 1-year	(2) 3-year	(3) 5-year	(4) 1-year	(5) 3-year	(6) 5-year	(7) 1-year	(8) 3-year	(9) 5-year	(10) 1-year	(11) 3-year	(12) 5-year	(13) 1-year	(14) 3-year	(15) 5-year
PID (excl. CEO on brd)	0.001	0.008*	0.017***												
	(0.32)	(1.94)	(3.78)												
PID (excl. nocontri)				-0.001	0.005	0.009**									
				(-0.37)	(1.31)	(1.98)									
PID (independent)							0.002	0.006*	0.018***						
							(0.64)	(1.71)	(4.00)						
PID (inside)										-0.000	0.003	0.010**			
										(-0.03)	(0.84)	(2.21)			
PID (outside)													0.006**	0.012***	0.015***
													(2.16)	(3.67)	(4.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,139	6,476	5,527	4,712	4,296	3,743	7,114	6,454	5,505	7,108	6,447	5,499	4,190	3,861	3,473
R^2	0.359	0.408	0.399	0.406	0.449	0.433	0.364	0.408	0.400	0.355	0.405	0.399	0.422	0.459	0.414

Table A2.8 The Role of Institutional Ownership in Post-deal Long-term Performance

This table presents the role of corporate governance, represented by institutional ownership, in improving the firm post-deal long-term performance in higher *PID* firms. Institutional ownership is denoted as the percentage of shares owned by institutions from Thomson Reuters institutional holdings (specifically Form 13F). We partition the sample into firms with high institutional ownership or low institutional ownership based on the median of institutional ownership with each fiscal year. Then we compare the coefficients of the main explanatory variable, *PID*, for the high institutional ownership level to the low institutional ownership level, comparing Column (1) to Column (2), Column (3) and Column (4), Column (5) and Column (6), Column (7) and Column (8), Column (9) and Column (10), respectively. Panel A, Panel B, and Panel C show the results of 1-, 2-, 3-, 4-, and 5-year BHARs, change in ROAs, and change in EBIT, respectively. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variables definitions are provided in Appendix A.

Panel A: BHARs

	Above or below median of institutional ownership									
Variables	(1) Above 1-year	(2) Below 1-year	(3) Above 2-year	(4) Below 2-year	(5) Above 3-year	(6) Below 3-year	(7) Above 4-year	(8) Below 4-year	(9) Above 5-year	(10)Below 5-year
PID	0.033	0.067*	0.110**	0.051	0.212***	0.022	0.311***	-0.041	0.419***	0.011
	(1.13)	(1.72)	(2.26)	(0.86)	(3.32)	(0.29)	(3.75)	(-0.42)	(4.15)	(0.09)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,502	2,701	3,502	2,703	3,483	2,692	3,363	2,612	3,217	2,509
Adjusted R^2	0.048	0.074	0.086	0.102	0.087	0.123	0.093	0.140	0.106	0.158

Panel B: Change in ROAs

	Above or below median of institutional ownership									
Variables	(1) Above 1-year	(2) Below 1-year	(3) Above 2-year	(4) Below 2-year	(5) Above 3-year	(6) Below 3-year	(7) Above 4-year	(8) Below 4-year	(9) Above 5-year	(10)Below 5-year
PID	0.061	0.668	0.739	0.135	1.889***	0.516	1.550*	1.162	2.132**	1.747*

	(0.07)	(0.61)	(0.87)	(0.12)	(2.72)	(0.51)	(1.87)	(1.04)	(2.51)	(1.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,803	3,097	3,532	2,973	3,242	2,812	2,943	2,635	2,623	2,438
Adjusted R^2	0.267	0.341	0.317	0.361	0.334	0.334	0.340	0.300	0.381	0.295

Panel C: Change in EBITs

	Above or below median of institutional ownership									
Variables	(1) Above 1-year	(2) Below 1-year	(3) Above 2-year	(4) Below 2-year	(5) Above 3-year	(6) Below 3-year	(7) Above 4-year	(8) Below 4-year	(9) Above 5-year	(10)Below 5-year
PID	-0.002	0.008	0.006	0.008	0.013**	0.002	0.019***	0.003	0.023***	0.013
	(-0.33)	(1.03)	(0.98)	(1.08)	(2.22)	(0.32)	(2.91)	(0.43)	(3.17)	(1.55)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,831	3,121	3,611	3,032	3,373	2,931	3,103	2,750	2,799	2,570
Adjusted R^2	0.313	0.399	0.350	0.436	0.376	0.436	0.374	0.395	0.406	0.383

Table A2.9 The Role of Independent Directors in Post-deal Long-term Performance

This table presents the role of corporate governance, represented by the proportion of independent director, in improving the firm post-deal long-term performance in higher *PID* firms. The proportion of independent directors is computed as the number of independent directors scaled by the total number of board members. We partition the sample into firms with a high proportion of independent directors or low independent directors based on the median of independent directors with each fiscal year. Then we compare the coefficients of the main explanatory variable, *PID*, for the high proportion of independent directors to the low proportion of independent directors, comparing Column (1) to Column (2), Column (3) and Column (4), Column (5) and Column (6), Column (7) and Column (8), Column (9) and Column (10), respectively. Panel A, Panel B, and Panel C show the results of 1-, 2-, 3-, 4-, and 5-year BHARs, change in ROAs, and change in EBIT, respectively. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variables definitions are provided in Appendix A.

Panel A: BHARs

	Above or below median of proportion of independent directors									
Variables	(1) Above 1-year	(2) Below 1-year	(3) Above 2-year	(4) Below 2-year	(5) Above 3-year	(6) Below 3-year	(7) Above 4-year	(8) Below 4-year	(9) Above 5-year	(10) Below 5-year
PID	0.062*	0.018	0.109**	0.054	0.143**	0.090	0.219**	0.030	0.294***	0.097
	(1.95)	(0.54)	(2.09)	(1.09)	(2.01)	(1.38)	(2.33)	(0.37)	(2.62)	(0.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,902	3,418	2,902	3,420	2,889	3,403	2,807	3,281	2,701	3,137
Adjusted R^2	0.065	0.038	0.078	0.076	0.088	0.092	0.099	0.102	0.108	0.121

Panel B: Change in ROAs

	Above or below median of proportion of independent directors									
Variables	(1) Above 1-year	(2) Below 1-year	(3) Above 2-year	(4) Below 2-year	(5) Above 3-year	(6) Below 3-year	(7) Above 4-year	(8) Below 4-year	(9) Above 5-year	(10) Below 5-year

PID	0.890	-0.406	1.181	-0.633	1.736**	0.560	1.639	1.041	2.334**	1.000
	(0.94)	(-0.43)	(1.23)	(-0.67)	(1.99)	(0.68)	(1.57)	(1.17)	(2.26)	(1.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,238	3,837	3,075	3,590	2,858	3,337	2,641	3,064	2,402	2,769
Adjusted R^2	0.271	0.306	0.302	0.336	0.318	0.313	0.311	0.303	0.345	0.318

Panel C: E Change in EBITs

	Above or below median of proportion of independent directors									
Variables	(1) Above 1-year	(2) Below 1-year	(3) Above 2-year	(4) Below 2-year	(5) Above 3-year	(6) Below 3-year	(7) Above 4-year	(8) Below 4-year	(9) Above 5-year	(10) Below 5-year
PID	0.000	0.001	0.008	0.002	0.009	0.008	0.015**	0.011*	0.025***	0.011
	(0.03)	(0.15)	(1.25)	(0.26)	(1.35)	(1.31)	(1.99)	(1.68)	(2.92)	(1.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,268	3,871	3,144	3,682	2,991	3,485	2,784	3,235	2,571	2,956
Adjusted R^2	0.319	0.361	0.355	0.394	0.400	0.402	0.376	0.368	0.382	0.389

3. Does Climate Change Exposure affect M&As?

3.1 Introduction

Merger and acquisition (M&A) represent one of the most critical corporate investment decisions to enhance firm value, achieve rapid growth, and adapt to an ever-evolving business environment (Andrade, Mitchell, and Stafford, 2001; Moeller, Schlingemann, and Stulz, 2004; Cartwright and Schoenberg, 2006). Moreover, over the past two decades the overall international M&A market has announced more than 790,000 deals worth more than $57.7 trillion (IMAA, 2020)[32], reflecting the significance of M&As in corporate strategies. The extant literature extensively discusses various determinants of M&As, that can influence the propensity of a firm to engage in such transactions, ranging from firm-specific attributes such as corporate liquidity, acquirer and target firm price valuation, CEO preferences (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004; Moeller and Schlingemann, 2019) and market conditions, such as industry shocks, product market competition, and market volatility (Harford, 2005; Martynova and Renneboog, 2008; Ahern and Harford, 2014; Bhagwat, Dam, and Harford, 2016), to regulatory environments, i.e., legal environment and policy uncertainty (Alimov, 2015; Nguyen and Phan, 2017). Still, there exists a growing interest in understanding the impact of environment, i.e., climate change, on global M&A activities. To this end, this study investigates the effect of climate change exposure on global M&As.

With growing concerns about global climate change, the implications of

[32] M&A Statistics, 2021, IMAA. Sourced from https://imaa-institute.org/mergers-and-acquisitions-statistics/.

environment-related uncertainties on corporate decision making cannot be underestimated. The Intergovernmental Panel on Climate Change (IPCC) is consistently drawing attention to the escalating threats of climate change – rising temperatures, sea-level surges, and the growing occurrences of catastrophic weather events etc. Moreover, the implementation of the Paris Agreement marks a shift to focus on how economies and businesses understand and respond to accelerating climate risks. In parallel, corporate structures and strategic decisions have recently been subject to greater scrutiny over how to tackle climate change challenges. Specifically, the extant literature shows that climate changes not only have profound physical implications but resonate deeply in the financial sector (Bernstein, Gustafson, and Lewis, 2019; Brown, Gustafson, and Ivanov, 2021), significantly influencing the valuation of assets, securities, and real estate (Huang, Kerstein, and Wang, 2018; Seltzer, Starks, and Zhu, 2022), financial and investment decisions (Bose, Minnick, and Shams, 2021; Javadi et al., 2023). This interweaving of climate change dynamics and corporate actions raises a compelling question: how does the pervasive uncertainty of climate change influence mergers and acquisitions activities? This study endeavours to answer this important question.

Firms view M&A activities as tools to hedge against uncertainties (Garfinkel and Hankins, 2011), thus M&A can be an effective hedge or risk management tool against threats posed by climate change, leading to increased involvement in acquisitions. Furthermore, Duchin and Schmidt (2013) suggest that uncertainty, including that stemming from climate change, may motivate firms to pursue acquisitions as a means of empire-building. This perspective is supported by opportunistic managers, particularly in firms with significant climate change exposure, might engage in M&As to advance their personal interests. Thus, this suggests that climate change exposure could drive an uptick in M&A activity as firms seek to mitigate risks and capitalise on strategic opportunities.

Conversely, heightened uncertainties in the business environment due to climate change may prompt firms to act more cautiously by avoiding significant strategic investments (Bhagwat et al., 2016). Prior studies show that firms facing higher economic, policy, and political uncertainties tend to be more cautious in their investments, making them less inclined to acquisitions (Nguyen and Phan, 2017; Nguyen, Petmezas, and Karampatsas, 2023). Moreover, climate change, emerging as a novel source of economic and financial uncertainty (Barnett et al., 2020; Giglio, Kelly, and Stroebel, 2021), can increase the cost of external financing (Greenwald and Stiglitz, 1990) and exacerbate existing financial constraints for firms (Ginglinger and Moreau, 2023), directly challenge the feasibility of pursuing such transactions. Moreover, the broader economic, policy and political instability associated with climate change may lead firms to prioritise stability and risk mitigation over aggressive expansion strategies. Consequently, increasing uncertainty related to climate change could significantly dampen firms' motivation to engage in M&A activities.

Drawing on these insights, while climate change exposure may present certain strategic opportunities for M&A, the prevailing evidence and theoretical considerations strongly suggest that the net effect of increased climate change exposure is to discourage firms from engaging in M&A activities, driven by heightened uncertainties, financial constraints, and the overarching imperative to adopt a more cautious strategic posture in an increasingly unpredictable business environment. Therefore, we hypothesize that climate change exposure negatively affects a firm's likelihood to pursue M&As. Specifically, firms with a higher level of climate change exposure are less likely to engage in M&A activities.

To identify firm-level climate change exposure, we employ the climate risk measures of Sautner et al. (2023). They develop a forward-looking and time-varying measure of firm exposure to climate change based on transcripts of earnings conference calls using a textual analysis, which provides a more comprehensive understanding of firm climate change issues. They capture the frequency of climate-related mentions in conference calls that refer to physical risks, regulatory shocks, and developmental (transitional) opportunities. This measure reflects the attention and opinion of management and other primary stakeholders on firms' climate change issues. Also, their approach addresses the limitation of analysing backward-looking annual reports which may not fully capture the dynamic and multifaceted nature of a firm’s exposure to climate change. In addition, this measure overcomes the problem of other traditional measures of climate change risks, such as relying solely on a specific issue of climate risks (e.g., extreme weather events, carbon emissions) or focusing only on regional-level data such as sea-level rise.

We employ a firm-level dataset across 34 countries from 2001-2019 and corresponding deal announcements spanning from 2002-2020.[33] We find a negative relationship between firm-level climate change exposure and acquisition likelihood. In economic terms, a one standard deviation increase in firm-level climate change exposure reduces approximately 0.76% to 0.92% likelihood of acquisitions. The magnitude of the impact is consistent with prior literature (Bonaime et al., 2018) and underscores the profound influence of environmental factors on corporate decisions. The baseline result remains consistent as we incorporate multiple fixed effects and perform a battery of robustness tests.

While we primarily consider climate change exposure as exogenous, we acknowledge multiple potential endogeneity concerns, including manager self-disclosure on conference calls, firm self-selection based on business environment sensitivity to climate change, and acquisition choices that might be affected by unobservable factors. To mitigate these concerns, we conducted several tests. First, we employ the entropy balancing approach to re-weight observations based on a covariate matrix, ensuring balance across multiple moments to address firm-characteristic biases (e.g., Hainmueller, 2012; McMullin and Schonberger, 2020). Second, we follow Lewbel (2012) and implement the two-step least squares (2SLS) approach with heteroskedasticity-based instruments, especially useful when external instruments are weak or non-existent (Iosifidi, 2016; Caliendo, Lee, and Mahlstedt, 2017; Hasan, Taylor, and Richardson, 2022). Finally, we employ a difference-in-differences (DID) approach exploiting the

[33] Firm-level accounting data spans from 2001 to 2019. Sautner et al. (2023) provide firm-level CCE data starting from 2001 on the official data website, available at https://osf.io/fd6jq/. Deal announcement data is from 2002 to 2020.

2015 Paris Agreement as an exogenous shock following Ginglinger and Moreau (2023) and Javadi et al. (2023). All results support our main finding that firms with high climate change exposure are less likely to engage in acquisitions.

To explain the influence of climate change exposure on acquisition likelihood, we identify two primary channels: the cost of external financing and investor confidence. Prior literature illustrates that a higher cost of external funding can shrink firms' investment activities, rendering substantial investments, such as acquisitions, less attractive (Philippon, 2009; Gilchrist and Zakrajsek, 2012). Mark Carney, the former Governor of the Bank of England, in his speech given at Lloyd's of London in 2015, emphasises that climate risk can threaten business, economy, and financial stability.[34] Greenwald and Stiglitz (1990) suggest that the cost of external financing increases due to economic and financial uncertainties. Consistent with these arguments and following Ginglinger and Moreau (2023), this study confirms when climate change uncertainties escalate, firms with significant climate change exposure often confront a rise in external financing costs. This increased cost makes them less inclined to pursue acquisitions as we find that climate change exposure is more pronounced, negatively affecting acquisition likelihood, for firms with higher costs of external financing. This result highlights why firms engage less in M&As as climate change exposure increases.

Similarly, consumer confidence, often linked to sentiment, plays a pivotal role in guiding firms' strategic decisions (Lemmon and Portniaguina, 2006; Danso et al., 2019).

[34] The speech is available here: https://www.bankofengland.co.uk/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability.

Several studies suggest consumer confidence mirrors the public's anticipation of future economic conditions, dictating their spending and saving behaviours (Carroll, Fuhrer, and Wilcox, 1994; Ludvigson, 2004). Shocks from climate change can erode consumer and, by extension, investor confidence. This pessimism-driven gloomy economic outlook can make firms more cautious before making any significant strategic decisions such as mergers and acquisitions. The impacts of climate change might lead firms to reassess their long-term strategies. In periods of low consumer confidence companies may prioritise stability and resilience over growth through acquisitions. In addition, low consumer confidence may reduce consumer spending leading to a decline in firm revenues and profits which can dictate firms to become more cautious in pursuing acquisitions, as they may prefer to conserve cash and resources to survive economic downturns. Moreover, the valuation of potential acquisition targets can become more complex and uncertain in such a consumer confidence-driven volatile market, making it riskier for firms to commit to large investments. In essence, high climate change exposure can dent consumer confidence, thereby making firms more hesitant to engage in acquisitions. In line with these assertions, we find a strong negative effect of climate change exposure on acquisition likelihood in periods of low consumer confidence. This reflects the critical role sentiment plays in this negative relationship.

Next, we conduct several robustness checks to confirm our main findings. We first examine long-term climate change exposure (spanning 3 to 7 years) to assess the persistent effects of climate change on acquisition likelihood. Although the effects diminish over time, a consistent negative impact remains adequately visible suggesting that with increasing climate uncertainty, firms tend to avoid acquisitions. We then decompose the elements of climate change exposure into opportunity, regulatory, and physical exposures. Our findings indicate that both opportunity and regulatory exposures correlate with reduced M&A activity. Contrarily, physical exposure seems to drive firms towards acquisitions, perhaps as a risk-mitigation strategy. We also consider potential confounders by integrating macroeconomic and governance indicators such as GDP, unemployment rates, and Worldwide Governance Indicators. These checks solidify the baseline results, confirming the negative relationship between climate exposure and acquisition likelihood. We also examine whether climate change exposure has a different impact on internal or external investment decisions. The results exhibit that firms exposed to anabatic climate change lean towards capital expenditures over acquisitions and R&D, reflecting that climate change uncertainty drives corporations to be discreet in high-risk investments.

We also conduct several additional cross-sectional tests to identify any firm-specific dimensions where the effect of climate change exposure on acquisitions may be more severe. First, following extant literature (Sharpe, 1994; Almeida and Campello, 2007), we find that the impact of climate change exposure on acquisition likelihood varies based on industry cyclicality. Specifically, firms operating in pro-cyclical industries that align with economic booms and busts exhibit a stronger negative relationship than their counter-cyclical counterparts. Second, financially constrained firms react more strongly to climate change exposure, likely due to increase in cash holdings for precautionary reasons (Fazzari, Hubbard, and Petersen, 1988; Faulkender and Wang, 2006; Javadi et al., 2023). Third, amid heightened climate change exposure smaller firms are more hesitant to pursue uncertain investments like acquisitions (Beck, Demirgüç-Kunt, and Maksimovic, 2008). Fourth, high growth firms demonstrate more pronounced negative reactions to climate change exposure in their acquisition decisions than value-oriented firms as such firms may be more risk-averse to external uncertainties (Capaul, Rowlev, and Sharpe 1993; Lang and Stulz, 1994; Griffin and Lemmon, 2002). Taken together, our cross-sectional analyses indicate that specific firm characteristics and industry dynamics are also important to understanding the negative impact of climate change exposure on acquisition likelihood.

Next, we examine the impact of climate change exposure on the deal process and subsequent performance. Our findings indicate that high climate change exposure is associated with a decreased probability of deal completion and extended deal durations. In addition, firms with higher climate change exposure exhibit lower short-term stock returns and weaker long-term post-deal operating performance. This empirical evidence posits that the ambiguities introduced by climate change do not contribute to wealth maximisation for firms via acquisitions.

Overall, this study bridges a critical gap by connecting climate change exposure to acquisition likelihood in the M&A domain, underscoring the significance of considering the environment in corporate decisions. This study makes several important contributions to the existing literature. First, this paper contributes to the strand of literature that emphasises the impact of climate risks on firm valuation and financial decision-making

(Barnett et al., 2020; Engle et al., 2020; Bolton and Kacperczyk, 2021). Specifically, natural disasters adversely impact agricultural yields, labour productivity, firm sales growth, and the value of corporation assets (e.g., Jones and Olken, 2010; Barrot and Sauvagnat, 2016; Bernstein et al., 2019). Moreover, abnormal weather is negatively associated with firms' equity performance (e.g., Bansal, Kiku, and Ochoa, 2016; Choi, Gao, and Jiang, 2020; Addoum, Ng, and Ortiz-Bobea, 2023). This research makes a distinctive contribution to the literature by presenting compelling evidence that climate change may dampen mergers and acquisitions (M&A) activities.

Second, this paper adds to the existing literature on the relationship between climate risks and M&As. Bose et al. (2021) point out that firms with higher carbon emissions are inclined to pursue cross-border mergers with targets in countries with weak environmental protection laws while less inclined towards domestic deals. Bai et al. (2021) examine that firms with higher sea-level rise (SLR) risk are more likely to make a deal with targets having low SLR risk and subsequently report significantly higher short-term cumulative abnormal share returns (CARs). Their research emphasises only the physical impacts of climate change. From the regulatory and policy perspectives of climate change, Li, Tang, and Xie (2022) find that targets are less likely to be acquired if their countries have stricter climate laws and regulations in cross-border M&As. Our study distinguishes itself by employing an aggregate measure of firm-level climate change exposure rather than focusing on a singular aspect of climate risk, physical or regulatory, to analyse the comprehensive nature of the relationship between climate change and M&A decisions.

Third, this study is also related to the literature on the determinants of M&A activity. Often, M&A decisions stem from perceived market valuation mismatches. Here, acquirers see target firms as undervalued, presenting lucrative investment opportunities (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004). Industry-specific factors, including cyclicality, shocks, and restructuring (Maksimovic and Phillips, 2001; Harford, 2005), and product market concentration or complementarity between acquirer and target (Rhodes-Kropf and Robinson, 2008; Hoberg and Phillips, 2010) can also affect M&A activity. Cultural and geographical proximities can drive cross-border M&As. Chakrabarti, Gupta-Mukherjee, and Jayaraman (2009) and Bereskin et al. (2018) exhibit a preference for merging with partners who share geographical and cultural similarities. The characteristics of firm top management, such as the CEO's or board's age, gender, religious beliefs, confidence levels, and board size, also influence M&A decisions (Malmendier and Tate, 2008; Yim, 2013; Chen, Crossland, and Huang, 2016; Elnahas and Kim, 2017). The likelihood of M&As is often shaped by environmental uncertainties, encompassing economic factors (Bhagwat et al., 2016), policy fluctuations (Nguyen and Phan, 2017; Bonaime, Gulen and Ion, 2018), and litigation risks (Huang, Ozkan, and Xu, 2023). Our study contributes to this strand by providing evidence that climate change exposure is also an important factor for M&A.

The remainder of the paper is organised as follows. Section 3.2 describes the data and sample. Section 3.3 discusses the empirical results, and Section 3.4 concludes the paper.

3.2 Data

3.2.1 Sample Selection

Our initial sample consists of firms from 82 countries covered in Compustat North America and Global during the period of 2001-2019. Consistent with prior literature, we exclude financial firms (SIC two codes 60-69) and regulated utilities (SIC two codes 49) to control for the effects of regulation on decision-making. We further require firms to have available financial information on Compustat to construct firm-level data.

To quantify firm-level climate change exposure, we employ data provided by Sautner et al. (2023). Sautner et al. (2023) use a machine learning algorithm to capture keywords of climate change (events or shocks) on transcripts of earnings conference calls to construct a time series of firm-level climate change exposure. The exposure metrics encompass four specific climate change bigrams: the aggregated firm-level climate change exposure, opportunity, and physical and regulatory shocks. These are computed based on the proportion of each specific bigram relative to the sum of bigrams present in the transcript. In this study, we mainly focus on the aggregated firm-level climate change exposure.

The advantages of their novel measures are: first, they reflect more authentic climate issues of management views with less "greenwashing" information and climate change exposure by views of various analysts and stakeholders; second, unlike traditional annual reports and disclosures, climate change information extracted from earnings calls tends to be more forward-looking; third, these measures capture a comprehensive range of climate shocks affecting firms, encompassing both positive and negative impacts, specifically, to physical threats, regulatory interventions, and technological opportunities; fourth, these measures are dynamic, varying over time across different firms and countries. Thus, firm-level climate change exposures provide a more comprehensive understanding of climate issues than single-dimensional measures, such as carbon intensities and sea-level risk, and it is beneficial to understand investment decisions based on individual firm characteristics. For our analysis, we gathered 68,182 firm-year observations across 34 countries from 2001 to 2019, incorporating accounting data and climate change exposure information.[35]

Our mergers and acquisitions (M&As) data, sourced from the Securities Data Company (SDC) database, comprises deals announced globally between 2002 and 2020. We include acquirers that are listed in both the Compustat and CRSP databases and hold less than 10% of the target's shares before the deal announcement and acquire over 50% ownership after the deal's completion to diminish the distraction of the less distinct change in firm control where acquirer already held a large portion of a target before deal announcement. Targets in the acquisition can be either public or private entities. Our deal sample excludes minority stake purchases, recapitalisations, acquisitions of remaining interests, self-tender offers, spin-offs, privatisations, reverse leverage buyouts, exchange offers, and repurchases. After refining the data to match firm-level accounting and climate

[35] Sautner et al. (2023) provide firm-level climate change exposure data mainly from 2002, but they contain 285 observations of climate change exposure. We include all of them in our analysis, thus our sample starts from 2001.

change exposure, our M&A sample comprises 39,336 deals.[36] The definition of all variables is provided in the Appendix B.

3.2.2 Summary Statistics

Table 3.1 provides a summary of the statistics for our sample. Climate change exposure values are multiplied by one hundred for a more straightforward interpretation in the empirical analysis. All the variables are winsorised at the 1% level to mitigate the impact of potential outliers. Panel A reports the descriptive statistics of the entire sample, which comprises 68,182 firm-year observations across 34 countries from 2001-2019, excluding entries lacking control variables. The mean climate change exposure is 0.105, and the standard deviation is 0.263, suggesting significant variability in climate change exposure. The mean of unconditional acquisition likelihood is 29.5%. Panel B provides descriptive statistics for the M&As dataset, encompassing 13,205 announced deals with available deal-level characteristics. Panel C displays the correlation matrix between variables in the overall sample.[37]

Table 3.2 reports the distribution of firm-year observations across 34 countries or regions for 2001-2019.[38] Appendix B Figure B2.1 depicts the time series trend of our primary variable of interest, climate change exposure, for the top 10 countries.[39] We

[36] The 39,336 deals are all deals announced by the corresponding firms, it does not consider whether the deal has relevant available deal-level characteristics. To test merger likelihood, we employ 39,336 deals. For deal performance analysis, we have all the required deal characteristics and financial data on 13,205 deals.
[37] The correlation matrix between variables in Panel C is for the baseline regression sample. The correlation matrix between variables of the M&A sample is in Appendix B Table B2.1.
[38] The 34 countries or regions are Austria, Australia, Belgium, Bermuda Island, Brazil Canada, Switzerland, Chile, China, Germany, Denmark, Spain, Finland, France, Greece, Hong Kong, Ireland, Israel, Indian, Italy, Japan, South Korea, Luxembourg, Mexico, Netherlands, Norway, New Zealand, Russia, Sweden, Singapore, Taiwan, United Kingdom, United States, and South Africa.
[39] The top 10 countries are the first 10 ranking countries or regions with the most distribution of firm-year observations, including United States, United Kingdom, Japan, China, Canada, Germany, France, Australia, India, and Brazil.

computed the average climate change exposure by country and year. The time trend illustrates variances in the distribution of climate change exposure, indicating that awareness of climate change issues differs across countries and over time.

3.3 Empirical Analysis

We begin our analysis by examining the impact of firm-level climate change exposure on the likelihood of M&As. First, we present the results from the baseline probit regressions. Subsequently, we conduct tests to address endogeneity concerns and explore potential channels through which climate change exposure might influence acquisition likelihood. Additionally, we perform several cross-sectional tests to ensure the robustness of our findings. Furthermore, once firms opt to pursue M&As, we examine how climate change exposure correlates with the probability of deal completion, the deal's duration, and its performance.

3.3.1 Climate Change Exposure and Acquisition Likelihood

3.3.1.1 Baseline Regression

Existing literature indicates that climate change adversely affects leverage but positively influences cash holdings due to concerns over increased cash flow risk, heightened default risk, and elevated cost of capital (Huang et al., 2018; Heo, 2021; Ginglinger and Moreau, 2023). Building on these arguments and considering the inherent uncertainty and risk of M&As for firms (Furfine and Rosen, 2011; Phan, 2014), we hypothesise that a firm's exposure to climate change negatively affects its likelihood of pursuing acquisitions.

To examine the effect of firm-level climate change exposure on acquisition likelihood, we estimate the following probit equation:

$$M\&A\ likelihood_{i,t+1} = \alpha + \beta * CCE_{i,t} + C_{i,t} + \gamma_t + \varepsilon_{i,t} \qquad (3.1.)$$

where $M\&A\ likelihood_{i,t+1}$, the independent variable, is a binary variable that takes the value of one if firm i engages at least one acquisition in year $t+1$, one leading period, and zero otherwise. $CCE_{i,t}$ is our key independent variable of interest, the firm-level climate change exposure of firm i at fiscal year t. $C_{i,t}$ is a vector of firm-level control variables constructed at year t, which have been evidenced in extant literature that affect the acquisitiveness of firms. Particularly, the control variables include firm size, leverage, market-to-book ratio, cash-to-assets ratio, sale growth, research and development expenditures (R&D), tangibility, and operating margin.[40] γ_t represents year, industry or year, industry, and country fixed effects[41], as our sample covers an extensive range of countries, and previous studies indicate year and industry affect acquisitions (Mitchell and Mulherin, 1996; Shleifer and Vishny, 1991, 2003). The standard errors are clustered by firm and year (Bertrand, Duflo, and Mullainathan, 2004) and adjusted for heteroscedasticity.

The baseline regression results are reported in Table 3.3. Probit coefficients are shown in Columns (1), (2), (3), and (5), while marginal effects for ease of interpretation are in Columns (4) and (6). Columns (1) and (2) feature univariate regressions of climate change exposure on likelihood of acquisition. In Columns (3) to (6), we conduct multivariate regressions with control variables. In all specifications, we consistently find

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[40] For the control of firm size, leverage, market-to-book ratio, cash to assets ratio, R&D expenditures, tangibility, and operating margin, see the example of Heeley et al. (2006), Alexandridis et al. (2010) and Lawrence et al. (2021).

[41] Industry fixed effect is using SIC two-digit code.

a negative association between climate change exposure and acquisition likelihood at the 1% significance level. The results indicate that increased climate change exposure reduces a firm's likelihood of engaging in acquisitions. This negative relationship is both statistically significant and economically meaningful. Regarding the economic significance, the marginal effect estimates in Column (4) and Column (6) are 0.034 and 0.028, respectively. This implies that a one standard deviation increase in climate change exposure correlates with a 0.92% (0.76%) reduction in a firm's probability of engaging in acquisitions, and this magnitude of the economic significance is consistent with extant literature of factors effect on acquisition likelihood (e.g., Bonaime et al., 2018). Relative to the unconditional mean likelihood of M&A (0.295), these results correspond to decreases of 3.12% (2.58%).

We further analyse whether the *CCE* has different impact on cross-border deals and domestic deals. Appendix B Table B2.2 provides the results. The dependent variable is the cross-border acquisition likelihood in Panel A, and the domestic acquisition likelihood in Panel B.[42] Throughout all analyses, there is a uniformly observed significant adverse impact of *CCE* on the probability of firms engaging in both cross-border and domestic acquisition transactions. These findings suggest that an increased level of *CCE* systematically reduces a firm's inclination to pursue any form of acquisition activities.

[42] In Panel A, the dependent variable is *Cross-border acquisition likelihood*, a binary variable takes the value of one if firm *i* engaged in at least one cross-border acquisition announcement in year *t+1*, otherwise zero. In Panel B, the dependent variable is *Domestic acquisition likelihood*, a binary variable takes the value of one if firm *i* engaged in at least one domestic acquisition announcement in year *t+1*, otherwise zero.

3.3.1.2 Endogeneity

While climate change exposure is generally exogenous, we address concerns about its potential endogeneity arising from managerial self-disclosures during conference calls, self-selection biases in firms' business environments, activities' sensitivity to climate change, and acquisition decisions. Additionally, we consider possible omitted variables influencing M&A nonparticipation. To mitigate these endogeneity issues, we employ entropy balancing, a two-stage least-squares (2SLS) regression, and a difference-in-differences approach using the Paris Accord as a significant climate shock, thereby addressing identification concerns.

To address concerns about potential biases from differences in firm characteristics, we employ the entropy balancing method, a sophisticated reweighting technique that ensures balance in the covariate distribution between treated and control groups (Hainmueller, 2012). This method not only balances means but also higher moments, such as variance and skewness of the covariates, leading to a reduction in estimation biases (McMullin and Schonberger, 2020). Our treatment group comprises firms with high climate change exposure (values above zero), while the control group includes those with low exposure (values at zero). Leveraging entropy balancing, we iteratively re-assign weights to each observation to achieve a balanced covariate matrix distribution across the treatment and control groups. This process continues until there is a similarity across the three moment dimensions between both sets of observations.

In Table 3.4, Panels A and B depict the comparison of the mean, variance, and skewness of firm characteristics in the treatment and control groups before and after entropy balancing. After balancing, both groups appear statistically indistinguishable, indicating that the reweighting process effectively mitigates sample selection biases. In Panel C, we rerun our main regression using the entropy-balanced observations. The coefficient of climate change exposure remains negative and statistically significant at the 1% level, consistent with our primary findings. This reaffirms the inverse relationship between firm-level climate change exposure and M&A activity, even after accounting for potential biases.[43]

To further address endogeneity concerns, we implement a two-step least squares (2SLS) approach, leveraging heteroskedasticity-based instruments in line with the methodology proposed by Lewbel (2012). This approach capitalises on internal instruments generated by the residuals from auxiliary regressions. These residuals are multiplied by each mean-centred exogenous variable to form the instruments. This method proves especially advantageous in situations where external instruments are either absent or weakly identified, as evidenced by studies such as Iosifidi (2016), Caliendo et al. (2017), Hasan et al. (2022), and Agostino et al. (2023).

Table 3.5 presents the results from our 2SLS instrumental variable regressions. The coefficients for the instrumented climate change exposure variables are consistently negative and statistically significant across both columns: in Column (1), coefficient = -0.021 ($p < 0.05$), and in Column (2), coefficient = -0.034 ($p < 0.01$). This consistency

[43] We also separate the full sample into the treatment and control groups by the median of the climate change exposure by each country and fiscal year. The treatment group is made up of firms with climate change exposure higher than the median, others are in the control group. Under this categorization, the entropy-balanced sample generates the same results that the relationship between climate change exposure and acquisition likelihood is negative and statistically significant at the 1% level. These results are provided in Appendix B Table B2.2.

reaffirms our baseline findings that increased climate change exposure reduces the likelihood of acquisitions. Additionally, the Kleibergen-Paap and Cragg-Donald Wald tests strongly reject the under-identification and weak identification hypotheses. Furthermore, the Hansen J statistics confirm that over-identification is not a concern. Collectively, these results effectively address potential endogeneity issues in our analysis.

Additionally, we employ a difference-in-differences (DID) analysis using the 2015 Paris Agreement as an exogenous shock. The Paris Agreement, a global accord adopted at the 2015 Paris Climate Change Conference, significantly elevated climate change awareness and commitments among nations. This universal binding agreement intensified focus on climate change risks, presumably leading firms to enhance their attention to climate change issues. Consequently, we anticipate an increase in firm-level climate change exposure post-2015. Our DID tests aim to observe if the negative impact of climate change exposure on merger and acquisition (M&A) likelihood is more pronounced in the period following the Paris Agreement. This approach helps substantiate the exogeneity of our climate change exposure measure and its impact on M&A activities.

We use the three years preceding and after the shock and propose the following model for DID estimation:

$$
\begin{aligned}
M\&A\ likelihood_{i,t+1} = {} & \alpha + \beta_1 * CCE_{i,t} * Post_{i,t} + \beta_2 * Post_{i,t} \\
& + \beta_3 * CCE_{i,t} + C_{i,t} + \varepsilon_{i,t} \qquad (3.2)
\end{aligned}
$$

where $M\&A\ likelihood_{i,t+1}$ is the likelihood of firm *i* in year *t+1*, taking the value of one if firm *i* engaged in at least one acquisition in year *t+1*. $CCE_{i,t}$ is the firm-level climate change exposure for firm *i* in year *t*. $Post_{i,t}$, an indicator variable equals one if year *t* is after the release of the Paris Agreement (the year 2015), otherwise zero. $C_{i,t}$ are the matrix of firm-level control variables in year t, including the same firm controls as in Equation (1). The industry, time, and country fixed effects are included as well. Standard errors are adjusted for heteroscedasticity and clustered by firm and year. Our interest is the interaction term between $CCE_{i,t}$ and $Post_{i,t}$.

Table 3.6 displays the results of our DID regressions. In Panel A, the interaction term's coefficient in Column (1) is positive and significant at the 10% level, while it is negative and significant at the 5% level in Column (2). These findings indicate that post-Paris Agreement, firms with heightened climate change exposure demonstrate a reduced likelihood of engaging in M&As. This trend is particularly noticeable among firms whose climate change exposure increased more significantly than those less affected by climate events. These observations align with the patterns found in our baseline model (Table 3. 2), reinforcing the validity of our initial findings. The DID regression analysis also supports the exogenous nature of the climate change exposure measure, particularly concerning M&A activities. This is further substantiated by Appendix B Figure B2.2, which verifies the parallel trend hypothesis. The graph depicts the effect of climate change exposure on acquisition likelihood over time. It includes the regression results controlling for firm-level variables and year, industry, and country fixed effects. In the pre-event period (three years before 2015), there is no statistically significant difference in the acquisition likelihood related to climate change exposure. This non-significance supports the parallel trend assumption. However, in the post-event period (three years after 2015), the effect becomes significantly negative. This shift suggests that the 2015

Paris Agreement played a crucial role in elevating the awareness of climate change exposure among firms. The significant change in the post-event period validates the hypothesis that the Paris Agreement intensified the impact of climate change exposure on firms' decision-making, particularly in relation to their participation in M&As. This evidence robustly confirms the impact of heightened climate awareness following a significant international agreement and its influence on corporate strategic decisions.

3.3.1.3 Potential Channels

Understanding the channels through which climate change exposure affects the likelihood of acquisitions is essential, as it provides a richer understanding of the underlying mechanisms driving these relationships. In this subsection, two potential channels are explored: the cost of external financing[44] and consumer confidence[45].

External financing costs are pivotal in influencing firm investments (Philippon, 2009; Gilchrist and Zakrajsek, 2012; Frank and Shen, 2016). Put simply, as the cost of external financing rises, which is proxied by the cost of debt, firms tend to reduce their investment activities. Given their irreversible nature, firms with a higher cost of external financing are less likely to finalise mergers and acquisitions. Drawing from Greenwald and Stiglitz (1990), we note that as operating uncertainty rises, firms encounter more significant challenges in securing external financing due to increased costs. Ginglinger and Moreau (2023) highlight that as climate risk—another source of uncertainty—

[44] Due to data restrictions for the global database, measures of cost of equity and implied cost of capital are unavailable to be obtained and analysed.
[45] We use country-level consumer confidence data as there is a data limitation on firm-level investor sentiment for all countries.

escalates, so does the cost of debt. Based on these insights, we posit that the diminished likelihood of acquisitions can be attributed to firms with higher climate change exposure, given their increased cost of debt and constrained capacity to raise external funds.

We use the total interest expense owed on the total debt as a proxy of the average cost of external financing (Frank and Shen, 2016). This is calculated by dividing the total interest and related expenses by the combined sum of long-term debt and current liabilities. Table 3.7 Panel A reports the results of the cost of debt. Columns (1) and (2) delineate the relationship between the cost of debt and climate change exposure. As we expected, firm-level climate change exposure positively affects the cost of debt at 1% significance level. Based on the median cost of debt within each year-country, we categorise firms into two groups: those with a high and low cost of debt. We then re-run our baseline regressions for both the high and low cost of debt subsamples. Columns (3) to (6) illustrate the impact of climate change exposure on the likelihood of acquisitions, segmented by firms with either high or low costs of debt. The results indicate that the negative effect of climate change exposure on acquisition likelihood is much more pronounced for firms with higher cost of debt (Columns (3) and (5) with coefficients of -0.129, $p < 0.01$, and -0.106, $p < 0.01$, respectively). As climate change exposure intensifies, firms grow more cautious about acquisitions, reflecting the increased cost of external financing.

Consumer perceptions can significantly influence a firm's operations. Companies perceived as not being environmentally responsible might face backlash from consumers.

If a firm is perceived to have great climate change exposure, it might signal to consumers that the firm is not environmentally responsible, leading to decreased consumer confidence. We employ the consumer confidence indicator to represent economic development expectation and investor optimism, aiming to elucidate the inverse relationship between climate change exposure and firm acquisitiveness. Several studies suggest that consumer confidence predicts future household consumption and saving behaviours, grounded in anticipations of forthcoming financial and economic scenarios (Carroll et al., 1994; Ludvigson, 2004). A higher level of period of consumer confidence signals individuals' positive outlook on upcoming economic and employment prospects, making them more inclined to spend and less likely to save in the subsequent year. The climate change shocks could exacerbate the weakening of consumer confidence, thereby exposing firms to heightened volatility in their future trajectories, which in turn may further diminish the propensity for acquisitions.

The consumer confidence indicator is computed as the annual average of consumer confidence at the national level from the OECD consumer opinion survey.[46] We first estimate the impact of climate change exposure on investor sentiment. Subsequently, the sample is divided into high and low periods of consumer confidence groups based on the median level within each country. We then re-estimate the baseline regression for these two subgroups. Panel B of Table 3.7 reports the results for the consumer confidence indicator. Columns (1) and (2) report that climate change exposure is negatively

[46] The consumer confidence indicator is available at: Organisation for Economic Co-operation and Development, Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: National Indicator, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CSCICP02ITM460S, October 1, 2023.

associated with consumer confidence. Columns (3) to (6) reveal a more pronounced negative association between climate change exposure and acquisition likelihood, particularly when the period of consumer confidence is relatively low. In essence, climate change exposure can undermine consumer confidence, lowering investor expectations regarding future financial developments and prompting firms to adopt a more cautious approach to M&As.

3.3.2 Additional Analysis

3.3.2.1 Robustness Checks

In this subsection, we conduct robustness checks to examine the relationship between climate change exposure and acquisition likelihood. First, we test whether the effect of climate change exposure on acquisition likelihood is persistent or merely temporary. Second, we analyse the influence of three distinct components of firm-level climate change exposure on the likelihood of acquisitions. Third, we assess the relationship between climate change exposure and acquisition likelihood, incorporating additional controls and utilising alternative fixed effects.

We examine the persistence of the effect of climate change exposure on the likelihood of acquisitions by using long-term climate change exposures to replace the year t climate change exposure. The long-term climate change exposures are helpful in analysing whether the effect of climate change on the likelihood of acquisition is temporary or long-lasting. If the negative effect of climate change exposure exists temporarily rather than persistently, the acquisition likelihood might reverse in the short run, leading to a swift dissipation of the negative impact. The long-term climate change exposures are *3-year CCE*, *5-year CCE*, and *7-year CCE*, calculated as the average of the prior three years (5 or 7 years) of firm-level climate change exposure. Table 3.8 Panel A presents the results. In all specifications, we use the same controls and fixed effects as in the baseline regression. The results in Panel A of Table 3.8 indicate a persistent, negative influence of climate change exposure on acquisition activities. While the coefficients of the long-term climate change exposures diminish over time (the estimate of the 7-year CCE is smaller than the 3-year's), all remain negative and statistically significant at the 1% level.

Specifically, we explore how acquisition likelihood correlates with different facets of climate change exposure, namely, the opportunity (*CCE opportunity*), regulation (*CCE regulation*), and physical (*CCE physical*) climate change exposures.[47] These components, as outlined by Sautner et al. (2023), represent distinct firm-level responses to climate change. Table 3.8 Panel B delineates the impact of each type of CCE on acquisition likelihood individually. Appendix B Table B2.3 Panel A aggregates the effects of all three CCE categories within the same regression regarding M&A propensity. Both opportunity and regulatory climate shocks exhibit a notable negative influence on acquisition likelihood. The opportunity climate change exposure, also called climate transitional risk, most negatively affects M&A likelihood. In contrast, physical climate shocks display a significant positive correlation. The findings imply that firms with greater exposure to opportunity or regulatory CCE are less likely to engage in M&As, instead directing more resources towards sustainable investments. Conversely, those contending with increased

[47] See Sautner et al. (2023) for definitions and details of *CCE opportunity*, *CCE regulation*, and *CCE physical*.

physical CCE seem more inclined towards acquisitions, potentially to acquire resources that counteract these physical climate risks, treating acquisitions as risk-mitigating measures (Garfinkel and Hankins, 2011). This underlines the diverse strategies firms adopt in response to varying climate challenges.

Furthermore, one potential concern is that other macroeconomic dynamics could influence the observed negative relationship between climate change exposure and acquisition likelihood. To control for potential omitted variable bias and address concerns of endogeneity, we introduce a set of macro-level and country governance variables into our primary regression, including GDP, GDP per capita, economic policy uncertainty (EPU), unemployment rate, and six components of world governance indicators (WGI). We define GDP and GDP per capita based on the respective country data in which the firm is situated.[48] The Worldwide Economic Policy Uncertainty (EPU) index, as defined by Davis (2016), captures the average yearly economic policy uncertainty of a firm's resident country.[49] The unemployment rate[50] represents the annual average proportion of the unemployed labour force relative to the total, as sourced from the International Labour Organisation. Furthermore, we incorporate six governance measures from the Worldwide Governance Indicators (WGI) that gauge the governance quality of the acquirer's nation, including factors such as corruption, government effectiveness, and political stability.[51]

[48] GDP and GDP per capita: sourced from World Development Indicators on world bank, available at https://databank.worldbank.org/source/world-development-indicators.
[49] EPU: sourced from Economic Policy Uncertainty indices for 22 countries, available at https://www.policyuncertainty.com/all_country_data.html.
[50] Unemployment rate: sourced from Labour Force Statistics database (LFS) International Labour Organization, available at https://ilostat.ilo.org/data/.
[51] The six components of WGI are sourced from the World Bank. Data available at: https://info.worldbank.org/governance/wgi/.

The results from these analyses, presented in Table 3.8 Panel D, indicate that climate change exposure remains a significant negative determinant of acquisition likelihood after controlling for these macroeconomic and governance variables.

Additionally, to verify the robustness of our findings, we incorporate various fixed effects into our model. In our baseline model, we consider alternative specifications t, incorporating fixed effects for industry-by-country, industry-by-year, and country-by-year to account for unobservable time-varying attributes. Panel E presents the results, highlighting the influence of climate change exposure on acquisition likelihood while controlling for these alternative fixed effects. In Appendix B Table B2.3 Panel B, we provide estimates derived from a linear (OLS) model, which regresses acquisition likelihood against firm-level climate change exposure using varied fixed effect controls. Across all models in both Table 3.8 Panel E and Appendix B Table B2.3 Panel B, the relationship between climate change exposure and acquisition likelihood consistently remains positive and statistically significant at the 1% level, underscoring the robustness of our primary results. Firms appear less inclined towards acquisitions as their climate change exposure intensifies.

3.3.2.2 Likelihood of Acquisition vs. CAPEX or R&D

To further examine the relationship between climate change exposure and corporate investment strategies, we test whether climate change exposure differentially impacts a firm's internal compared to its external investment decisions. By employing the seemingly unrelated regression (SUR), where the two regressions are estimated simultaneously with different dependent variables and correlated residuals, we examine the influence of climate change exposure on acquisitions (representing external investments) and on either capital expenditures (CAPEX) or research and development (R&D) spending (symbolising internal investments).[52]

Table 3.9 shows the results of the SUR. Panel A presents the influence of climate change exposure on acquisition decisions relative to CAPEX, while Panel B delineates its effect on acquisition versus R&D decisions. In Columns (1) and (3) of Panel A and Panel B, the dependent variable is the acquisition likelihood, taking the value of one if firm *i* makes at least one deal in year *t+1*, otherwise zero. In Panel A Columns (2) and (4), the dependent variable is CAPEX as a proportion of total assets, while in Panel B Columns (2) and (4), it's R&D scaled by total assets. The estimates indicate that climate change exposure has a negative impact on both acquisition likelihood and R&D expenditures while exerting a positive effect on CAPEX. The findings suggest that firms with greater climate change exposure tend to prioritise capital expenditures over external and innovative investments. Climate change exposure curtails firms' propensity to undertake investments with heightened uncertainties.

3.3.2.3 Cross-sectional Analysis

Within this analysis, we undertake a series of cross-sectional examinations to discern the distinct impacts of climate change exposure on the likelihood of acquisitions, separating it from influences of industry cycles, attributes like firm size and financial constraints, and financial metrics such as the book-to-market ratio.

[52] The CAPEX and R&D represent internal investment decisions. We run the SUR for likelihood of M&A and CAPEX, and likelihood of M&A and R&D.

First, our objective is to discern if climate change exposure consistently influences the likelihood of acquisitions across various business cyclical conditions. Specifically, firms within pro-cyclical sectors may curtail investments, opting instead to preserve cash during potential economic downturns. We partition the sample into two groups: pro-cyclical and counter-cyclical industries. Following the prior literature (e.g., Sharpe, 1994; Almeida and Campello, 2007; Bin Hasan et al., 2022), we use the sales cyclicality of firms as a proxy to identify the industry cyclicality. Initially, we calculate the correlation between each firm's revenues and the country's Gross National Income (GNI)[53] over the 2001-2019 period. Subsequently, we determine the average correlation for firms within the same 2-digit SIC industry category by country. Industries with average correlation coefficients above the median are classified as pro-cyclical; those below are deemed counter-cyclical. We then re-conduct our baseline regression on these differentiated subsamples for comparison. As depicted in Table 3.10, Panel A, the negative influence of firm-level climate change exposure on acquisition likelihood is markedly more significant for pro-cyclical industries.

Second, financially constrained firms typically have limited ability in internal financing and access to external financing, often resulting in higher associated costs.[54] Such firms tend to maintain more extensive cash reserves and display a preference for internal investments, as observed by Fazzari et al. (1988) and Faulkender and Wang

[53] GNI: sourced from the World Bank, available at https://data.worldbank.org/indicator/NY.GNP.MKTP.CD.
[54] We also checked the high cash holding firms and low cash holdings firms and M&As. The results are in line with financially constrained firms results. The negative effect of climate change exposure on M&A likelihood is more pronounced in low cash holdings firms, indicating low cash holding firms may keep the cash buffer to confront unforeseeable future operating and economic environment. Details are available on request.

(2006). Additionally, Javadi et al. (2023) noted a positive correlation between climate change and firm cash holdings based on data from 41 countries. Building on these premises, an escalation in climate change exposure suggests that financially constrained firms, driven by heightened precautionary motives and challenges like liquidity risks and external financing hurdles, may likely curtail their growth strategies, especially for high-risk ventures like mergers and acquisitions.

Following Whited and Wu (2006)[55], we construct the measure of firm financial constraints. We then categorise firms into two groups based on the median of the *ww-index* (Whited and Wu financial constraints index) for each year-country-industry: financially constrained and unconstrained firms.[56] To capture the difference between financial-constrained and non-constrained firms, we assess the impact of climate change exposure on acquisition likelihood separately for each group. The findings, presented in Table 3.10 Panel B, highlight that the inhibitive effect of climate change exposure on acquisition likelihood is more pronounced for financially constrained firms. This underscores the extent of financial constraints and amplifies the negative association between climate change exposure and a firm's inclination to pursue acquisitions.

Third, in exploring the size effect and its moderation of the relationship between climate change exposure and acquisition likelihood, we use market capitalization as a proxy for firm size. This metric is calculated as the year-end total market value of a

[55] See Whited and Wu (2006) index for details.
[56] If firm's *ww-index* is higher than the median, then the firm is financial constrained firm or the higher financial constraint firm. Otherwise, if its ww-index is lower than median, it is a non-constrained or lower financial constraint firm.

company's outstanding stock. Beck et al. (2008) contend that smaller firms depend more on internal financing and encounter greater challenges in securing external funds, thereby increasing their susceptibility to financial constraints. When climate change exposure increases, relatively small firms face more difficulties raising capital than larger firms, leading them to opt for less risky corporate investment decisions. Table 3.10 Panel C reports the size effect concerning the relationship between climate change and acquisition likelihood. Firms are classified as large or small based on the median market capitalization within their respective countries. The findings reveal that the adverse impact of climate change exposure on acquisition likelihood is more significant for smaller firms, indicating that such firms exercise increased caution in making uncertain investments as climate change exposure rises.

Fourth, to understand the differential impacts of climate change exposure on acquisition activities, we distinguish between growth and value firms using the book-to-market value ratio. This ratio is calculated as the total book assets divided by the sum of the market capitalization of equity and total liabilities. Capaul et al. (1993) demonstrate that firms with lower book-to-market values possess higher growth potential often reflected in rising stock prices. Conversely, firms with higher book-to-market values are linked to appreciable asset values and diminished growth prospects. Given that growth firms have expanded investment opportunities (Lang and Stulz, 1994), they are typically more inclined towards acquisitions. However, Griffin and Lemmon (2002) identify a correlation between higher book-to-market equity and elevated distress risk. Using this framework, it can be postulated that as climate change exposure intensifies, growth firms, navigating increased uncertainties, will exercise greater caution in committing to risk-laden investment decisions like acquisitions to mitigate potential risks. The findings in Table 3.10, Panel D, corroborate this hypothesis, indicating that growth firms are more adversely influenced by climate change exposure than value firms when contemplating acquisitions.

3.3.3 M&A Outcomes

3.3.3.1 Deal Completion and Duration

In this subsection, to enrich our analysis, we investigate the implications of climate change exposure on the M&A process, focusing specifically on the metrics of deal completion and deal duration. The deal completion, a binary variable, is defined as the probability that an announced deal has been successfully completed.[57] The deal duration is the time to complete the M&A deal.[58] To assess the potential effects of climate change exposure on these metrics, we adopt the Probit model for evaluating deal completion and the Tobit model for measuring deal duration.[59] Throughout these regressions, it is crucial to account for potential confounding factors. As such, we integrate controls for both firm-specific and deal-specific attributes that could influence the acquisition process.[60]

[57] The deal completion, an indicator variable, takes a value of one if the announced deal is completed, otherwise zero (withdrawn or pending or unknown).
[58] Consistent with prior literature, such as the works of Nguyen and Phan (2017) and Lawrence, Raithatha, and Rodriguez (2021), deal duration is gauged by taking the natural logarithm of the sum of one day plus the number of days elapsed between the announcement date and the deal's effective date.
[59] We use the Tobit model to gauge the effect of climate change exposure on deal duration because the time to complete a deal is more than zero.
[60] Firm-level controls include firm size (Moeller et al., 2004), leverage ratio (Maloney, McCormick and Mitchell, 1993), market to book (Dong et al., 2006), cash to assets (Harford, 1999), sales growth (Bates, 2005), R&D (Phillips and Zhdanov, 2013), tangibility (Almeida and Campello, 2007), and operating margin (Nickell, 1978). Deal-level characteristics are value of acquisition (Golubov, Petmezas, and Travlos, 2012), target public status (Capron and Shen, 2007), diversify (Campa and Kedia, 2002), including stock payment dummy (Travlos, 1987), all cash payment dummy (Martin, 1996), friendly deal attitude (Servaes, 1991), cross-border dummy (Moeller and Schlingemann, 2005), relative size (Fuller et al., 2002). Definitions of variables are provided in Appendix B.

Additionally, fixed effects for the year, industry, and acquirer's country of origin are meticulously considered in our analysis.

The findings from Table 3.11 offer crucial insights into the relationship between climate change exposure and M&A deal processes. In Columns (1) and (2), where deal completion is the dependent variable, the analysis via probit coefficients and marginal effects reveals a negative, albeit marginally significant, impact of climate change exposure on the likelihood of deal completion. Column (3) shifts the focus to deal duration, highlighting a significant and positive correlation between climate change exposure and the time required to finalise a deal. Collectively, these results suggest that higher climate change exposure introduces more considerable uncertainty into the firm's operational environment and the deal process itself, thereby reducing the probability of successfully completing deals and prolonging the evaluation and completion time for acquisitions.

3.3.3.2 Short-run and Long-run Performance

In this subsection, we discuss the effect of climate change exposure on the acquirer's short-term and long-term performance. We examine acquirers' announcement return and operating performance change using the M&A sample between 2002 and 2020 described previously.

For the short-term performance, we measure the acquirer’s announcement period stock abnormal returns. In line with extant literature (e.g., Masulis, Wang, and Xie, 2007; Golubov, Yawson, and Zhang, 2015), our main independent variable is the five-day cumulative abnormal returns of the acquirers during the deal announcement, CAR (-2, +2), where day 0 is the deal announcement date. The CAR is measured by the market model[61], using parameters estimated from trading data spanning 241 days to 41 days before the announcement. We control for a host of firm-specific and deal-related characteristics known to influence acquirer short-term returns (e.g., Harford, 1999; Masulis et al., 2007), including the *deal value*, *public target*, *diversify*, *including stock payment*, *all cash payment*, *friendly*, *cross-border*, *runup*, *sigma*, *firm size*, *relative size*, *leverage*, *market to book*, *cash to assets*, *sales growth*, *R&D*, *tangibility*, and *operating margin*.[62] We further control macroeconomic and governance variables, including GDP and GDP per capita for both the acquirer and target nations. We also integrate governance metrics derived from the Worldwide Governance Indicators (WGI) for the acquirer's country. Detailed definitions of all these variables are provided in the Appendix B. In all specifications, the year, industry, and country fixed effects are included. Table 3.12 Panel A reports the OLS regression results for short-term acquirer returns. Columns (1) and (3) contain firm-level and deal-level controls, and Columns (2) and (4) further control macroeconomic and governance factors. The effects of other control variables on acquirer CARs are consistent with prior literature. Importantly, our results consistently highlight a significant negative relationship between climate change exposure and acquirer CARs across all model specifications.

To complement the analysis of deal performance, we then investigate the

[61] The market return is a return of market index constructed by including all stocks listed in each acquirer's country where the data is available on Compustat.
[62] Please see footnote 59 for the details of the references on the control variables.

relationship between climate change exposure and the long-term operating performance of acquirers. We employ two core metrics to represent operational performance: the change in return on assets (ΔROA) and earnings before interests and taxes (ΔEBIT). The ROA is the acquirer's operating income before depreciation divided by total assets, and the EBIT is the acquirer's earnings before interest and taxes scaled by its total assets. The dependent variable is the change in operating performance, calculated as the post-deal (1-year, 2-year, or 3-year after deal announcement year) ROA (or EBIT) minus the last available ROA (or EBIT) before deal announcement. Our findings, as presented in Table 3.12's Panels B and C, are the outcomes of cross-sectional regression analyses centred on this shift in operational performance. While Panel B corresponds to ΔROA, Panel C is dedicated to ΔEBIT. Both panels incorporate the same set of controls as detailed in Panel A's second specification[63], with an additional consideration given to operational performance before the deal announcement.[64] The coefficient estimates of climate change exposure are significantly negative, at least 5% level in all specifications of both Panel B and Panel C. The climate change exposure negatively affects the ROA (EBIT) change by 1.3%, 1.5%, and 1.5% (1.1%, 1.2%, and 1.0%) over the 1-year, 2-year, and 3-year post-deal announcement period, respectively. These results underscore the tangible impact that climate change exposure can have on the sustained operational success of acquiring firms.

In sum, the results in Table 3.12 suggest that the firms associated with higher

[63] We use the control of firm-level, deal-level, macroeconomic and governance variables.
[64] We control the *ROA prior*, the return on assets in one year prior to the deal announcement, in the regressions of change in ROAs; and the *EBIT/Assets prior*, the EBIT to assets ratio in one year prior to the deal announcement, in the regressions of change in EBIT/Assets. For brevity, we report only the coefficients of climate change exposure and omit all the other control variables.

climate change exposure are inclined towards deals that reflect unfavourable short-term stock market reactions and underwhelming long-term operational outcomes. As climate change exposure amplifies, firms exhibit increased reticence towards acquisitions, reinforcing that heightened environmental uncertainties deter firms from making perilous investment choices. However, a critical observation is that even when these firms opt for acquisitions amid elevated climate change exposure, they do not necessarily elevate shareholder value or overall firm performance. Any anticipated synergies seemingly remain unrealized. This could be attributed to the compounded uncertainties and operational risks inherent in firms with pronounced climate change exposure. Moreover, even meticulous target selection does not appear to offer an effective buffer or risk mitigation against the challenges posed by climate change.

3.4 Conclusion

This study highlights the significance of climate change in shaping firms' acquisition strategies. Employing Sautner et al.'s (2023) innovative climate change exposure measure, our analysis offers compelling evidence that a negative association exists between climate change exposure and firms' acquisition decisions on a global scale. This negative relationship remains consistent even after addressing potential endogeneity concerns and various macroeconomic control variables. The diminishing propensity for acquisitions due to an increase in climate change exposure intensifies external financing challenges and for periods of dampen consumer confidence. Our analysis shows that this pattern persists over an extended period of about seven years, suggesting that companies with significant climate change exposure may move away from major M&A investments.

Our study dissects various facets of climate change exposure, pinpointing the unique effects of physical, opportunity, and regulatory climate exposures on M&A activity. We also shed light on how firm-specific attributes moderate these effects. We find that the negative impact on M&A likelihood is more pronounced for firms with high external financing costs, operate in pro-cyclical industries, have financial constraints, small sized, and with a growth-centric orientation. Also, our analysis indicates that when exposed to higher levels of climate change risks, firms demonstrate a marked preference for CAPEX over M&A. This inclination suggests that firms prioritise strengthening their internal capabilities and assets than making risky investments aiming to better withstand the exposure posed by the climate change. Beyond the decision-making process, we find higher exposure leads to a lower probability of deal completions, extended deal durations, weaker short-term stock performances, and deteriorating long-term operational results post-acquisition. This paints a picture of the challenges and implications firms must grapple with in a rapidly changing climate landscape.

The findings emphasise the need to consider climate change in strategic decision-making and M&A due diligence. Policymakers can also leverage these insights to formulate regulations that encourage sustainable and climate-resilient M&A practices, harmonising corporate strategies with overarching sustainability and climate objectives at the country level.

3.5 Tables, Figures and Appendices

Table 3.1 Summary Statistics

This table presents the descriptive statistics of the baseline sample of listed firms in 34 countries with available firm-level climate change exposure (*CCE*) data and financial data from Compustat between 2001-2019 and the sample of mergers and acquisitions during 2002-2020, where data are from the SDC M&A database. We include all deals where the acquirer owns less than 10% shares of the target prior to the deal announcement and owns more than 50% of the target after the deal completion. We exclude the minority stake purchases, recapitalisations, acquisitions of remaining interests, self-tender offers, spin-offs, privatisations, reverse leverage buyouts, exchange offers, and repurchases. Panel A exhibits the process of sample construction. The table also reports the number of observations (N), mean, standard deviation, 25th percentile, median, and 75th percentile for the entire sample in Panel B and for the M&As sample in Panel C. Panel D provides the correlation matrix of the entire sample. Definitions of all variables are provided in the Appendix B.

Panel A: Sample Construction		
	Number of Observations	Number of Countries
Initial Sample from Compustat	90,295	82
Merged with Climate Change Exposure	68,182	34
Merged with SDC M&A Deals	39,336	34
Deals Performance Analysis	13,205	34

Panel B: Full Sample						
	N	Mean	Std. Dev	25th Pct	Median	75th Pct
CCE	68,182	0.105	0.263	0.010	0.032	0.082
3-year average CCE	42,682	0.311	0.729	0.050	0.099	0.242
5-year average CCE	31,744	0.527	1.176	0.091	0.171	0.420
7-year average CCE	23,404	0.753	1.630	0.135	0.246	0.612
CCE (opportunity)	68,182	0.032	0.127	0	0	0.015
CCE (regulation)	68,182	0.004	0.023	0	0	0
CCE (physical)	68,182	0.001	0.011	0	0	0
Acquisition likelihood	68,182	0.295	0.461	0	0	1
Firm size	68,182	7.502	2.439	5.857	7.333	8.896
Book leverage	68,182	0.255	0.278	0.055	0.220	0.373
Tobin's Q	68,182	1.930	1.486	1.056	1.431	2.170
Cash to assets	68,182	0.184	0.201	0.041	0.107	0.253
Sales growth	68,182	0.122	0.362	-0.022	0.065	0.182
R&D	68,182	0.043	0.091	0	0	0.045
Tangibility	68,182	0.498	0.417	0.162	0.374	0.758
Operating margin	68,182	-0.051	1.327	0.058	0.133	0.234

Panel C: M&As Sample						
	N	Mean	Std. Dev	25th Pct	Median	75th Pct

CCE	13,205	0.084	0.185	0.012	0.031	0.078
Complete	13,205	0.896	0.306	1	1	1
Time to complete(log)	12,221	2.707	2.056	0	3.466	4.344
5-day CAR	13,205	0.007	0.116	-0.025	0.004	0.036
1-year change in ROA	12,561	-0.012	0.103	-0.033	-0.005	0.017
2-year change in ROA	11,895	-0.013	0.105	-0.039	-0.007	0.019
3-year change in ROA	11,068	-0.048	3.449	-0.042	-0.009	0.021
1-year change in EBIT	12,584	-0.013	0.109	-0.034	-0.006	0.015
2-year change in EBIT	11,926	-0.015	0.112	-0.040	-0.008	0.017
3-year change in EBIT	11,098	-0.064	4.980	-0.044	-0.010	0.018
Deal value	13,205	4.429	1.947	3.045	4.382	5.737
Public target	13,205	0.155	0.362	0	0	0
Diversify	13,205	0.412	0.492	0	0	1
Incl. stock payment	13,205	0.116	0.321	0	0	0
All cash payment	13,205	0.371	0.483	0	0	1
Friendly	13,205	0.969	0.174	1	1	1
Cross-border	13,205	0.286	0.452	0	0	1
Run up	13,205	-0.027	0.591	-0.232	-0.021	0.182
Sigma	13,205	0.509	3.066	0.016	0.022	0.032
Firm size	13,205	7.798	1.872	6.484	7.723	9.105
Relative size	13,205	0.140	0.276	0.011	0.039	0.127
Book leverage	13,205	0.235	0.196	0.063	0.215	0.355
Tobin's Q	13,205	2.008	1.235	1.209	1.634	2.368
Cash to assets	13,205	0.170	0.173	0.041	0.107	0.244
Sales growth	13,205	0.169	0.328	0.015	0.104	0.233
R&D	13,205	0.032	0.052	0	0.003	0.047
Tangibility	13,205	0.433	0.365	0.149	0.306	0.653
Operating margin	13,205	0.181	0.180	0.093	0.165	0.264
ROA prior deal	13,205	0.120	0.094	0.078	0.121	0.168
EBIT prior deal	13,205	0.080	0.093	0.044	0.082	0.126

Panel D: Correlation matrix

	Acq likelihood	*CCE*	*Firm size*	*Book leverage*	*Market to book*	*Cash to assets*	*Sales growth*	*R&D*	*Tangibility*	*Operating margin*
Acq. likelihood	1.000									
CCE	-0.035	1.000								
Firm size	0.173	0.080	1.000							
Book leverage	-0.037	0.032	0.122	1.000						
Tobin's Q	0.005	-0.072	-0.219	-0.054	1.000					
Cash to assets	-0.074	-0.084	-0.366	-0.272	0.397	1.000				
Sales growth	0.029	-0.009	-0.080	-0.029	0.180	0.135	1.000			
R&D	-0.062	-0.035	-0.257	0.007	0.265	0.361	0.068	1.000		
Tangibility	-0.081	0.131	0.169	0.197	-0.169	-0.337	-0.115	-0.103	1.000	
Operating margin	0.011	0.004	0.019	-0.001	-0.015	-0.040	0.014	-0.061	0.008	1.000

Table 3.2 Distribution of Firms across Countries

This table presents the distribution of firms across 34 countries during 2001-2019.

Country/Region	N	Percent
Austria	171	0.25
Australia	1,111	1.63
Belgium	234	0.34
Bermuda Island	501	0.73
Brazil	856	1.26
Canada	1,264	1.85
Switzerland	813	1.19
Chile	173	0.25
China	1,307	1.92
Germany	1,202	1.76
Denmark	383	0.56
Spain	419	0.61
Finland	429	0.63
France	1,162	1.70
Greece	198	0.29
Hong Kong	436	0.64
Ireland	592	0.87
Israel	652	0.96
India	944	1.38
Italy	478	0.70
Japan	1,466	2.15
South Korea	236	0.35
Luxembourg	242	0.35
Mexico	486	0.71
Netherlands	695	1.02
Norway	383	0.56
New Zealand	155	0.23
Russia	311	0.46
Sweden	792	1.16
Singapore	198	0.29
Taiwan	324	0.48
United Kingdom	2,920	4.28
United States	46,271	67.86
South Africa	378	0.55
Total	68,182	100

Table 3.3 Firm-level Climate Change Exposure and Acquisition Likelihood

This table presents the results of probit regressions for the effect of firm-level climate change exposure (*CCE*) on the acquisition likelihood. The dependent variable is *acquisition likelihood*, a binary variable takes the value of one if firm *i* engaged in at least one acquisition announcement in year *t+1*, otherwise zero. The key independent variable, *CCE*, is firm-level climate change exposure constructed by Sautner et al. (2023). All independent variables are from year *t*. Columns (1) and (2) show univariate tests of climate change on likelihood of M&As. Columns (3) to (6) add controls to analyse the effect of *CCE* on the likelihood of M&As. Columns (1), (2), (3), and (5) show the direct regression coefficients. Columns (4) and (6) present marginal effects from probit regressions to ease interpretation. In all models, we control year, two-digit SIC industry fixed effects. In Columns (2), (5), and (6), we further control country fixed effects. All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: *Acquisition likelihood*					
Variables	(1)	(2)	(3)	(4) *dy/dx*	(5)	(6) *dy/dx*
CCE	-0.122***	-0.123***	-0.107***	-0.035***	-0.091***	-0.029***
	(-5.31)	(-5.06)	(-4.30)	(-4.30)	(-3.46)	(-3.46)
Firm size			0.122***	0.039***	0.191***	0.059***
			(47.68)	(49.98)	(54.93)	(58.90)
Leverage			-0.263***	-0.084***	-0.364***	-0.113***
			(-10.06)	(-10.08)	(-12.87)	(-12.92)
Tobin's Q			0.044***	0.014***	0.053***	0.016***
			(10.71)	(10.74)	(12.43)	(12.47)
Cash to assets			-0.538***	-0.171***	-0.270***	-0.083***
			(-13.90)	(-13.96)	(-6.70)	(-6.71)
Sales growth			0.135***	0.043***	0.169***	0.052***
			(8.57)	(8.58)	(10.48)	(10.50)
R&D			-0.763***	-0.242***	-0.901***	-0.279***
			(-7.90)	(-7.90)	(-8.86)	(-8.86)
Tangibility			-0.369***	-0.117***	-0.294***	-0.091***
			(-20.72)	(-20.91)	(-15.96)	(-16.04)
Operating margin			0.077***	0.024***	0.067***	0.021***
			(7.95)	(7.97)	(7.33)	(7.35)
Constant	-0.031	0.463***	-0.940***		-1.345***	
	(-0.20)	(2.60)	(-5.76)		(-6.83)	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	No	Yes	Yes
N	80,205	80,205	68,182	68,182	68,182	68,182
Pseudo R^2	0.034	0.050	0.091	0.091	0.114	0.114

Table 3.4 Entropy Balancing

This table presents the results of the entropy balancing approach of the effect of *CCE* on acquisition likelihood. First, we split the full sample into two groups: one is firms with *CCE* above zero, and the other one is firms with zero *CCE*. The treatment group are firms with *CCE* higher than zero; others are in the control group. We choose the mean, variance, and skewness as moment properties and the same matching variables in the main regression to re-weight observations in control groups. After weighting the control variables from three-moment properties, these control variables should be identical in the treatment and control groups. Thus, the covariate distribution balance is achieved. Panel A presents the differences in the means, variance, and skewness of variables in the treatment and control groups before entropy balancing. Panel B represents the three dimensions of the matched variables across treatment and control groups after entropy balancing. Panel C shows the results of *CCE* on acquisition likelihood with an entropy-weighted sample. In all models, we control the same independent variables, year, two-digit SIC industry fixed effects, or year, industry, and country fixed effects. All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Before entropy balancing (without weighting)

	Above zero or zero *climate change exposure*					
	Treat (N: 54,814)			Control (N:13,371)		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
Firm size	7.651	5.602	0.563	6.893	6.904	0.895
Leverage	0.257	0.067	6.754	0.247	0.120	13.200
Tobin's Q	1.898	2.049	2.831	2.064	2.834	2.497
Cash to assets	0.175	0.037	1.667	0.222	0.053	1.324
Sales growth	0.119	0.120	3.130	0.138	0.176	2.894
R&D	0.040	0.007	3.443	0.056	0.012	2.756
Tangibility	0.513	0.174	0.994	0.434	0.168	1.370
Operating margin	-0.013	1.477	-7.902	-0.205	2.891	-5.596

Panel B: After entropy balancing (with weighting)

	Above zero or zero *climate change exposure*					
	Treat (N: 54,814)			Control (N: 13,371)		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
Firm size	7.651	5.602	0.563	7.651	5.602	0.563
Leverage	0.257	0.067	6.754	0.257	0.067	6.820
Tobin's Q	1.898	2.049	2.831	1.898	2.050	2.831
Cash to assets	0.175	0.037	1.667	0.175	0.037	1.666
Sales growth	0.119	0.120	3.130	0.119	0.120	3.130
R&D	0.040	0.007	3.443	0.040	0.007	3.443
Tangibility	0.513	0.174	0.994	0.513	0.174	0.994
Operating margin	-0.013	1.477	-7.902	-0.014	1.478	-7.901

Panel C: Regressions after entropy balancing

Variables	*Acquisition likelihood*	*Acquisition likelihood*
CCE	-0.055**	-0.077***
	(-2.02)	(-2.60)
Controls	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Country FE	No	Yes
N	68,182	68,182
Pseudo R^2	0.082	0.110

Table 3.5 2SLS Regression

This table presents the results of a two-step least square (2SLS) regression of the impact of *CCE* on the likelihood of M&As. Following Lewbel (2012), the instrumental variables are generated internally based on the heteroskedasticity of the data. Columns (1) and (2) show the 2SLS instrumental variable regression, where the dependent variable is the acquisition likelihood. In all models, we control the same firm accounting variables and year and two-digit SIC industry fixed effects, and we further control country fixed effects in Column (2). All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Two-stage instrumental variable (IV) approach		
	Lewbel (2012)	
Variables	(1)	(2)
CCE Fitted	-0.021**	-0.034***
	(-2.24)	(-5.38)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Country FE	No	Yes
N	68,185	68,185
Adjusted R^2	0.101	0.126
Underidentification test:		
Kleibergen-Paap LM-statistic (P-value)	676.366 (0.000)	1696.582 (0.000)
Weak identification test:		
Cragg-Donald Wald F-statistic	1241.878	8907.702
Overidentification test:		
Hansen J statistic (P-value)	33.717 (0.114)	44.417 (0.102)

Table 3.6 Difference-in-Differences (DID) Approach.

This table presents the results of difference-in-difference regressions of the impact of firm-level climate change exposure (*CCE*) on the likelihood of M&As. Columns (1) and (2) display the coefficient estimates for difference-in-difference regressions using the 2015 Paris Agreement as an exogenous shock. We keep three years prior and post the year of exogenous shock. The dependent variable is the acquisition likelihood at year *t+1*. The treated firms are firms with *CCE* more than zero, and the control firms are firms with zero *CCE*. *Post-event* is a binary variable taking the value of one after the 2015 Paris Agreement and otherwise zero. In all models, we control the same firm accounting variables and year and two-digit SIC industry fixed effects, and we further control country fixed effects in Column (2). All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

DID		
	Paris Agreement	
Variables	(1) *Acquisition likelihood*	(2) *Acquisition likelihood*
*CCE * Post-event*	-0.095*	-0.119**
	(-1.68)	(-2.01)
Post-event	-0.603***	-0.603***
	(-18.47)	(-17.98)
CCE	-0.055	0.043
	(-0.79)	(0.59)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Country FE	No	Yes
N	25,819	25,819
Pseudo R^2	0.104	0.139

Table 3.7 Channel Analysis

This table reports the channel analysis of which *CCE* affects the acquisition likelihood. Panel A presents the cost of debt, explaining the lower likelihood of M&A for high *CCE* firms. The *cost of debt* is computed as total interest and related expense divided by total debt at year *t*. Panel B displays consumer confidence in explaining the negative relationship between *CCE* and acquisition likelihood. The consumer confidence indicator is an annual average of consumer confidence at the national level from the FRED consumer opinion survey, representing the consumption and saving of households in expectation of future developments. Columns (1) and (2) in Panel A and B present regression results of different channels on the *CCE*. Columns (3) to (6) report results of acquisition likelihood on *CCE* for subsamples of firms separated by a median cost of debt and consumer confidence index by country and year. In all models, we control the same firm accounting variables and year, and two-digit SIC industry fixed effects, and we further control country fixed effects in Columns (2), (5), and (6). All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cost of external financing						
Dependent variable:	*Cost of debt*		*Acquisition likelihood*		*Acquisition likelihood*	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables			High	Low	High	Low
CCE	0.027***	0.024***	-0.129***	-0.061	-0.106***	-0.057
	(3.38)	(3.10)	(-3.91)	(-1.23)	(-2.97)	(-1.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	No	Yes	Yes
N	68,185	68,185	37,321	30,860	37,321	30,860
Adjusted R^2	0.135	0.145				
Pseudo R^2			0.096	0.092	0.116	0.119

Panel B: Consumer confidence						
Dependent variable:	*Consumer confidence*		*Acquisition likelihood*		*Acquisition likelihood*	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables			High	Low	High	Low
CCE	-0.026***	-0.021***	-0.055	-0.127***	-0.030	-0.122***
	(-4.75)	(-4.54)	(-1.01)	(-3.96)	(-0.73)	(-3.56)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	No	Yes	Yes
N	67,871	67,871	29,215	38,653	29,215	38,653
Adjusted R^2	0.557	0.646				
Pseudo R^2			0.101	0.090	0.116	0.116

Table 3.8 Robustness Checks

This table reports robustness checks for the effect of *CCE* on the acquisition likelihood. In Panel A, we use long-term *CCE* as the key independent variable to proxy the persistence of firm-level climate change exposure. The *3-year CCE* (*5-year CCE* or *7-year CCE*) is the average of three (five or seven) years of *CCE* before year *t+1*. Columns (1) and (4), (2) and (5), and (3) and (6) show the long-run *CCE* of *3-year*, *5-year,* and *7-year CCE* on the acquisition likelihood, respectively. Panel B and Panel C present results of probit regressions for the effect of three different *CCE* on the acquisition likelihood, specifically, the opportunity climate change exposure (*CCE opportunity*), the regulation climate change exposure (*CCE regulation*), and the physical climate change exposure (*CCE physical*). The *CCE opportunity*, *CCE regulation*, and *CCE physical* are three components of firm-level climate change exposures constructed by Sautner et al. (2023). Panel B shows the effect of *opportunity*, *regulation,* and *physical CCE* on acquisition likelihood. Panel C presents results of probit regressions for the effect of *CCE* on the acquisition likelihood with further controls of macroeconomic and governance variables, specifically, the *GDP*, *GDP per capita*, *economic policy uncertainty* (*EPU*), *unemployment rate,* and six components of *World Governance Indicators (WGI)*. GDP and GDP per capita are the gross domestic product (GDP) and GDP per capita of the country where the firm sits. The Economic policy uncertainty (*EPU*) is defined as the average economic policy uncertainty of a firm's country by each year obtained from the national and global EPU index. The unemployment rate is the annual proportion of the unemployment labour force of the total labour force sourced from an international labour organisation. WGI measures country-level governance, including *Corruption*, *Government Effectiveness*, *Political Stability*, *Rule of Law*, *Regulatory Quality*, and *Voice and Accountability.* Panel D is the results of the effect of *CCE* on acquisition likelihood with control of alternative fixed effects. All independent variables are from year *t*. In all models, we control the same firm accounting variables and year and two-digit SIC industry, or year, industry, and country fixed effects. All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Persistence of firm-level climate change exposure

	Dependent variable: *Acquisition likelihood*					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
3-year CCE	-0.050***			-0.047***		
	(-4.20)			(-3.76)		
5-year CCE		-0.034***			-0.034***	
		(-3.79)			(-3.76)	
7-year CCE			-0.022***			-0.024***
			(-2.81)			(-3.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
N	42,682	31,744	23,404	42,682	31,744	23,404

Pseudo R^2	0.091	0.093	0.094	0.113	0.114	0.115

Panel B: Three-component of firm-level climate change exposure

	Dependent variable: *Acquisition likelihood*					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CCE (Opportunity)	-0.227***			-0.195***		
	(-4.55)			(-3.59)		
CCE (Regulation)		-0.462*			-0.580**	
		(-1.88)			(-2.16)	
CCE (Physical)			0.876*			1.217**
			(1.88)			(2.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
N	68,182	68,182	68,182	68,182	68,182	68,182
Pseudo R^2	0.091	0.091	0.091	0.114	0.114	0.114

Panel C: Climate change exposure and acquisition likelihood with additional controls

	Dependent variable: *Acquisition likelihood*			
Variables	(1)	(2)	(3)	(4)
CCE	-0.083***	-0.085***	-0.076***	-0.082***
	(-2.90)	(-2.91)	(-2.67)	(-2.81)
GDP	-0.000	0.000*	-0.000***	0.000***
	(-0.02)	(1.88)	(-2.77)	(2.88)
GDP per capita	0.000***	-0.000	0.000***	-0.000**
	(17.95)	(-0.35)	(11.91)	(-1.97)
EPU	-0.000	-0.001***	-0.000	-0.001**
	(-0.39)	(-2.69)	(-1.03)	(-2.47)
Unemployment rate	0.090***	0.033***	0.093***	0.038***
	(17.18)	(3.38)	(14.46)	(3.28)
WGI Corruption			0.122	0.309***
			(1.49)	(2.73)
WGI Government Effectiveness			-0.025	-0.568***
			(-0.26)	(-3.93)
WGI Political Stability			-0.244***	-0.083
			(-5.92)	(-1.09)
WGI Rule of Law			-0.187*	0.187
			(-1.69)	(0.97)
WGI Regulatory Quality			0.029	0.100
			(0.41)	(0.81)
WGI Voice and Accountability			0.042	0.077
			(0.76)	(0.33)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Country FE	No	Yes	No	Yes
N	55,056	55,056	54,857	54,857
Pseudo R^2	0.106	0.114	0.107	0.113

Panel D: Climate change exposure and acquisition likelihood with alternative fixed effects

	Dependent variable: *Acquisition likelihood*		
Variables	(1)	(2)	(3)
CCE	-0.071***	-0.097***	-0.081***
	(-2.72)	(-3.60)	(-3.07)
Controls	Yes	Yes	Yes
Year FE	Yes	No	No
Industry-country FE	Yes	No	No
Industry FE	No	Yes	Yes
Year-industry FE	No	Yes	No
Year-country FE	No	No	Yes
N	67,539	67,596	67,886
Pseudo R^2	0.123	0.134	0.121

Table 3.9 Additional Analysis: Acquisition Likelihood versus CAPEX or R&D

This table presents the estimated relations of *CCE* on M&A decisions and capital expenditures (*CAPEX*) or research and development expenses (*R&D*) using seemingly unrelated regressions (SUR). In Columns (1) and (3), the dependent variable takes the value of 1 if a firm makes at least one acquisition announcement in year $t+1$ and zero otherwise. In Panel A Columns (2) and (4), the dependent variable is the *CAPEX* divided by total assets in year $t+1$; in Panel B Columns (2) and (4), the dependent variable is the *R&D* divided by total assets in year $t+1$. In all models, we control the same firm accounting variables and year, and two-digit SIC industry fixed effects, and we further control country fixed effects in Columns (3) and (4). All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Acquisition likelihood vs CAPEX

	Acquisition likelihood	CAPEX	*Acquisition likelihood*	CAPEX
Variables	(1)	(2)	(3)	(4)
CCE	-0.030***	0.002***	-0.023***	0.003***
	(-3.89)	(3.98)	(-3.05)	(4.12)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
N	65,151	65,151	65,151	65,151
Adjusted R^2	0.100	0.440	0.130	0.450

Panel B: Acquisition likelihood vs R&D

	Acquisition likelihood	R&D	*Acquisition likelihood*	R&D
Variables	(1)	(2)	(3)	(4)
CCE	-0.029***	-0.014***	-0.022***	-0.012***
	(-3.77)	(-6.92)	(-2.96)	(-6.00)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
N	65,451	65,451	65,451	65,451
Adjusted R^2	0.100	0.310	0.130	0.310

Table 3.10 Cross-sectional Analysis

This table presents several cross-sectional tests of the effect of *CCE* on acquisition likelihood. The dependent variable is *acquisition likelihood*, a binary variable takes the value of one if firm *i* engaged in at least one acquisition announcement in year *t+1*, otherwise zero. In Panel A, we report whether the lower likelihood of M&A for high *CCE* firms differs for the firm's industry cycle. The *industry cycle* is categorised by the firm into pro-cyclical industry and counter-cyclical industry. We first find the correlation between a firm's revenues and the Gross National Income (GNI) over the sample period of 2001-2019 by country. Then, we compute the 2-digit SIC industry average correlation of firms by country. If the industry average correlation coefficient is above the median correlation, then this 2-digit SIC industry is pro-cyclical; otherwise, it is a counter-cyclical industry. Panel B shows whether high *CCE* firms with financial constraints are less involved in acquisitions. *Financial constraints,* this variable is proxied as Whited and Wu index (2006) suggested at year *t*. See Whited and Wu's formula for more details. The firm is classified as financially constrained if its Whited-Wu index is higher than the median within each country; otherwise, it is without financial constraints. Panel C exhibits whether there exists a different effect of *CCE* on acquisition likelihood for firms with large or small market capitalization. If the firm has a market capitalization higher than the median within each country, it is defined as a larger size; otherwise, it is small. Panel D presents results for comparing the effect of *CCE* on acquisition likelihood for value and growth firms. When the firm's book-to-market ratio is above the country's median, it is a value firm; otherwise, it is a growth firm. All independent variables are from year *t*. In all models, we control the same independent variables. In Columns (1) and (2), we control year, two-digit SIC industry fixed effects, and in Columns (3) and (4), we control year, industry, and country fixed effects. All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Industry cycle				
	Acquisition likelihood		*Acquisition likelihood*	
Variables	(1) Pro-cyclical	(2) Counter-cyclical	(3) Pro-cyclical	(4) Counter-cyclical
CCE	-0.137***	-0.066	-0.140***	-0.041
	(-3.44)	(-1.58)	(-3.31)	(-1.17)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
N	29,270	37,670	29,270	37,670
Pseudo R^2	0.100	0.090	0.123	0.113

Panel B: Financial constraints				
	Acquisition likelihood		*Acquisition likelihood*	
Variables	(1) Constraint	(2) No constraint	(3) Constraint	(4) No constraint
CCE	-0.102***	-0.061	-0.100***	-0.036
	(-2.78)	(-1.24)	(-2.70)	(-0.84)
Controls	Yes	Yes	Yes	Yes

Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
N	29,289	31,178	29,284	31,178
Pseudo R^2	0.086	0.075	0.104	0.099

Panel C: Market capitalisation

	Acquisition likelihood		*Acquisition likelihood*	
Variables	(1) Large	(2) Small	(3) Large	(4) Small
CCE	-0.042	-0.096***	-0.038	-0.097***
	(-1.09)	(-2.68)	(-0.95)	(-2.58)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
N	30,768	32,166	30,768	32,166
Pseudo R^2	0.075	0.073	0.095	0.090

Panel D: Value vs. growth firms

	Acquisition likelihood		*Acquisition likelihood*	
Variables	(1) Value	(2) Growth	(3) Value	(4) Growth
CCE	-0.076	-0.132***	-0.084*	-0.092**
	(-1.61)	(-3.75)	(-1.74)	(-2.55)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
N	30,170	38,012	30,170	38,012
Pseudo R^2	0.088	0.099	0.103	0.130

Table 3.11 Probability of Deal Completion and Time to Complete the Deal

This table provides probit model results of deal completion and Tobit model results of the duration of deal completion. The M&As sample from SDC Database of firms from 34 countries between 2002 and 2020. M&A deals are applied for the selection as follows: i) excluding the minority stake purchases, recapitalisations, acquisitions of remaining interests, self-tenders, spin-offs, privatisations, reverse leverage buyouts, exchange offers, and repurchases; ii) requiring the acquirer owned less than 10% shares of the target prior and to hold more than 50% of the target after the deal completion. Columns (1) and (2) show the *CCE* and deal completion results. The dependent variable, denoted by *Deal completion*, equals one if the acquisition is completed. If the acquisition is ongoing or withdrawn, it takes the value of zero. Columns (3) and (4) show the impact of *CCE* on time to complete a deal. The dependent variable, denoted by *time to complete*, is the natural logarithm of one plus the number of days between the announcement date and the effective date. The control variables include *Deal value, Public target, Diversify, Including stock payment, All cash payment, Friendly, Cross-border, Firm size, Relative size, Leverage, Tobin's Q, Cash to assets, Sales growth, R&D, Tangibility, and Operating margin*. In all models, we control the same independent variables with constant, year, two-digit SIC industry fixed effects or year, industry, and country fixed effects. All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Deal completion		*Time to complete*	
	(1)	(2)	(3)	(4)
Variables				
CCE	-0.192**	-0.195**	0.406***	0.375***
	(-2.19)	(-2.21)	(3.18)	(2.94)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes
N	14,623	14,623	13,634	13,634
Pseudo R^2	0.097	0.104	0.106	0.111

Table 3.12 Acquirers Performance

This table presents the results of OLS regressions for the effect of *CCE* on the acquirer's short-term and operating performance. The M&A sample consists of all deal announcements reported in the SDC database between 2002 and 2020 that were described previously. In Panel A, the dependent variable is a five-day (-2, +2) cumulative abnormal return for acquirers, where day 0 is the deal announcement date, using the market model with parameters estimated over the period starting 241 days and ending 41 days preceding the announcement date. The market return is the index computed using all stocks listed in each acquirer's country on Compustat. Columns (1) and (3) exhibit results with control of deal and firm characteristics. The control variables include *Deal value, Public target, Diversify, Including stock payment, All cash payment, Friendly, Cross-border, Run-up, Sigma, Firm size, Relative size, Leverage, Tobin's Q, Cash to assets, Sales growth, R&D, Tangibility, and Operating margin*. Columns (2) and (4) add further control of macroeconomic and governance variables. The macroeconomic variables are *Acquirer GDP, Target GDP, Acquirer GDP per capita, Target GDP per capita*, and the governance variables are *WGI Corruption, WGI Government Effectiveness, WGI Political Stability, WGI Rule of Law, WGI Regulatory Quality, WGI Voice and Accountability*. Panel B and Panel C present the effect of *CCE* on the acquirer's long-run operating performance, specifically, change in return on assets (*ROAs*) and earnings before interest and taxes ratio (*EBITs*). Panel B shows the results of *CCE* on the change in *ROAs*, defined as the bidder's ROA in year $t + 1$, $t + 2$, and $t + 3$ minus its ROA in year $t – 1$, where *t* is the year of the deal announcement. Panel C presents the results of *CCE* on the change in *EBITs*, defined as the bidder's EBIT divided by total assets in year $t + 1$, $t + 2$, and $t + 3$ minus its EBIT ratio in year $t – 1$, where *t* is the year of the deal announcement. We add the last fiscal year's ROA or EBIT ratio before the deal announcement to control variables, and other controls are the same as in Panel A (with additional control of acquirer and target countries' GDP, GDP per capita, and WGI six factors). In all models, we control the same independent variables, year, two-digit SIC industry fixed effects, or year, industry, and country fixed effects. All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Acquirer CARs (-2, +2)				
	Dependent variable: 5-*day acquirer CARs*			
Variables	(1)	(2)	(3)	(4)
CCE	-0.014**	-0.011*	-0.016**	-0.013**
	(-1.99)	(-1.69)	(-2.27)	(-2.05)
Acquirer GDP		-0.000		-0.058
		(-0.08)		(-1.11)
Target GDP		-0.000		-0.000
		(-0.14)		(-0.12)
Acquirer GDP per capita		-0.003		0.005
		(-0.34)		(0.09)
Target GDP per capita		-0.002		-0.001
		(-0.68)		(-0.51)

WGI Corruption		0.026		0.029
		(1.33)		(1.17)
WGI Government Effectiveness		-0.024		0.013
		(-1.14)		(0.44)
WGI Political Stability		-0.020*		0.009
		(-1.72)		(0.56)
WGI Rule of Law		0.033		-0.013
		(1.44)		(-0.32)
WGI Regulatory Quality		-0.020		-0.011
		(-1.31)		(-0.49)
WGI Voice and Accountability		-0.004		0.048
		(-0.27)		(1.03)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
N	13,205	12,892	13,205	12,892
Adjusted R^2	0.018	0.019	0.022	0.023

Panel B: Change in ROAs

	Dependent variable: *change in ROAs*					
Variables	(1) 1-year	(2) 2-year	(3) 3-year	(4) 1-year	(5) 2-year	(6) 3-year
CCE	-0.013***	-0.016***	-0.016***	-0.013***	-0.016***	-0.016***
	(-3.15)	(-3.73)	(-3.42)	(-3.12)	(-3.65)	(-3.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
N	12,283	11,679	10,991	12,283	11,679	10,991
Adjusted R^2	0.209	0.251	0.261	0.213	0.255	0.264

Panel C: Change in EBITs

	Dependent variable: *change in EBITs*					
Variables	(1) 1-year	(2) 2-year	(3) 3-year	(4) 1-year	(5) 2-year	(6) 3-year
CCE	-0.011**	-0.013***	-0.011**	-0.011**	-0.013***	-0.011**
	(-2.50)	(-2.76)	(-2.27)	(-2.50)	(-2.71)	(-2.18)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
N	12,306	11,704	11,021	12,306	11,704	11,021
Adjusted R^2	0.214	0.260	0.265	0.217	0.262	0.268

Appendix B. Definitions of Variables and Complementary Tables (Essay Two)

Appendix B1. Definitions of Variables

Variable	Description
CCE	Firm-level climate change exposure constructed on the transcripts of earnings conference calls by Saunter et al. (2023) multiplied by one hundred. (Firm level climate change exposure * 100)
3-year CCE	The average of the prior three years of firm-level climate change exposure.
5-year CCE	The average of the prior five years of firm-level climate change exposure.
7-year CCE	The average of the prior seven years of firm-level climate change exposure.
Acquisition likelihood	The binary variable takes the value of 1, where the firm makes at least one acquisition bid in year t+1.
Complete	The binary variable takes the value of 1 if the deal status is completed, otherwise, it is zero.
Time to complete	Natural logarithm of one plus the number of days between the announcement and effective dates.
CAR (-2, +2)	Acquirers' cumulative abnormal return (CAR) in the 5-day event window (-2, +2), where 0 is the announcement day. The returns are computed using the market model with the market model parameters estimated over the period starting 241 days and ending 41 days prior to the announcement. The market index is constructed by including all stocks listed in each acquirer's country where the data is available on Compustat.
ROA change (-1, +t)	Acquirer's operating income before depreciation divided by total assets 1-, 2-, and 3-years after the deal announcement, minus the value in the year prior to the deal announcement.
EBIT change (-1, +t)	Acquirer's earnings before interest and tax divided by total assets 1-, 2-, and 3-years after the deal announcement, minus the value in the year prior to the deal announcement.
Cost of debt	Total amount of interest and related expense scaled by total debt.
Consumer confidence	Measuring consumption and saving of households in respect of future developments, based on answers of their expected financial situation, sentiment about the general economic situation, unemployment, and capability of savings. Obtained from Consumer confidence national indicators on Federal Reserve Economic Data.
Industry cycle	The binary variable takes the value of 1 where the firm's industry is procyclical, otherwise zero (zero for countercyclical industries).
Financial constraints	Firm financial constraints index, defined by Whited and Wu (2006). See Whited and Wu (2006) Equation (13) for details.
Market capitalisation	Year-end total market value of a company's outstanding shares of stock.
Book to market value	Book value of assets divided by the sum of the year-end market capitalization and the difference between book value of assets and book value of common equity.
Firm size (log)	Natural logarithm of total assets.
Book leverage	Long-term debt and current liabilities divided by the book value of total assets.
Tobin's Q	Market value of total assets over book value of total assets.
Cash to assets	Cash and short-term investments divided by total assets.
Sales growth	Sales minus prior year sales, divided by prior year sales.
R&D	Research and development expenses divided by total assets.
CAPEX	Capital expenditures divided by total assets.
Tangibility	Total property, plant, and equipment divided by total assets.
Operating margin	Operating income before depreciation scaled by sales.
Deal value (log)	Natural logarithm of value of the transaction from SDC.
Public target	Binary variable where 1 signifies that target is listed.
Diversify	Binary variable where 1 signifies that the first 2 digits of SICs of the acquirer and the target are different.
Including stock payment	The binary variable takes the value of 1 where the payment of acquisitions includes the percentage of stock payment.
All cash payment	The binary variable takes the value of 1 where the payment of acquisitions is 100% cash.
Friendly	Binary variable where 1 signifies that the deal attitude is friendly.
Cross-border	Binary variable where 1 denotes that the deal is a cross-border deal, the

	countries of the acquirer and the target are different.
Size (log)	Natural logarithm of acquirer market value one month prior to the announcement.
Relative Size	The ratio of deal value to acquirer market value one month prior to the deal announcement.
Runup	Market-adjusted buy-and-hold return of the acquirer's stock over the period beginning 205 days and ending 6 days prior to the announcement date.
Sigma	The standard deviation of the acquirer's market-adjusted daily returns over the period beginning 205 and ending 6 days before the deal announcement
ROA prior	The ratio of operating income before depreciation to the book value of total assets the year prior to the deal announcement.
EBIT prior	Acquirer's earnings before interest and tax divided by total assets the year prior to the deal announcement.
Acquirer GDP	The GDP in current dollars of the country of the acquirer.
Acquirer GDP per capita	The GDP per capita in current dollars of the country of acquirer.
Acquirer EPU	The average of 12 months of economic policy uncertainty in the acquirer's country.
Acquirer unemployment rate	The unemployment rate is measured as the unemployment of the total labour force of the country of the acquirer.
Target GDP	The GDP in current dollars of the country of target.
Acquirer GDP per capita	The GDP per capita in current dollars of the country of target.
WGI Corruption	The average of the measurements of control of corruption by each year and country of acquirer from Worldwide Governance Indicators.
WGI Government effectiveness	The average of the measurements of government effectiveness by each year and country of acquirer from Worldwide Governance Indicators.
WGI Political stability	The average of the measurements of political stability and absence of violence or terrorism by each year and country of acquirer from Worldwide Governance Indicators.
WGI Rule of law	The average of the measurements of the rule of Law by each year and country of acquirer from Worldwide Governance Indicators.
WGI Regulatory quality	The average of the measurements of regulatory quality by each year and country of acquirer from Worldwide Governance Indicators.
WGI Voice and accountability	The average of the measurements of voice and accountability by each year and country of acquirer from Worldwide Governance Indicators.

Appendix B2. Complementary Tables (Essay Two)

Figure B2.1 Time Trend of Average Climate Change Exposure across Countries

This figure presents the time trend of average *CCE* by country and year from 2001 to 2019 of the top 10 countries (with the most distribution of firm observations). The average *CCE* is each country's mean of *CCE* by year.

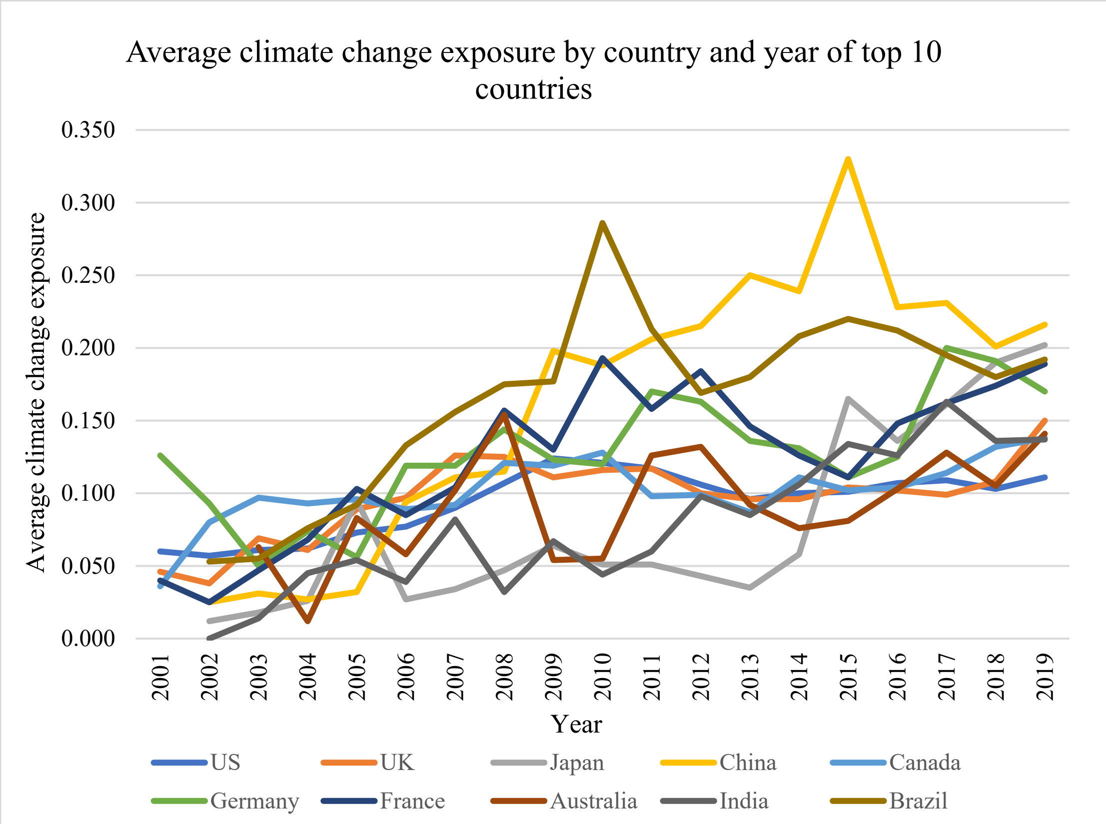

Table B2.1 Correlation Matrix of the M&As Sample

This table provides the correlation matrix of the M&A sample. Definitions of all variables are provided in the Appendix B.

Panel A: Correlation matrix of the M&As sample

	Complete	*Time to complete*	*CAR (-2, +2）*	*1-year ΔROA*	*2-year ΔROA*	*3-year ΔROA*	*1-year ΔEBIT*	*2-year ΔEBIT*	*3-year ΔEBIT*	*CCE*	*Deal value*	*Public target*	*Diversify*	*Incl. stock payment*
Complete	1.000													
Time to complete	-0.166	1.000												
CAR (-2, +2）	0.012	0.007	1.000											
1-year ΔROA	0.010	-0.005	0.014	1.000										
2-year ΔROA	-0.002	-0.001	0.031	0.551	1.000									
3-year ΔROA	-0.003	-0.004	-0.010	0.038	0.032	1.000								
1-year ΔEBIT	0.008	0.001	0.013	0.980	0.534	0.035	1.000							
2-year ΔEBIT	-0.003	0.003	0.031	0.536	0.979	0.028	0.551	1.000						
3-year ΔEBIT	-0.003	-0.004	-0.011	0.034	0.026	1.000	0.031	0.023	1.000					
CCE	-0.023	0.015	-0.008	0.001	0.008	0.000	-0.001	0.007	0.000	1.000				
Deal value	0.000	0.559	-0.013	-0.018	-0.025	0.015	-0.013	-0.019	0.015	0.010	1.000			
Public target	-0.062	0.380	-0.046	-0.015	-0.013	0.004	-0.011	-0.009	0.004	-0.010	0.378	1.000		
Diversify	0.038	-0.082	0.007	0.007	-0.006	0.008	0.004	-0.005	0.008	0.039	-0.044	-0.051	1.000	
Incl. stock payment	0.015	0.097	0.010	-0.020	-0.018	0.002	-0.020	-0.020	0.003	0.001	0.141	0.115	-0.079	1.000
All cash payment	0.046	0.076	0.006	-0.007	-0.003	0.008	-0.009	-0.006	0.007	-0.045	0.074	0.126	0.013	-0.279
Friendly	0.177	-0.118	0.024	0.010	0.009	-0.002	0.007	0.005	-0.002	-0.013	-0.177	-0.207	0.032	-0.025
Cross-border	-0.051	0.002	-0.013	-0.006	-0.010	0.006	-0.002	-0.005	0.006	0.007	-0.004	-0.022	0.023	-0.086
Run up	0.005	0.009	-0.042	0.015	0.007	0.016	0.018	0.006	0.016	0.003	0.014	0.014	-0.007	0.003
Sigma	-0.038	0.055	-0.045	0.003	-0.007	0.000	0.003	-0.006	0.001	0.019	0.044	0.047	-0.009	-0.018

Firm size	-0.048	0.270	-0.085	0.007	-0.018	0.022	0.018	-0.005	0.022	-0.020	0.512	0.173	0.059	-0.124
Relative size	-0.049	0.263	0.067	-0.027	-0.002	0.001	-0.027	-0.004	0.000	0.002	0.376	0.233	-0.078	0.256
Book leverage	-0.050	0.067	0.012	0.041	0.001	-0.005	0.045	0.009	-0.005	0.046	0.153	-0.009	0.026	-0.045
Tobin's Q	0.004	-0.066	-0.017	-0.065	-0.083	-0.003	-0.057	-0.077	-0.002	-0.093	-0.037	-0.018	-0.070	0.050
Cash to assets	0.023	-0.060	-0.007	-0.003	0.011	0.008	-0.022	-0.010	0.008	-0.076	-0.144	0.008	-0.053	0.098
Sales growth	0.002	-0.026	-0.003	-0.060	-0.053	-0.020	-0.075	-0.073	-0.020	-0.011	-0.033	-0.011	-0.029	0.082
R&D	0.044	-0.052	-0.022	0.025	0.051	0.007	0.024	0.057	0.007	-0.074	-0.107	0.039	-0.068	0.085
Tangibility	-0.077	0.117	0.003	-0.028	-0.025	-0.015	-0.004	-0.003	-0.015	0.121	0.104	0.044	-0.077	-0.012
Operating margin	-0.040	0.086	-0.035	-0.248	-0.266	0.010	-0.233	-0.252	0.013	-0.033	0.218	0.045	-0.059	-0.085

Panel B: Correlation matrix of the M&As sample continued

	All cash payment	***Friendly***	***Cross-border***	***Run up***	***Sigma***	***Firm size***	***Relative size***	***Book leverage***	***Tobin's Q***	***Cash to assets***	***Sales growth***	***R&D***	***Tangibility***	***Operating margin***
All cash payment	1.000													
Friendly	-0.029	1.000												
Cross-border	-0.017	-0.028	1.000											
Run up	0.001	0.004	-0.013	1.000										
Sigma	-0.006	-0.025	0.043	0.020	1.000									
Firm size	0.098	-0.089	0.147	0.023	0.108	1.000								
Relative size	-0.073	-0.136	-0.093	-0.016	-0.014	-0.268	1.000							
Book leverage	-0.049	-0.043	-0.066	-0.005	0.014	0.082	0.109	1.000						
Tobin's Q	0.003	0.024	0.016	-0.022	-0.062	0.143	-0.132	-0.241	1.000					
Cash to assets	0.046	0.028	0.010	-0.003	-0.043	-0.133	-0.044	-0.414	0.388	1.000				
Sales growth	-0.044	0.004	-0.057	-0.032	-0.007	-0.088	0.038	-0.004	0.134	0.060	1.000			
R&D	0.035	0.037	0.032	0.025	-0.034	-0.084	-0.046	-0.316	0.343	0.555	0.014	1.000		
Tangibility	-0.071	-0.033	-0.030	-0.005	0.095	0.064	0.081	0.252	-0.203	-0.339	-0.085	-0.250	1.000	
Operating margin	0.046	-0.044	0.015	-0.012	0.042	0.351	-0.045	0.200	0.051	-0.213	0.053	-0.247	0.177	1.000

Table B2.2 Firm-level climate change exposure and cross-border acquisition likelihood or domestic acquisition likelihood

This table presents the results of probit regressions for the effect of *CCE* on the cross-border acquisition likelihood and domestic acquisition likelihood. In Panel A, the dependent variable is *Cross-border acquisition likelihood*, a binary variable takes the value of one if firm *i* engaged in at least one cross-border acquisition announcement in year *t+1*, otherwise zero. In Panel B, the dependent variable is *Domestic acquisition likelihood*, a binary variable takes the value of one if firm *i* engaged in at least one domestic acquisition announcement in year *t+1*, otherwise zero. The key independent variable, *CCE*, is firm-level climate change exposure constructed by Sautner et al. (2023). All independent variables are from year *t*. Columns (1) and (3) show the direct regression coefficients. Columns (2) and (4) present marginal effects from probit regressions to ease interpretation. In all models, we control firm-level characteristics same as Table 3.3, year, two-digit SIC industry fixed effects. In Columns (2) and (4), we further control country fixed effects. All variables' definitions are provided in the Appendix. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Likelihood of cross-border deals				
	Dependent variable: *Cross-border Acquisition likelihood*			
Variables	(1)	(2) *dy/dx*	(3)	(4) *dy/dx*
CCE	-0.088***	-0.017***	-0.105***	-0.019***
	(-2.56)	(-2.56)	(-2.64)	(-2.64)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
N	68,182	68,182	68,182	68,182
Pseudo R^2	0.140	0.140	0.192	0.192
Panel B: Likelihood of domestic deals				
	Dependent variable: *Domestic Acquisition likelihood*			
Variables	(1)	(2) *dy/dx*	(3)	(4) *dy/dx*
CCE	-0.102***	-0.027***	-0.104***	-0.027***
	(-3.34)	(-3.34)	(-3.54)	(-3.54)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
N	68,182	68,182	68,182	68,182
Pseudo R^2	0.074	0.074	0.099	0.099

Table B2.3 Entropy Balancing (Split Treatment and Control by the Median of Climate Change Exposure)

This table presents the results of the entropy balancing approach of the effect of *CCE* on acquisition likelihood. First, we split the sample into above and below the median *CCE* within each year and country. The treatment group are firms with *CCE* higher than the median, and others are in the control group. We choose the mean, variance, and skewness as moment properties and the same matching variables in the main regression to re-weight observations in control groups. After weighting the control variables from three-moment properties, these control variables should be identical in the treatment and control groups; thus, the covariate distribution balance is achieved. Panel A presents the differences in the means, variance, and skewness of variables in the treatment and control groups before entropy balancing. Panel B represents the three dimensions of the matched variables across treatment and control groups after entropy balancing. Panel C shows the results of *CCE* on acquisition likelihood with an entropy-weighted sample. In all models, we control the same independent variables, year, two-digit SIC industry fixed effects, or year, industry, and country fixed effects. All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Before entropy balancing (without weighting)						
	Above or below median *climate change exposure*					
	Treat (N: 35,854)			Control (N:32,331)		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
Firm size	7.703	5.988	0.562	7.279	5.809	0.647
Leverage	0.261	0.065	7.585	0.249	0.091	10.410
Tobin's Q	1.790	1.769	3.100	2.086	2.648	2.469
Cash to assets	0.162	0.033	1.805	0.210	0.047	1.396
Sales growth	0.116	0.123	3.105	0.130	0.139	3.081
R&D	0.037	0.007	3.714	0.050	0.010	2.928
Tangibility	0.556	0.177	0.833	0.432	0.162	1.379
Operating margin	-0.004	1.366	-8.140	-0.103	2.193	-6.518
Panel B: After entropy balancing (with weighting)						
	Above or below median *climate change exposure*					
	Treat (N: 35,854)			Control (N:32,331)		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
Firm size	7.703	5.988	0.562	7.703	5.988	0.562
Leverage	0.261	0.065	7.585	0.261	0.065	7.587
Tobin's Q	1.790	1.769	3.100	1.790	1.769	3.100
Cash to assets	0.162	0.033	1.805	0.162	0.033	1.805
Sales growth	0.116	0.123	3.105	0.116	0.123	3.105
R&D	0.037	0.007	3.714	0.037	0.007	3.714
Tangibility	0.556	0.177	0.833	0.556	0.177	0.833
Operating margin	-0.004	1.366	-8.140	-0.004	1.366	-8.140

Panel C: Regressions after entropy balancing		
Variables	*Acquisition likelihood*	*Acquisition likelihood*
CCE	-0.094***	-0.084***
	(-3.78)	(-3.19)
Controls	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Country FE	No	Yes
N	68,182	68,182
Pseudo R^2	0.088	0.112

Figure B2.2 Parallel Trends of DID Test

This figure shows the parallel trend of difference-in-difference regressions of the impact of *CCE* on the likelihood of M&As, using the 2015 Paris Agreement as an exogenous shock. We keep three years prior and post the year of exogenous shock. The dependent variable is the acquisition likelihood at year *t+1*. The treated firms are firms with *CCE* more than zero, and the control firms are firms with zero *CCE*. *Post-event* is a binary variable taking the value of one after the 2015 Paris Agreement and otherwise zero. In the line graphs, we control the same firm accounting variables and year, and two-digit SIC industry fixed effects, and we further control country fixed effects in the right figure. Bands corresponding to 95% confidence intervals based on standard errors clustered by both firm and year are included.

Parallel trend tests

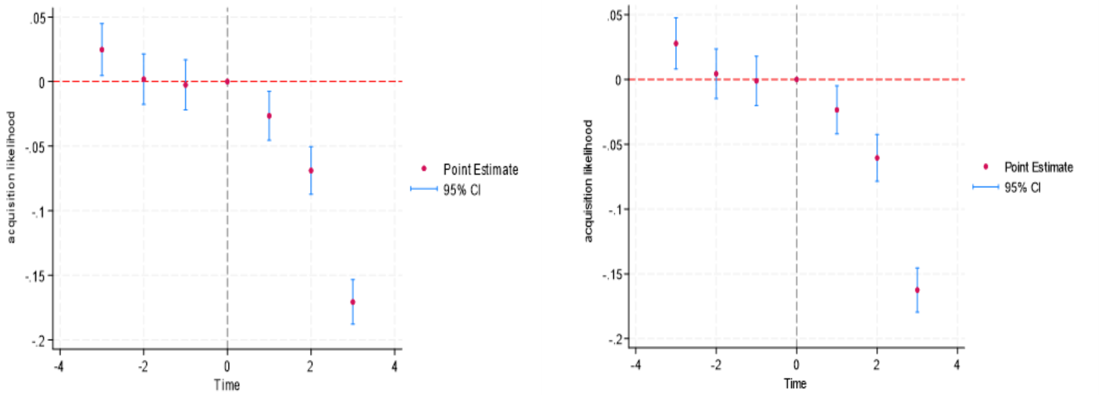

Table B2.4 Robustness Checks

This table reports robustness checks for the effect of *CCE* on the acquisition likelihood. Panel A reports the impact of three different categories of *CCE* in the same regression on the likelihood of M&As. Panel B exhibits the results of the effect of *CCE* on acquisition likelihood with control alternative fixed effects of using OLS regressions. All variables' definitions are provided in the Appendix B. Heteroscedasticity-robust standard errors are clustered by both firm and year. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Three-component of firm-level climate change exposure in the same regression

	Dependent variable: *Acquisition likelihood*	
Variables	(1)	(2)
CCE (Opportunity)	-0.235***	-0.197***
	(-4.58)	(-3.58)
CCE (Regulation)	-0.256	-0.414
	(-1.04)	(-1.54)
CCE (Physical)	1.248***	1.528***
	(2.65)	(3.11)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Country FE	No	Yes
N	68,182	68,182
Pseudo R^2	0.090	0.110

Panel B: Different fixed effects in OLS regressions

	Dependent variable: *Acquisition likelihood*					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CCE	-0.030***	-0.023***	-0.018***	-0.026***	-0.021***	-0.019***
	(-4.64)	(-3.62)	(-2.74)	(-3.94)	(-3.18)	(-2.71)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	No	No	Yes	No
Country FE	No	Yes	No	No	No	No
Year-industry FE	No	No	No	Yes	No	No
Year-country FE	No	No	No	Yes	Yes	No
Industry-country FE	No	No	Yes	No	No	No
Year-industry-country FE	No	No	No	No	No	Yes
N	68,185	68,185	68,148	68,149	68,171	65,121
Adjusted R^2	0.101	0.125	0.134	0.130	0.128	0.130

4. Technology Mergers and Acquisitions Around the World: Boon or Bane?

4.1 Introduction

Gaining access to innovative technology assets has been one of the most important strategic motives for M&As. For technology companies, assimilating external technologies serves to enhance their core tech portfolio and capabilities or to effectively neutralise competition. Non-technology companies primarily pursue acquisitions of technology assets to facilitate transformative changes in their product or service offerings, aligning with their digital strategy. At present, the world has entered a new economic era dominated by technological advancements. Technology companies have been spearheading economic expansion via innovation, as well as reshaping more traditional sectors, such as commerce. It is not only retail and wholesale commerce that has been revamped by technological applications, but almost every sector of the economy. A representative example is the acquisition of the AI company Dynamic Yield by McDonald’s in order to improve its offering in real-time (Financial Times, 2019). McDonald’s is barely alone in its effort to employ high technological solutions to improve its operations and enhance its competitive advantage against industry peers.

Notably, the share of technology M&As has grown from 6% to 20% of total M&A volume during 2006-2018, signifying the escalating strategic importance of technology in the product and service markets. This trend has been further amplified due to the COVID-19 pandemic since businesses adopt technology solutions to remain viable and competitive. After a short pause in most deal-making during the early months of the pandemic, M&A activity, especially in tech, saw a remarkable resurgence, setting historical records in volumes and numbers (EY, 2021).

The uptrend in technology M&As is a global phenomenon. Both developed and emerging economies have seen a surge in tech deals, while the Asian region, especially China and India, is increasingly taking centre stage in high-tech-driven mergers. Prior literature in tech M&As has been predominantly focused on the U.S. market and niche technology sectors. After the "Dotcom Bubble" period, when North America and Europe dominated the tech M&A market, there has been a notable shift, with a large proportion of tech deals now occurring in emerging countries. For instance, the Chinese market ranks third in the volume of all technology deals, and 20% of Chinese M&A targets belong to the high-tech industry (BCG, 2019). This shifting dynamic highlights the increasing significance of tech M&As in shaping the future trajectory of the technology industry on a global scale.

The landscape of participants in technology mergers and acquisitions (M&As) has also undergone a profound transformation. Until the end of the ‘Dotcom Bubble’, tech acquisitions primarily involved tech firms acting as both acquirers and targets. However, in recent years, there has been a significant increase in cross-industry acquisitions featuring tech firms as either the acquirers or targets, emphasising their growing strategic importance. Cross-industry acquisitions with tech firms as either acquirers or targets have increased in numbers and strategic importance. For instance, Walmart acquired Flipkart, India's biggest e-commerce firm for $16 billion in 2018 (Walmart, 2018). L'Oreal took the majority stake in Modiface in 2018, a leading firm in augmented reality and artificial intelligence (Financial Times, 2018); McDonald's signed merger contracts with an AI company and an automated voice agent, Dynamic Yield and Apprente in 2019 (Financial Times, 2019; Bloomberg, 2019); and Morgan Stanley bought E-Trade, an online fintech brokerage, in 2020 (Financial Times, 2020). These cross-industry tech M&As highlight the dynamic shift in the M&A landscape and demonstrate the strategic importance of technology integration across diverse sectors.

The lack of recent, global, and industry-wide evidence on the impact of tech M&As makes it paramount to investigate the value creation of the aggregate technology M&A market using a worldwide sample. In light of this, this study utilises a novel and comprehensive data set to examine the impact and outcomes of technology M&As. Our sample comprises 79,455 deals over the period 1990-2018, covering 52 countries. This extensive dataset allows us to gain a comprehensive understanding of the dynamics and implications of technology M&As worldwide.

This is the first study, to the best of our knowledge, to differentiate deals by the technological classification of acquirers and targets. Specifically, I categorise acquirers and targets as High Tech (Hi) companies and Non-High Tech (Non) companies. This results in four deal types per the technological classification of the acquirer-target pair: *Hi-Hi, Hi-Non, Non-Non,* and *Non-Hi*. I proceed to study the characteristics, wealth effects, and overall performance of the four deal-type combinations.

Bena and Li (2014) show that M&As characterised by a higher degree of technological relatedness between the acquirer and the target can lead to an increase in post-deal patent applications and combined innovation. This suggests that transactions involving firms with established technological credentials (referred to as *Hi-Hi* deals) are more likely to achieve superior performance outcomes, owing to their ability to leverage existing technological competencies to realise enhanced synergies. Conversely, transactions that exhibit a larger technological disparity—specifically those categorized as *Non-Hi* and *Hi-Non* deals—are posited to generate lesser value. This diminished value creation is attributed to the limited commonalities between the firms involved and the increased integration efforts required.

Contrary to this viewpoint, extant literature underscores the significance of resource complementarity differences in the success of M&As. This perspective emphasises the crucial role of resource redeployment and exploitation in generating value, thereby facilitating improvements in efficiency, turnover, and market growth (Helfat, 1997; Larsson and Finkelstein, 1999). Makri, Hitt, and Lane (2010) further this argument by suggesting that acquisitions characterised by high technological complementarity between the acquiring and target firms are more likely to culminate in greater innovation outputs and, consequently, superior financial performance. For firms outside the technology sector acquiring technology-oriented targets, this dynamic often entails access to innovative and disruptive technologies that can precipitate transformative changes in their product or service offerings, which could help them access new market segments, utilise novel logistics and communication channels, and optimise production and operations efficiencies. Similarly, technology firms acquiring non-technology targets may utilise their advanced technological capabilities to optimise the operations and market offerings of the acquired firms, by expanding their sales network and increasing efficiencies versus competitors in both acquirer and target industries. In essence, acquirer and target firms can mutually facilitate each other's long-term strategic plans, aligning with the complementarity cornerstone theory (Makri et al., 2010; Colombo and Rabbiosi, 2014), which purports that fewer technological similarities between acquirers and targets lead to greater wealth creation for shareholders. In contrast, deals with similar tech profiles for acquirers and targets (*Hi-Hi*, *Non-Non*) are less likely to emulate efficiencies and synergies of comparable nature and magnitude.

Drawing upon this discourse, I hypothesise that M&As with high technological distance (*Hi-Non* and *Non-Hi* deals) are more likely to result in significant value creation for shareholders due to the potential for unlocking unique synergies and innovation opportunities, making strategic transformation more likely. Such deals are strategically positioned to enhance competitive advantages and operational efficiencies, leading to improved performance post-acquisition. To validate our hypothesis, this essay compares value creation across the different technology deal types.

The analysis of this study reveals positive and statistically significant announcement returns for technologically distant deals (*Non-Hi*, *Hi-Non*), exhibiting an average acquirer cumulative abnormal return (CAR) of 2.22%, compared to 1.46% for technologically similar deals (*Hi-Hi*, *Non-Non*), and *Non-Hi* deals display the highest gains among all deal types with a CAR of 2.69%. The economic significance of this finding is substantial, as the average technologically distant deal generates an increase of $56.40 million in the acquirer's market capitalisation. These results strongly support our hypothesis, indicating a higher potential for synergies and growth opportunities in technologically distant deals, reaffirming the strategic advantage of such transactions in the technology M&A landscape.

Then, this study proceeded to conduct analysis of public acquirers merging with private and public targets, respectively, to discuss whether the positive effect of technology-distant deals is different between the public and private targets. In addition to analysing the deal performance for all target types, the study then separates the sample into public-to-public, and public-to-private deals according to the list status of targets on four technology deal-pair categories. The literature suggests public firms can be overvalued (e.g., Moeller et al., 2004), making the acquisition of public targets potentially expensive and potentially obscuring the value creation in technologically distant deals. According to this argument, I hypothesise the positive wealth effects for technologically distant deals are expected to be more pronounced in private target deals. This expectation arises due to the absence of a mark-to-market equity value for private targets, which can often reflect overoptimistic investor expectations. The results confirm that technologically distant deals involving private targets yield higher returns than the public targets for acquirer shareholders, aligning with prior findings on the positive value effects of private deals (e.g., Capron and Shen, 2007; Erel et al.,2012). I also find that most of the High-Tech targets in the sample are young start-ups and not publicly listed. The results also suggest that the Non-Hi private target deals brought the most value creation for public acquirers.

In addition to the short-term stock performance, this study discusses the operating performance of the acquirers according to the list status of the target on the four different tech-classification deals. The synergies and operational improvements of successful M&As may not materialise until years after the deal conclusion due to integration and assimilation difficulties. This challenge can be amplified in the case of technologically distant deals, where the combined companies differ not only in the sectors they operate in but also in terms of management styles and labour force culture. Consequently, effective integration and dispersion of innovation can be prolonged and uncertain, leading to delays in achieving projected productivity and market power improvements than expected (Bloom and Van Reenen, 2002). Nevertheless, if deal participants integrate and strategically align soon after the deal's conclusion, they stand to achieve significant gains in output and competitiveness. In light of this, I investigate the long-run operating performance of tech-related deals as measured by changes in acquirer ROA before and after the deal.

Private *Non-Hi* deals exhibit the greatest improvement in ROA, with an average increase of 2.45% immediately after deal completion, even accounting for other factors. This finding suggests that non-technological acquirers are ready to deploy the target's assets and realise synergies soon after deal completion. In contrast, *Hi-Non* deals have a negative change in ROA post-deal completion, which indicates acquirers face challenges in effectively leveraging the sales network and capabilities of the targets, resulting in increased integration costs. Similarly, pure tech deals (*Hi-Hi*) demonstrate negative changes in ROA, highlighting difficulties in integrating different technological assets. By contrast, non-technology acquisitions (*Non-Non*) experience a positive change in operating performance. These results suggest that investor expectations of deal success may not materialise immediately, while some promising tech-related deals can disappoint operating performance for years after completion.

This paper makes significant contributions to various facets of the M&A literature. First, our study contributes to the strand of technology M&As by providing evidence on the comprehensive performance of technology deals. For the first time in literature, I classify deals into technologically distant and technologically similar, enabling a thorough examination and comparison of their value-creation profiles. The results suggest that technologically distant deals generally create more value for shareholders, but improvements in operational efficiency depend on the technological direction of the acquirer-target pair. Our findings support the complementarity perspective of mergers (Makri et al., 2010; Valentini and DiGuardo, 2012; Bena and Li, 2014), where acquirers benefit by obtaining competencies from technologically distant firms. Second, our study complements prior research that was focused on niche technology segments (i.e., computers, biotechnology, and pharmaceuticals), pure technology M&As, and technology target acquisitions concentrated on the U.S. market (see, e.g., Kohers and Kohers, 2001; Dalziel, 2008; Lusyana and Sherif, 2016). Finally, our study contributes to the literature on factors of value creation in M&As. Our study suggests that technological distance between acquirers and targets can be a source of substantial gains, thereby empowering managers seeking to maximise shareholder value to strategically plan their acquisitions accordingly.

The rest of the study is organised as follows. Section 4.2 offers a brief literature review on technology M&As. Section 4.3 describes the sample and summary statistics. Section 4.4 presents the univariate tests and main empirical results. Section 4.5 reports the results of the propensity score matching analysis. Section 4.6 discusses the findings along with the additional robustness tests. Section 4.7 provides insight into synergy gains for public technology deals. Finally, section 4.8 concludes the paper.

4.2 Literature Review

Technology can be developed through two main approaches: organically, i.e., internally, or inorganically, i.e., through mergers and acquisitions (M&As). In general, inorganic growth is deemed the most effective strategy for gaining faster access to different markets, competencies, and advantages over competitors (Hall, 1988; Hitt et al., 2000; Cartwright and Schoenberg, 2006). The technology sector, in particular, presents opportunities for even more accelerated growth compared to other industries, making it an attractive domain for M&As. This strategic advantage is evident in the technology sector's higher growth potential in equity markets (Kogan et al., 2017). As companies seek to leverage the rapid pace of technological advancements and secure a strong market position, M&As become instrumental in facilitating their expansion and sustaining their competitive edge in the dynamic landscape of the technology industry.

Previous studies investigating technology mergers and acquisitions (M&As) have yielded mixed results, leading to a lack of consensus on their overall impact. While some research suggests that high-tech mergers enhance acquirer value and have a positive effect on the research and development (R&D) process (Ahuja and Katila, 2001; Porrini, 2004), others indicate that acquirers may underperform after deal completion (Paruchuri et al., 2006). The findings on the performance of technology acquisitions are also inconsistent over time, with some studies showing improvements in the short-run but negative effects in the long-run (Kohers and Kohers, 2000, 2001). Additionally, the performance of tech deals has varied across different periods; for instance, tech deals performed better during the years 2007-2014 compared to the period 1996-2006, which encompassed the 'Dotcom Bubble' years (Lusyana and Sherif, 2016). Altogether, the existing literature does not provide a conclusive answer as to whether tech deals consistently add value or lead to value destruction for acquirer shareholders.

In addition to the strands of the tech M&A literature that have examined the R&D integration process, there exists a consensus suggesting that longer integration processes lead to better R&D outcomes for both acquirer shareholders and target-firm inventors (Birkinshaw et al., 2000; Miller, 2004; Paruchure et al., 2006). However, the existing literature has primarily focused on specific geographies, such as the US, limited time frames, such as the 'Dotcom Bubble' era, and acquiring technology assets in niche technology industries, such as pharmaceuticals, biotechnology, computers, and software (Dalziel, 2008; Ranft and Lord, 2002; Ahuja and Katila, 2001; Kohers and Kohers, 2000; Lusyana and Sherif, 2016). The dearth of evidence with a global perspective, a recent sample, and a comprehensive outlook on tech M&As has motivated and incentivized the undertaking of our study. By providing insights derived from a broad range of countries and a contemporary dataset, our research aims to bridge the gaps in the existing literature and contribute a more holistic understanding of the performance and outcomes of technology M&As.

4.3 Data and Descriptive Statistics

The global M&A data are obtained from Thomson Financial SDC for the period 1990-2018. To ensure data accuracy and relevance, I apply the following screening criteria: i) I exclude minority stake purchases, recapitalisations, acquisitions of remaining interests, self-tenders, spin-offs, privatisations, reverse leverage buyouts, exchange offers, and repurchases; ii) The bidder is required to own less than 10% shares of the target prior to the announcement and seek to own more than 50% after the acquisition; iii) the deal value is at least $1 million in 2018 dollar terms. After implementing these stringent restrictions, the final sample consists of 220,910 transactions, enabling a comprehensive analysis of technology M&A activity on a global scale.

Subsequently, this study focuses on deals where acquirers have available stock performance data on DataStream Worldscope (105,556 deals are eliminated). Then, I exclude transactions involving acquirer and target firms with the same ultimate parent. I also require the relative deal size to be at least 1%. After applying these additional criteria, our refined dataset comprises 79,455 observations, with an aggregate value of $26.1 trillion across 52 countries. For comprehensive insights into the data, Table 4.1 presents summary statistics of the full SDC sample and the sample of SDC merged with DataStream.

The high-tech acquirers and targets are identified using the industry classification schematic provided by SDC, consistent with previous literature (Kohers and Kohers, 2001; Lusyana and Sherif, 2016). SDC employs SIC codes, NAIC codes, and business descriptions to categorise companies across various industries. The high-technology industry classification by SDC encompasses a diverse range of high-tech sectors, including computers and peripherals, e-commerce and business-to-business, electronics, hardware, software, internet infrastructure, internet software services, semiconductors, chemicals, pharmaceuticals, biotechnology, telecommunications, and other high-tech sectors. This comprehensive classification enables a robust identification of high-tech acquirers and targets in our dataset, ensuring an accurate and extensive analysis of technology M&A activity.

The main objective of our study is to examine whether tech-related M&As, precisely technologically distant deals, create more value than non-tech deals. To achieve this, I first classify acquirers and targets into Hi-tech or Non-tech companies according to the SDC industry classification. Then, the deals are classified into four categories according to the deal's industry pairing. The four deal types are high-tech bidder to non-high-tech target (*Hi-Non*), non-high-tech bidder to high-tech target (*Non-Hi*); an acquirer and target are both in the high-tech sector (*Hi-Hi*); neither acquirer nor target are in the high-tech sector (*Non-Non*). Of particular interest are the *Non-Hi* and *Hi-Non* deals, which represent technologically distant deals and are expected to generate greater shareholder wealth.

Table 4.2 presents the distribution of deals across the top 20 nations for each deal type, with Panel A focusing on the acquirer country and Panel B on the target country. The analysis reveals that the five most active acquirer nations are the United States, accounting for approximately 38% of the total activity, followed by the United Kingdom (13%), Canada (9.5%), Australia (6.1%), and China (5.4%).[65] These countries are particularly active in technology acquisitions, including deals involving high-tech acquirers and targets (*Hi-H*i), non-high-tech acquirers, and high-tech targets (*Hi-Non*), as well as non-high-tech acquirers and targets (*Non-Hi*). Additionally, Japan, Canada, Australia, Germany, and South Korea also play significant roles in technology-related acquisitions, contributing to the dynamic landscape of global tech M&A activity.

The distribution of deals over the 29 years in our sample is presented in Table 4.3, Figure 4.1, and Figure 4.2. Figure 4.1a illustrates highly cyclical merger activity regarding the total number of deals and total deal value ($ billion). The period of 1993-2000 corresponds to the fifth merger wave, which ended with the recession after the "Dotcom bubble" (Moeller et al., 2005; Harford, 2005; Rhodes-Kropf et al., 2005). The sixth merger wave started in 2003, peaked in late 2006, and ended at the start of 2008 due to the Global Financial Crisis (Alexandridis et al., 2012). Global acquisition activity was reignited in 2010, while total deal values recovered after 2013. Over the last decade, deal

[65] The top five most targeted countries are the US (40%), UK (11.6%), Canada (7%), China (6%), and Australia (5.9%).

numbers rebounded faster than deal values, implying a temporary scarcity in mega deals. The recovery of total deal values reached near record levels, with a total of $ 2.31 trillion in 2015. The average deal value in 2013-2018 was $4.3 billion, more than 1.5 times the average deal value in the last merger wave (2003-2008 average deal value $2.7 billion). The M&A activity stabilised after 2016, whereas the average deal value grew larger (mean $4.4 billion from 2016 to 2018). This trend indicates a gradual shift towards larger deals, reminiscent of patterns observed near the peaks of previous merger waves.

Furthermore, I present the distribution of the four deal types (*Hi-Hi, Hi-Non, Non-Non, Non-Hi*) separately in Figure 4.1b, along with the proportion of each deal type in the overall M&A market over time in Figure 4.2. Notably, all deal types display similar wave patterns to the aggregate M&A activity in Figure 4.1a. In the tech-driven fifth merger wave, more than one-third of deals are associated with technology-intensive industries, mainly in the information technology sector. This trend was supported by high-tech firms' rampant share price growth during the 'Dotcom Bubble', attracting other companies to seek technological innovation opportunities (Kohers and Kohers, 2000; Kleinert and Klodt, 2002).

As described in Table 4.2 Panel A, technology-related deals *(Hi-Hi, Hi-Non, Non-Hi*) account for 36% of all deals in our sample, with *Hi-Hi* deals comprising 20%, *Hi-Non* deals 11%, and *Non-Hi* deals 4.9%, totaling 1,662 deals. These technology-related transactions hold substantial value, exceeding $1.42 trillion, representing over 60% of the total deal value ($2.37 trillion) during the peak of the technology merger wave in 1999.

The momentum continued into 2000, with technology-related deals representing more than 50% of the total deals (4,498 deals) and 51% of the total deal volume, equivalent to $1.77 trillion. The average deal value in our sample was $1.55 billion ($0.9 billion) for technology-related (tech-unrelated) deals during the early 1990s, and it rose to $3.45 billion ($2.85 billion) and (*Non-Non*) between 1996 and 2001. This pattern also reflects two underlying trends: the surge in share prices near the peak of the 'Dotcom Bubble' and the growing investor appetite for larger-scale deals as companies sought to capitalise on technological innovations and market potential during this transformative period of technology-driven M&A activity.

During 2003-2008, non-tech deals (*Non-Non*) outpaced tech-related deals in both number and deal value, representing more than 73% (amounting to $18.2 trillion) during the final two years of the sixth merger wave. The growth in acquisition activity for non-technology acquirers, accounting for 20% (*Non-Non*) and 25% (*Non-Hi*), respectively, contrasted with the relatively lower acquisition rates of tech companies, constituting 12% (*Hi-Hi*) and 16% (*Hi-Non*). This discrepancy can be attributed to the sixth cycle's principal focus on ample liquidity (Alexandridis et al., 2012). High-technology firms with significant R&D expenditures tend to have limited cash reserves and liquidity compared to more traditional firms, dampening their merger activities during this period. However, starting in 2010, the resurgence of deal activities gained momentum and has continued to the present day, with technology playing a crucial role in driving M&A activity throughout the decade (Deloitte, 2018; Bain, 2020). Technology acquisitions accounted for over 40% of all deals, and high-tech intensive firms witnessed an upward trend in their involvement in deal volume, resulting in a four-fold increase in their aggregated deal value compared to five years ago. They occupied more than 55% of the value of acquisitions in 2015, increasing 23% from the previous year, remaining at a 50% level afterward. A significant number of deals are focused on semiconductors, internet services, big and cloud data, and healthcare. Half of the ten biggest deals are technology acquisitions over the past five years, for example, Dow Chemical's takeover of DuPont for $130 billion, Walt Disney costs $85 billion to buy 21st Century Fox, and CVs acquires Aetna with $68 billion. After all, *Non-Hi* and *Hi-Hi* deals are upbeat over time, comprising more than 50% of the global M&A market (see Fig. 4.2).

A pattern that attracted attention is, to some extent, the prominent role of high-tech targets in driving the current cycle of the M&A market. Notably, in both *Non-Hi* and *Hi-Hi* deals, the aggregated value growth rate saw a remarkable acceleration in 2014, reaching 305% and 238%, respectively. In contrast, deals with targets in non-high technology industries experienced a surge the following year, with *Hi-Non* and *Non-Non* deals growing at 134% and 43%, respectively. The average transaction value of *Hi-Hi* and *Non-Hi* deals in 2015 reached unprecedented levels at $10.6 billion and $5.6 billion, respectively, a significant increase from $3.2 billion and $1.8 billion in 2010. Recent data reveals that technology-intensive industry deals, regardless of technological differentials or pure technology-related focus (*Hi-Non* at $4.5 billion, *Non-Hi* at $3.7 billion, and *Hi-Hi* at $7.1 billion), surpass other sectors ($3.5 billion) in average deal value, suggesting an increased frequency and pronounced rise in deal values in these domains. Moreover, the acceleration of technology discrepancy deals (*Hi-Non* and *Non-Hi*) since 2013 has been the most significant increase observed in the last thirty years, indicating a growing number of companies are actively pursuing opportunities to diversify into new industries or strengthen their positions by adding new capabilities.

Additionally, deal characteristics are obtained from SDC, and annual financial performance information is from Thomson Financial DataStream. Table 4.4 exhibits deal and firm descriptive statistics for the above sample and is classified into groups according to deal technology category and differentials between technology discrepancies deals with others (*Hi-Non* and *Non-Hi* deals). To remove outliers, accounting ratios are winsorised at 1% and 99% levels. Variables are defined in Appendix C. Table 4.4 Panel A presents summary statistics for public targets, and Panel B focuses on private targets. Private target deals constitute 87% of our sample, in line with the findings of Netter et al. (2011), highlighting the prevalence of private targets in M&As. Within the sub-group of technology differential deals (*Hi-Non* and *Non-Hi*), private targets account for an even higher proportion at 91% and 89%, respectively. It is noteworthy that the *Hi-Hi* deals exhibit the highest average deal value among all categories, regardless of whether the target is listed or unlisted. The average deal size for public targets is $2,791 million ($194.46 million for private targets) when both the acquirer and target are in the high-tech industry, representing an increase of almost 35% (18% for private targets) compared to other categories, indicating a higher occurrence of mega-deals (deals valued at least $500 million) in this technology-intensive group. The technology giants, such as Accenture, Cisco Systems, Dell, and Amazon, are energetically involved in larger acquisitions of technology-intensive companies.

The relative deal size, calculated as the ratio of the deal value to the acquirer's market value one month before the announcement, is more remarkable for non-hi-tech bidders to hi-tech targets in both public and private targets, more than 65% (20% higher than other sub-sets. This observation is not unexpected, considering that acquirers in this technology group tend to be relatively smaller in size. Acquirers operating in the technology-intensive industry (*Hi-Non* and *Hi-Hi*) are likely to be overvalued, as evidenced by the low book-to-market ratio. The low book-to-market ratio is common as technology firms do not always have plenty of tangible assets, and this potentially indicates that investors are pleased to pay more for the projected future premiums generated by technology firms.

A notable finding is that acquirers in technology-intensive deals (at least one party is in the high-tech industry) show a greater preference for financing deals with pure cash when the target is public, while they tend to use their stocks as the main currency when the target is private. On average, 33% of technology-intensive public deals are executed with 100% cash financing, which is 7% higher than non-tech transactions, with *Non-Hi* deals having the highest proportion of 36% using cash financing. Conversely, in private deals, approximately 35% of technology deals are paid with stock, while 22% are financed with cash. Interestingly, technology differential transactions financed with stock exhibit a 4.6% significance compared to other sub-groups. Previous literature suggests mixed results of stock payment on return around the deal announcement (Travlos, 1987; Fuller, Netter, and Stegemoller, 2002; Dutta, Saadi, and Zhu, 2013). Commonly, stock swaps seem to be value-destroying (Travlos), while in recent years, literature in international

M&A research back-up stock financing positively affected returns (Alexandridis et al., 2010). Consequently, it is intriguing to explore how the payment method influences the performance of technology deals based on the listed status of the targets involved.

In addition, the proportion of cross-border deals is higher for technology-intensive deals, accounting for more than a quarter on average. Among the subsets, the *Non-Hi* group stands out as the most frequent acquirer of cross-border public targets (28%), while the larger groups in private cross-border deals are the *Hi-Hi* and *Hi-Non* categories, making up 31% and 28%, respective

ely. This observation can possibly be explained by the technology industry's focus on innovation capabilities, making it more flexible with a greater emphasis on intangible resources and less constrained by geographical boundaries. Interestingly, the synergy proxy representing deal motivation in the acquisition statements is significantly greater for pure technology deals. This implies that the integration process may be more straightforward and result in greater synergistic gains when the acquirer and target have similar levels of technological expertise within the industry.

4.4 Main Regression Results

4.4.1 Univariate Analysis

A key objective of our empirical analysis is to study how the high-tech intensive M&A deals perform. Table 4.5 reports the announcement period excess returns and long-run operating performance. I first compare stock market reactions to the four different technology deal types. To examine the returns of acquisition announcements, I require daily stock prices and corresponding market indices data for the bidders in Thomson Financial DataStream, resulting in 79,455 transactions from 52 countries that meet the criteria. I calculate the three-day cumulative abnormal returns (CARs) as the sum of the market-adjusted return of acquirers over the event window (-1, +1) around the announcement date, using parameters estimated over 301 to 30 days prior to the deal announcement date (e.g., Brown and Warner, 1985; Bris and Cabolis 2008; Golubov, 2015)[66]. The market return as the benchmark is the corresponding value-weighted market index daily return of the acquirers' nation[67]. The returns are winsorised at the 1% and 99% levels to remove extreme values.

The first panel of Table 4.5 provides the average and median univariate tests of the three-day CARs for the technology deal groups[68] and target listed status. I also estimate the difference between public and private targets for each tech deal type. The mean and median acquirer CARs are 1.58% and 0.56% for all deals, and both are significantly more than zero at the 1% level. The positive returns stem from the private target deal once I segregated deals by target public status, consistent with findings from previous studies that public targets do not generate additional value for acquiring firms' shareholders (Fuller et al., 2002; Moeller et al., 2004). Specifically, public deals have -0.42% (-0.43% median) returns, while private targets create 1.90% (0.71% median) additional wealth for shareholders. Regarding the segregated deals by technology type, all the other deals in the public deals have statistically significant negative abnormal returns at the 1% level,

[66] I also measure the CARs over the event window (-2, +2) and (-22, +1). The results remain similar.
[67] The value-weighted market index returns are obtained from the Thomson Financial DataStream.
[68] I also create a new group to put the technology differential deals together, the *Hi-Non* and *Non-Hi* deals.

except the *Non-Hi* subset, with 0.05% gains on average. The median of the *Non-Hi* public deals is also more remarkable than the remaining bidders of the public target, which is -0.09%, while the *Hi-Hi* public deals have the lowest value creation -0.70% (also lowest in mean, -1.06%).

In the context of mergers involving private target companies, those occurring within technology differential transactions, specifically the *Non-Hi* and *Hi-Non* deals, exhibit significantly greater abnormal returns compared to other private targets. The average excess gains for acquirers in *Non-Hi* and *Hi-Non* deals are 3.05 and 2.23 percentage points, respectively. Notably, the private *Non-Hi* deals, similar to public *Non-Hi* deals, yield the most substantial gains, with additional value creation around the announcement being almost 1.5 times larger than other deals. The difference in means and medians between technology differential deals (*Hi-Non* and *Non-Hi*) and deals with homogeneous technology levels (*Hi-Hi* and *Non-Non*) are positively significant at the 1% level. The CARs in *Non-Hi* and *Hi-Non* are 2.47% greater than *Hi-Hi* and *Non-Non*. This observation lends support to the complementarity theory, where resources that are complementary but differ to some extent can generate mutual benefits, leading to more effective utilisation and potentially greater synergistic gains (Makri et al., 2010). When acquiring high-tech dependent targets, non-technology bidders experience higher returns after the deal announcement, indicating a consensus among shareholders regarding the complementarity. The technology deals are worth acquiring in the short-term period. I further find that the technology differential deals (*Non-Hi* & *Hi-Non*) generate higher additional returns for acquirers when compared to private targets with public targets. The mean (median) return difference between the private and public targets in technology differential deals is 2.63% (1.11%), and this difference is strongly significant ($p<0.01$). Overall, regardless of the listed status of the target, the findings indicate that technology differential deals tend to outperform other deal types. Among these, *Non-Hi* transactions exhibit the most substantial outperformance, possibly attributed to markets recognising the pivotal role of transforming technology assets in reshaping the acquirer's business. The accelerating technology-altering effect brings new ways into traditional business.

To gain deeper insight into the value creation of the technology deals, I then examine post-acquisition operating performance changes to determine whether the remarkable wealth creation observed around the announcement persists regarding improved operational efficiency. It may not adequately reflect the effect of technology deals as the stock reaction exclusively reflects short-term acquisition value. Existing studies use return on assets (ROA) as the proxy for operating performance (Kaplan, 1989; Harford, 1999; Makismovic et al., 2013), where the ROA indicates how effectively the acquirers utilise assets to generate earnings. Following Golubov and Xiong (2020), I computed the changes in ROA for the first three years post-merger to examine improvements in bidders operating efficiency. Specifically, the ROA in year *t* is defined as net income before extraordinary items scaled by total assets at the end of fiscal *t* year, and the 1st and 99th percentiles are trimmed to remove extreme values. I then adjust the absolute value of ROA by the ROA mean of bidders in the same Fama-French 10 industry in year t. The primary variable, ΔROA (*t-1, t+1*) (or *t+2* or *t+3*), is the bidder industry average adjusted return on the asset in the post-one year subtracted by the operating performance in the last available year before the deal announcement, where the *t* is the announcement year. The exclusion of the *t*-year performance accounts for classification challenges between pre- and post-deal periods, and the time required for operating performance changes to become evident due to adjustment complexities in accounting measures.

Panel B of Table 4.5 presents three-year post-merger changes in ROA for public and private targets, categorised by technology deal types.[69] Notably, changes in ROAs are negative for all public deals. However, among these, the *Non-Hi* public deals demonstrate a better operating performance enhancement than other types. Specifically, the *Non-Hi* transactions involving public targets exhibit the most minor negative change in operating performance, suggesting that acquiring technology assets has a comparatively less detrimental impact on wealth creation. Turning the focus bidders into private targets, the improvement in efficiency is primarily driven by technology differential deals. Remarkably, the operating performance of *Non-Hi* private deals experience the most substantial enhancement during the three-year post-acquisition period, with changes of 7.26%, 6.02%, and 5.59%, respectively, all significantly above zero. This improvement is nearly ten times higher than that observed in other transaction types, highlighting the potential of technology to drive superior performance improvements and substantiating its capacity for disruptive and transformative effects. The positive changes in operating performance are majorly attributed to *Non-Hi* deals,

[69] The results are similar if I use operating income as the nominator for the ratio of return on assets. I also find similar results if I use return on equity as a measure for operating performance.

while *Hi-Non* deals demonstrate significantly positive changes in the first year, which taper off in the subsequent years.

Aligning with the gains observed during the announcement period, the findings indicate that, on average, private target acquisitions generate more substantial improvements in operating performance compared to public target deals. Improvements in ROAs for private target deals are higher than the public by 2.59%, 2.39%, and 2.41% in the first three years, as evidenced in the bottom of Panel B. These improvements are all statistically significant at the 1% level. Hence, I report the superior gains achieved by acquirers and the more pronounced enhancements in operating performance, particularly within the *Non-Hi* deal category and in the context of private deals. The *Hi-Non* deals exhibit higher wealth creation around the announcement and no more than two years during the post-merger period. The analysis of acquirer stock returns and operating performance on technology deals is further analysed as follows.

4.4.2 Acquirer Gain Regressions

In this subsection, I conduct several cross-sectional regressions to estimate the relationship between technology deal types and the flow and performance of acquisitions to obtain a comprehensive understanding. The baseline specification estimate is as follows:

$$ACAR_i = \alpha + \beta * Technology\ dummy + \mu_i + \varepsilon_i \qquad (4.1.)$$

The main independent variable, $Technology\ dummy$, is the technology deal indicator, which takes the value of one if the acquirer and target are classified in the specific technology deal type and zero otherwise. Table 4.6 reports our multivariate analysis results in which the dependent variable is the acquirer of three-day CARs (-1, +1). Panel A reports the full sample results; private target deals are in Panel B, and public deals are in Panel C.

In our analysis, I employ a range of control variables known to be associated with acquisition returns, as evidenced by existing literature.[70] Our results indicate that the size of the acquirer, measured by the natural logarithm of the acquirer's market capitalization one month before the announcement, has a negative impact on acquirer returns at a significant level of 1% for all deals, consistent with prior findings (Moeller et al., 2004; Alexandridis et al., 2010). The coefficient of relative size, as proxied to target-to-bidder relative size (Fuller et al., 2002), is positive and significantly impacts the performance of private target deals at a 1% level while remaining at least non-negative and significant for public deals. This suggests that larger private target deals yield more excess returns. Public deals result in lower returns than private ones for larger transactions, but the detrimental effect is not as pronounced as early studies indicated (Jensen and Ruback, 1983; Travlos, 1987). Moreover, as Alexandridis (2017) documented, larger deals and mega-deals (exceeding $500 million) generate advanced wealth, whether in private or public deals in the U.S., during recent decades, with larger private deals showing even greater gains. Our results mirror these results on an international scale that sizeable

[70] The vector of control variables includes size (Moeller et al., 2004), relative size (Fuller et al., 2002), book to market (Dong et al., 2006), hostile (Servaes, 1991), tender (Jensen and Ruback, 1983), private target dummy (Capron and Shen, 2007), payment including stock (Travlos, 1987), cross-border dummy (Moeller and Schlingemann, 2005), competing bidder (Hirshleifer and Png, 1989), leverage (Maloney, McCormick and Mitchell, 1993), and synergy dummy (Dutordoir, Roosenboom, and Vasconcelos, 2014).

acquisitions are linked to higher returns with the worldwide acquisition sample, reflecting why the trend of making scale deals is more frequent in recent years.

Furthermore, it has been noted that the acquirers with a higher book-to-market ratio do not outperform glamour firms with a lower book-to-market ratio (Rau and Vermaelen, 1998; Megginson et al., 2004). I find the negative but insignificant effect of hostile deals on stock gains (Schwert, 2000). Using a private target dummy variable to capture the positive impact of private targets on acquirer returns aligns with earlier research (Fuller et al., 2002), with transactions involving private targets outperforming returns by 2.23% compared to public targets on a one standard deviation increase. Regarding the method of payment, defined as the payment including stocks or not, I discover a negative and significant effect on acquisition abnormal returns in public deals (Travlos, 1987; Loughran and Vijh, 1997), while a positive and significant impact emerges in private target transactions. This suggests that investors may interpret the use of stock as an indicator that target shareholders will hold acquirer stocks to share in future growth.

Moreover, the cross-border dummy variable, representing whether the bidder and target are from different countries, its coefficient demonstrates that cross-border deals generate higher short-term wealth (e.g., Rossi and Volpin, 2004; Erel et al., 2012), with this effect being more pronounced in technology deals (*Hi-Non, Non-Hi, and Hi-Hi*). The coefficient of leverage, defined as the acquirer debt to equity ratio, is negative and significant for private target deals but positive and significant for public deals. In public deals, lower leverage reduces transaction burden, whereas, in private target deals, improved financing capability with fewer constraints appears beneficial. In addition, I find that synergy, proxied by the dummy variable if the announcement statements state the synergy gains as an objective, yields positive gains only in private target deals. Lastly, I control for year- and country-fixed effects in all regressions to account for unobservable variations across time and country. The coefficients for firm and deal characteristics remain consistent across the four technology deal types, suggesting that the superior acquirer gains are primarily driven by the distinct technology deal categories.

In Table 4.6, regression models (1), (6), and (11), as well as models (2), (7), and (12), report the coefficients on *Hi-Non* and *Non-Hi* technology variables. Models (5), (10), and (15) focus on the combination of technology differential deals for the entire sample, private targets, and public deals, respectively. In line with our univariate findings, the coefficients for technology differential dummies (*Hi-Non* and *Non-Hi*) are positive and statistically significant, indicating a strong association between these variables and acquirers' excess returns at the 1% significance level. This reaffirms our earlier univariate outcomes. Across the full sample, the gains for acquirers are approximately 0.336% higher when engaging in technology differential deals compared to those executed within the same technology level (*Hi-Hi* and *Non-Non*). Notably, this gain is more pronounced in private target deals than public targets, with a coefficient of 0.309%, statistically significant at 1% level. For public deals, the estimate is 0.114%, but with no significance. Remarkably, the return improvement is most prominent in the private *Non-Hi* target deals, roughly 0.454% greater compared to others. This suggests that traditional non-hi-tech firms acquiring technology-intensive assets generate significantly greater value than deals without hi-tech elements or deals within the same technology category. In the case of *Hi-Non* private deals, an approximately 0.211% increase in announcement period returns is observed, supporting the concept of complementarity in acquisitions. This is especially true for hi-tech firms, which, possessing technological innovation capabilities, acquire resources that were previously lacking, leading to enhanced market performance. However, the impact of *Hi-Hi* deals on private deals is inconclusive, while *Hi-Hi* public deals consistently underperform, significantly so at the 5% level.

To identify the differences in the type of technology deal impact on the acquirer gains, I then conduct regressions that include three (*Hi-Non, Non-Hi,* and *Hi-Hi*) and four technology dummy variables (*Hi-Non, Non-Hi, Hi-Hi,* and *Non-Non*) within the same regression. Models (1), (3), and (5) in Table 4.7 include the three technology dummies with the constant in the same regression, and models (2), (4), and (6) display the regressions of four technology dummies without the intercept. In Tabel 4.7, Panel A reports results for the full sample, Panel B is for the private targets, and Panel C is related to public deals. In model (5), there are no significant parameters for the technology dummies in public deals, except for *Hi-Hi*, which exerts a significant but negative influence on gains. Conversely, the *Non-Hi* dummy is the only positive estimator compared to *Hi-Hi* and *Hi-Non*. In regressions (1) and (3), both *Hi-Non* and *Non-Hi* coefficients are positively significant at the 5% level. The *Non-Hi* dummy's coefficient stands at 0.509%, and the *Hi-Non* dummy is 0.263%. This reflects the fact that technology differential deals yield higher returns than other deals, with *Non-Hi* deals generating approximately double the advanced returns of *Hi-Non* deals. Overall, these results affirm that technology differential transactions involving private targets are capable of creating superior value, particularly those classified as *Non-Hi* transactions.

4.4.3 Mechanisms of Acquirers' Return of Technologically Distant Deals

This subsection discusses mechanisms by which technologically distant acquisitions, characterised by the acquisition of companies in significantly different technology sectors, specifically, the Non-Hi and Hi-Non deals, positively influence acquirer returns, through three key channels: low cash flow volatility, lower Tobin's Q as a proxy for value firms, and lower level of economic policy uncertainty (EPU).

First, low cash flow volatility, as a measure of a firm’s financial stability and predictability of cash flows, is found to correlate with higher acquirer returns for technologically distant deals. This suggests that firms with financial stability and predictability in cash flows are valued by investors, thereby enhancing investor confidence and firm valuation (Minton and Schrand, 1999). Firms are split into high and low cash flow volatility groups, based on the median of the year-country pair. Table 4.8 Panel A presents the results. The empirical evidence indicates that technologically distant deals are associated with lower cash flow volatility, suggesting a mechanism through which these acquisitions enhance short-term acquirer returns.

Second, the analysis segments firms into growth and value categories using Tobin’s Q, with value firms showing a stronger positive relationship with acquirer returns in the context of technologically distant deals. The firms are separated based on the median of Tobin’s Q of each country and each year. Value firms, typically having a lower Tobin's

Q than the median, are often undervalued by the market (Fama and French, 1992). Hence, acquisitions made by these firms may be viewed as strategic moves to correct market mis-valuations, leverage synergistic potentials unrecognised by the market or engage in more growth opportunities, thereby generating more positive returns. The results are shown in Table 4.8 Panel B, which supports that technologically distant deals are more beneficial for value firms, and could lead to better acquirer returns.

Last, the role of EPU in moderating the returns of technologically distant acquisitions is significant. Firms operating in environments with lower EPU, as indicated by their country's average EPU index, tend to experience higher returns post-acquisition. Baker et al. (2016) argue that lower EPU fosters a conducive environment for such strategic investments, by reducing the uncertainty that could otherwise inhibit the realisation of potential acquisition benefits. This posits that a stable economic policy environment reduces the uncertainty associated with technologically distant acquisitions, thus making them more favourable in the eyes of investors. The segmentation into high and low EPU firms according to the median of country-year pairs in Table 4.8 Panel C clarifies how the backdrop of economic policy stability is a critical factor for the success of such transactions.

In sum, the positive impact of technologically distant deals on acquirer returns is rooted in the stability and predictability of cash flows, the market undervaluation of acquiring firms, and the broader economic policy environment within which these firms operate. These findings underscore the interplay between firm-specific financial characteristics and the macroeconomic environment in determining the success of technologically distant acquisitions where technological diversification can enhance firm performance by leveraging complementary assets and capabilities, supporting the premise that technologically distant acquisitions can generate superior returns for acquirers by accessing new markets, technologies, and competencies.

4.4.4 Operating Performance Changes Analysis

I have demonstrated the wealth creation effects of technology differential transactions on acquirers' short-run stock markets. To further substantiate the long-term performance implications of technology deals, I maintain the same control variables while examining the operating performance of acquirers. This approach provides a comprehensive view of the sustained impact of technology-oriented deals.

$$\Delta ROA_{i(t-1,t+n)} = \alpha + \beta * Technology\ dummy + \mu_i + \varepsilon_i \quad (t = 1,2,3) \qquad (4.2.)$$

Table 4.9 reveals the estimation results segregated according to private and public target distinctions. Panel A displays one-year post changes in operating performance, Panel B covers the subsequent two years, and Panel C extends to three years post-transaction. Overall, the effect of control variables on improvement efficiency remains homogeneous to short-term returns. Acquirer size and book-to-market ratio have negative and statistically significant influences on changes in return on assets. The prominence of operating performance enhancement becomes more evident with larger relative sizes, underscoring the strategic value of acquiring assets at scale. Cross-border transactions persist in yielding superior post-merger profitability compared to domestic counterparts.

Deviating slightly from the findings in acquirer stock returns, the coefficients for payment involving share swaps and leverage now display a positive and significant impact on the improvement in operating performance, applicable to both private and public target deals. Moreover, enhanced operating performance is associated with higher leverage ratios and stock payment methods. Payment with the stock exchange implies that the acquirer and target shareholders share the anticipation of synergistic benefits, underscoring the value proposition of combined entities. This suggests substantial transactions, often associated with stock financing, generate greater value. For the estimates of leverage, it could be explained by the leveraged firms are manipulating earnings less before the acquisitions than the firms with a lower amount of financing by debt lenders (Alsharairi and Slama, 2012). Thus, the leveraged firm could undertake the acquisition decisions more prudently and acquire healthy firms to facilitate its expansion.

In line with the patterns observed in gains during the announcement period, I find that the *Non-Hi* private target deals exhibit significantly more substantial operating performance improvements over the three years post-merger, with changes of 2.435%, 2.188%, and 2.454%, all statistically significant at the 1% level. These results persist after accounting for bid-specific characteristics. This indicates that when the non-technology bidders acquire hi-tech private targets, the asset reallocations are promoted more effectively, resulting in the realisation of synergies that contribute to increased shareholder value over time. However, the findings regarding *Hi-Non* deals diverge from the short-term gains. While the coefficient for *Hi-Non* remains notably significant, it is negative in relation to the improvement of operating performance. Unlike the significant premium observed for *Hi-Non* deals during the announcement period, the long-term value enhancement for shareholders is not elevated regarding operating performance. It would provide a side reflection of the importance of technology disruptive functions on traditional and non-technology intensive businesses, as the advanced improvement in performance is pronounced in the *Non-Hi* deals rather than the *Hi-Non* deals where both of these deals have a difference and complementarity in technology level. Although technology asset acquisitions entail inherent uncertainties, they hold the capacity to complement existing resources and innovation capabilities, thereby facilitating an efficient transformation of non-technology firms' operations. In the next section, I use propensity score matching techniques to assess our results rigorously.

4.5 Acquisition Gains for the Long-term and Propensity Score Matching

To address potential unobserved factors affecting our M&A sample, I use the propensity score matching (PSM) approach to match technology differential deals (*Hi-Non* or *Non-Hi*) with other deal types that possess similar characteristics. Specifically, I pair *Non-Hi* (or *Hi-Non*) deals with counterparts that have comparable bidder attributes but belong to different deal type categories. Through this approach, I can then analyse and compare the stock gains and improvements in the operating performance of these matched transactions.

First, I conduct a probit regression where the *Non-Hi* dummy variable (or *Hi-Non* dummy) is the dependent variable, and the independent variables are acquirer and deal characteristics. Subsequently, I use the probit model estimates to calculate propensity scores, enabling us to match the acquirer with comparable counterparts. The dependent variable is the performance measures proxied by acquirer CARs and changes in return on assets during the three post-merger years. The PSM results are obtained through three distinct methodologies: nearest-neighbour matching (one-to-one, one-to-five, thirty, and fifty neighbours), Radius Caliper, and Gaussian kernel matching.

Table 4.10 reports the probit regression in Panel A and matching results for acquisition gains around the announcement date of private and public deals in Panel B and Panel C, respectively. I also include the 3-year prior deal announcement buy and hold return (*Pre-BHR*) and 3-year post deal announcement buy and hold return (*Post-BHR*) as independent variables in baseline regression, defined as the buy and hold returns of bidders three years prior to and post the acquisition. In Panel B (Panel C), the treated group encompasses the acquirer CARs for *Non-Hi* (or *Hi-Non*) private (public) target transactions, and the control group consists of CARs from the matched deals. The results confirm that the excess returns of *Non-Hi* private target deals are higher than control samples. The differences between the treated and control groups are positive and significant at the 1% level using all matching techniques, varying from 0.630% to 0.912%. For the group of public mergers, the returns of *Non-Hi* deals are positive, while the control sample CARs are below zero, though their difference is insignificant. Besides, *Hi-Non* bidder returns are higher but insignificant than control samples.

Furthermore, in Table 4.11, I replicate our PSM procedures by replacing the dependent variable with operating performance changes. Given that Section 3 indicated performance enhancement solely in *Non-Hi* deals, I investigate the improvement in return on assets (ROA) for *Non-Hi* deals during the three years post-acquisition. In the probit regression, I added the bidder's mean adjusted ROA to the ROA changes (-2, -1) in the last fiscal year prior to the announcement to measure the prior performance because the pre-acquisition operating performance should also be controlled (Healy et al., 1992). Table 4.11 Panel B displays that the $\Delta ROAs$ of the treated sample corresponded to *Non-Hi* private targets are positive, whereas the $\Delta ROAs$ of the matched sample are all negative. The changes in ROA for *Non-Hi* private target deals consistently outperform other deal types, ranging from 1.473% to 3.377%, 1.345% to 3.065%, and 1.442% to 3.378% in first-, second-, and third-year post-merger, respectively. In the public *Non-Hi* deals, the changes in ROA are consistently negative; however, the treated sample performs better than deals in other types.

Overall, the PSM results corroborate the primary findings from the principal multivariate regression analysis in Section 4.3, indicating the robustness of our results. Specifically, the announcement date returns are significantly higher for technology differential M&As when the target is private. However, there exists a divergence in the long-term performance between the two subcategories of technology differential deals. While the post-bid long-term performance of *Hi-Non* mergers does not exhibit substantial enhancement, the *Non-Hi* deals distinguish themselves by surpassing all other transaction types. This outperformance encompasses the generation of superior returns during the announcement period and a sustained improvement in asset utilisation and operational efficiency over the long term.

4.6 Robustness Tests

In this section, I provide robustness checks on our results with additional tests. I first explore the performance of technology-intensive transactions and probe whether the observed technology differential effect persists when altering the classification of the technology industry. I consider the four alternative proxies for the technology industry classification: the Fama-French 10 industry, the primary business, the macro industry, and the ultimate parent industry of companies. Detailed descriptions of the technology industry classification are provided in the Appendix C. Subsequently, I subject the deals to the same analytical procedure as previously done with the SDC hi-technology classification in the main regression analysis, categorising them into *Hi-Non, Non-Hi, Hi-Hi,* and *Non-Non* types based on acquirer and target industries. The results are consistent with the major part of our study, confirming that the *Non-Hi* deals can outperform others in the last three decades and yield greater shareholder values in both the short and long term after controlling for bidder and deal characteristics. The *Hi-Non* deals generated higher value for shareholders in the announcement period, while the *Hi-Hi* deals consistently demonstrate a negative association with gains and operating performance.[71]

To provide further support for the findings, I conduct a temporal analysis by dividing the sample into two distinct periods: 1990-2008 (38,082 deals) and 2009-2018 (25,291 deals). Such an analysis of assessing early-stage technology deals and late-stage after the financial distress provides deeper insights into potential sources of acquisition

[71] The results of FF10, macro industry, primary-business industry, and ultimate parent industry are available if requested.

gains.[72] Table 4.12 and Table 4.13 indicate that the relationship between technology differential deals and bidders' performance remains consistent over time. Similar to the earlier findings in sections 4.3 and 4.4, the results in Table 4.12 reveal that the positive impact of the technology differential effect, particularly evident in *Non-Hi* deals, on the acquirer's wealth creation holds steadfast across different periods. This effect becomes even more pronounced in the latter period after the financial distress, hinting at a more conspicuous manifestation of technology-industry-specific complementarity in recent years. Pure technology acquisitions exhibit a tendency towards value destruction. I further examine the post-merger improvements in ROA across different periods in Table 4.13. The coefficients on the *Non-Hi* dummy are strongly positive and significant, while those associated with *Hi-Non* deals display a negative and significant trend in the pre-financial distress period but transform into positive and insignificant figures in the subsequent years. The *Hi-Hi* dummy is negatively related to long-term performance. Remarkably, the post-2008 period witnesses *Non-Hi* deals generating almost 1.5 times more improvement in acquirer operating performance compared to the years from 1990 to 2008. Overall, the results strongly support that the technology differential deals, especially the *Non-Hi*, have a more substantial enhancement of shareholder value creation, and this phenomenon is more pronounced in the post-2008 period.

4.7 The Post-bid Performance for Public Technology M&As

In this section, I examined how the technology deals affect the combined gains of the

[72] I also tested the results for 1990-2002, and 2002-2018, comparing the performance before and after the Dotcom bubble. The findings remain similar.

acquirer and target for a comprehensive understanding, where the combined gains are available when the acquirer and target are both listed firms. Table 4.14 reports regression results based on a sample of 6,459 public deals announced between 1990 and 2018.

The dependent variable, termed synergy gains, is defined as the combined weighted average abnormal return of the acquirer and target around the announcement (-1, +1).[73] I assigned weights to the acquirer and target according to their market value one month before the announcement date. The coefficients on the *Hi-Non* and *Non-Hi* dummies are positive but insignificant, while the *Hi-Hi* dummy has a significant and negative coefficient, and the *Non-Non* has a significant and positive coefficient. This pattern is consistent with our previous observations, wherein I noted that the technology differential effects, particularly those of *Non-Hi* or *Hi-Non* categories, primarily impact deals involving private targets. This result suggests that the positive and significant technology differential effect predominantly emerges in deals with private targets. The *Non-Non* deals are associated with less uncertainty and risky on the prospects of combined firms. Thus, the reaction to the deal announcement and subsequent expectations can be promptly reflected in the combined firm, reflecting a more assured integration process and indicating superior synergistic gains than in technology-related mergers. In the context of the technology deals initiated by the non-tech bidders, while the potential benefits are considerable, the realisation of these benefits requires a more extended timeframe due to inherent uncertainties. This, in turn, diminishes the synergy returns. Moreover, public

[73] I also test the synergy gains over the five-day event window, the (-2, +2) combined acquirer and target abnormal returns around announcement date. The results remain unchanged.

technology firms typically maintain elevated valuations and are positioned in mature stages, rendering the anticipation of their acquisition outcomes unpredictable. Consequently, the anticipated synergy gains in such scenarios may not materialise as effectively as in *Non-Non* deals.

4.8 Conclusion

In conclusion, this study has provided a comprehensive analysis of the intricate relationship between technology differential mergers and acquisitions and their impact on acquirer gains and operational performance. First, I find technologically distant deals experience significantly higher acquirer announcement gains than non-technology deals, particularly when the target is private. In contrast, pure technology deals have the lowest wealth creation for acquirers. Second, our examination of the interplay between acquirer-target technological disparity and operating performance sheds light on crucial dynamics. Notably, non-technology firms displayed prowess in effecting seamless digital transformation and industry convergence following their acquisition of technology firms. This underscores the rapid and positive effect of disruptive technology assets on the realisation of strategic corporate goals. Interestingly, while high-tech firms experience improvements in operating performance through acquisitions of similar technology entities, they have not seen the same enhancement when the target is a non-tech firm. The disparities in post-acquisition operating performance underline substantial differences in integration processes between high- and low-tech systems.

This study pioneers an investigation into the performance disparities intrinsic to the technology profiles of deal participants. The discerned patterns suggest that pure technology deals are perceived as less value-enhancing by investors, whereas technology-related transactions can potentially augment shareholder value and foster operational improvements. This research contributes to the evolving discourse on technology-oriented M&A strategies, offering insights into their consequences and implications for the corporate landscape. As a potential avenue for future research, delving deeper into the mechanisms underlying the observed trends could yield valuable insights. Additionally, examining the role of industry-specific factors, regulatory environments, and cultural considerations in shaping the outcomes of technology differential transactions could contribute to a more nuanced understanding of their dynamics.

4.9 Tables, Figures and Appendices

Table 4.1 Mergers and Acquisitions Sample Summary Statistics

The table exhibits summary statistics on M&A announcements in the SDC database between 1990 and 2018. Deals must value at least \$1 million (in 2018 dollars), excluding minority stake purchases, recapitalisations, acquisitions of remaining interests, self-tenders, spin-offs, privatisations, reverse leverage buyouts, exchange offers, and repurchases. The bidders must hold less than 10% control of the target before the announcement but must own more than 50% through the deal. Panel A covers all deals that satisfy SDC filters. Further, the SDC acquirers are merged with available data from DataStream. The relative size of the target to the acquirer, calculated as deal value divided by the acquirer's market capitalisation, must be at least 1% before the announcement. The market value of the bidder is no less than \$1 million (in 2018 dollars). Deals with the same ultimate parent's name of acquirer and target are excluded. Panel B involves deals that satisfy all filters.

	Number of deals	Average deal size (in \$mil)	Median deal size (in \$mi)
Panel A: SDC sample			
All deals	220,910	271.65	23.46
Public acquirer	127,347	327.12	25.00
Private acquirer	93,563	196.16	21.66
Panel B: SDC sample merged with DataStream			
All deals	95,935	381.63	34.36
Public acquirer	12,847	1781.09	186.61
Private acquirer	83,088	164.32	27.80

Table 4.2 The Number of M&A Activities of Top 20 Countries

This table shows the annual number of deals in the top 20 countries based on technology deal types as the sample described in Table 4.1. Panel A is the annual number of deals of the acquirer's origin, and Panel B is the target. Total is the total sample size covering 120 countries in each deal category.

Panel A: Top 20 acquirer's origin country									
All Deals		*Non-Hi*		*Hi-Non*		*Hi-Hi*		*Non-Non*	
Total 95,935		Total 4,593		Total 10,220		Total 20,082		Total 61,040	
Country	N	Country	N	Country	N	Country	N	Country	N
US	36,733	US	1,465	US	4,398	US	10,236	US	20,634
UK	12,392	UK	615	UK	1,274	UK	2,041	UK	8,462
Canada	9,095	China	563	China	702	Canada	1,082	Canada	7,201
Australia	5,852	Canada	336	Japan	624	China	985	Australia	4,444
China	5,223	Australia	284	Canada	476	Japan	739	China	2,973
Japan	4,066	Japan	235	Australia	434	Australia	690	Japan	2,468
South Korea	1,718	South Korea	207	South Korea	355	Sweden	451	Malaysia	1,321
Malaysia	1,558	Hong Kong	114	Hong Kong	202	France	394	Hong Kong	987
Sweden	1,552	Sweden	86	Sweden	171	South Korea	383	Singapore	844
Hong Kong	1,449	Singapore	59	France	133	Germany	283	Sweden	844
France	1,328	France	58	Singapore	126	India	260	South Korea	773
Singapore	1,165	Germany	50	Germany	117	Israel	237	South Africa	769
South Africa	993	South Africa	49	Malaysia	105	Taiwan	192	France	743
Germany	936	Malaysia	45	India	99	Norway	176	Italy	582
India	903	India	40	Taiwan	98	Italy	165	India	504
Italy	848	Israel	31	Ireland-Rep	93	Hong Kong	146	Spain	497
Netherlands	645	Italy	30	Norway	90	Singapore	136	Germany	486
Spain	623	New Zealand	27	Italy	71	Netherlands	124	Netherlands	425
Norway	620	Netherlands	26	Netherlands	70	Switzerland	122	Brazil	416
Ireland	582	Norway	23		64	Finland	119	Ireland	361
Panel B: Top 20 target's origin country									
All Deals		*Non-Hi*		*Hi-Non*		*Hi-Hi*		*Non-Non*	
Total 95,935		Total 4,593		Total 10,220		Total 20,082		Total 61,040	
Country	N	Country	N	Country	N	Country	N	Country	N
US	38,226	US	1,686	US	4,276	US	10,419	US	21,845
UK	11,148	China	614	UK	1,241	UK	1,807	UK	7,601
Canada	7,033	UK	499	China	766	China	1,068	Canada	5,491
China	5,776	Canada	271	Japan	543	Canada	873	Australia	4,044
Australia	5,347	Australia	238	Australia	418	Australia	647	China	3,328
Japan	3,542	South Korea	208	Canada	398	Japan	604	Japan	2,208
Germany	1,797	Japan	187	South Korea	353	Germany	511	Malaysia	1,247
South Korea	1,654	Germany	79	Germany	234	France	431	Germany	973
France	1,583	Hong Kong	73	Hong Kong	176	South Korea	374	France	930
Malaysia	1,475	France	60	Sweden	174	Sweden	364	South Africa	804
Sweden	1,279	Sweden	57	France	162	Netherlands	216	Hong Kong	752
Hong Kong	1,130	Singapore	49	Singapore	124	Israel	176	South Korea	719
South Africa	1,010	Malaysia	43	Netherlands	116	Norway	172	Sweden	684
Italy	955	South Africa	42	Italy	101	Taiwan	170	Italy	659
Singapore	904	India	41	Malaysia	98	Italy	164	Brazil	616
Netherlands	892	Netherlands	35	Taiwan	77	India	161	Singapore	612
Spain	783	Israel	31	Norway	66	Switzerland	148	Spain	572
Brazil	746	Italy	31	India	63	Denmark	134	Netherlands	525
India	678	Norway	31	Switzerland	62	Hong Kong	129	Mexico	449
Norway	637	Spain	28		61	Finland	127	India	413

Table 4.3 Sample Distribution by Year and Technology Deal Type

The table presents the annual deal number and aggregated deal value ($billion) by technology deal type. The sample covers all announced deals of listed bidders in the SDC from 1990-2018 with at least $1 million inflation-adjusted deal value, and the target-to-acquirer relative size is no less than 1%, where the acquirer holds less than 10% shares of targets before the announcement and more than 50% shares following the deal, excluding leverage buyouts, spin-offs, repurchases, recapitalisations, self-tenders, exchange offers, and minority-stake purchases. The *Non-Hi* represents non-hi-tech bidders acquiring hi-tech targets. The *Hi-Non* are the hi-tech acquirers who take non-hi-tech targets. The *Hi-Hi* is the acquirer, and the target are both in the hi-tech industry; in contrast, the bidder and target of the *Non-Non* deals are not in the hi-technology related industry. Deal value ($billion) is the sum of the deal value in the sample covering 120 countries by year. N is the number of deal activities in the world by year.

Year	All deals		*Hi-Non* deals		*Non-Hi* deals		*Hi-Hi* deals		*Non-Non* deals	
	N	Deal value ($bil)	N	Deal value ($bil)	N	Deal value ($bil)	N	Deal value ($bil)	N	Deal value ($bil)
1990	1,058	1,512	176	305	19	41	67	193	796	974
1991	1,076	1,084	143	159	25	25	96	135	812	764
1992	1,273	1,026	166	152	41	47	146	60	920	767
1993	1,715	1,912	222	344	31	42	173	578	1,289	948
1994	2,279	2,253	279	433	63	71	255	391	1,682	1,358
1995	2,429	3,795	340	568	63	89	303	835	1,723	2,302
1996	3,150	5,571	444	648	98	171	433	1,392	2,175	3,360
1997	4,129	8,238	438	749	120	151	613	1,463	2,958	5,874
1998	4,795	15,075	495	804	139	323	867	4,651	3,294	9,297
1999	4,157	23,698	459	1,731	162	1,147	1,041	11,526	2,495	9,295
2000	4,498	17,675	518	978	258	668	1,485	6,955	2,237	9,074
2001	3,135	9,493	357	886	169	121	934	3,082	1,675	5,404
2002	2,711	4,547	297	287	114	159	694	1,366	1,606	2,735
2003	2,686	4,119	256	317	103	42	732	1,002	1,595	2,759
2004	3,430	8,799	330	308	172	161	923	2,850	2,005	5,480
2005	3,918	10,631	439	534	172	237	979	3,371	2,328	6,488
2006	4,602	15,476	416	464	238	431	1,055	4,011	2,893	10,570
2007	5,090	15,537	459	600	230	382	1,168	3,261	3,233	11,294
2008	3,752	9,982	352	419	188	299	864	2,485	2,348	6,778
2009	2,834	7,304	260	490	110	223	631	2,609	1,833	3,982
2010	3,523	8,749	335	497	137	248	722	2,364	2,329	5,640
2011	3,529	8,871	347	519	135	725	731	1,985	2,316	5,642
2012	3,372	7,268	331	764	153	395	678	1,820	2,210	4,288
2013	3,270	7,627	298	526	168	288	632	2,406	2,172	4,406
2014	4,137	17,724	394	672	248	1,167	832	8,122	2,663	7,763
2015	4,232	24,527	436	1,573	340	1,897	937	9,965	2,519	11,092
2016	3,712	15,737	390	2,127	311	731	702	5,402	2,309	7,478
2017	3,820	15,958	392	1,911	301	1,459	676	4,088	2,451	8,500
2018	3,623	16,521	451	1,519	285	1,062	713	5,302	2,174	8,638
Total	95,935	290,707	10,220	21,284	4,593	12,802	20,082	93,672	61,040	162,950

Figure 4.1 Merger Waves by Technology Deal Types
This figure provides the distribution of the deal number and the aggregated deal value ($bil) through time for the sample described in Table 4.3.

Figure 4.1a The trend of all deals by deal number and aggregate deal value (billion $) from 1990-2018

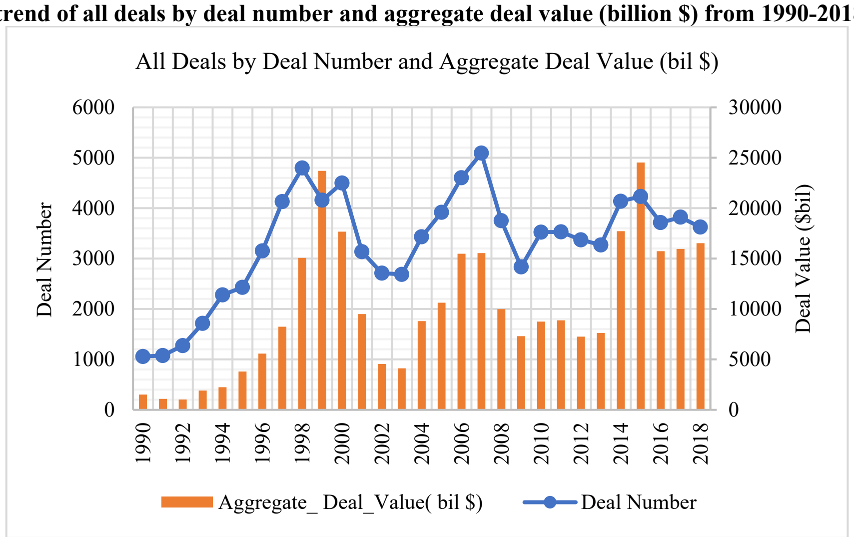

Figure 4.1b The trend of four technology deal types by deal number and aggregate deal value (billion $) from 1990-2018.

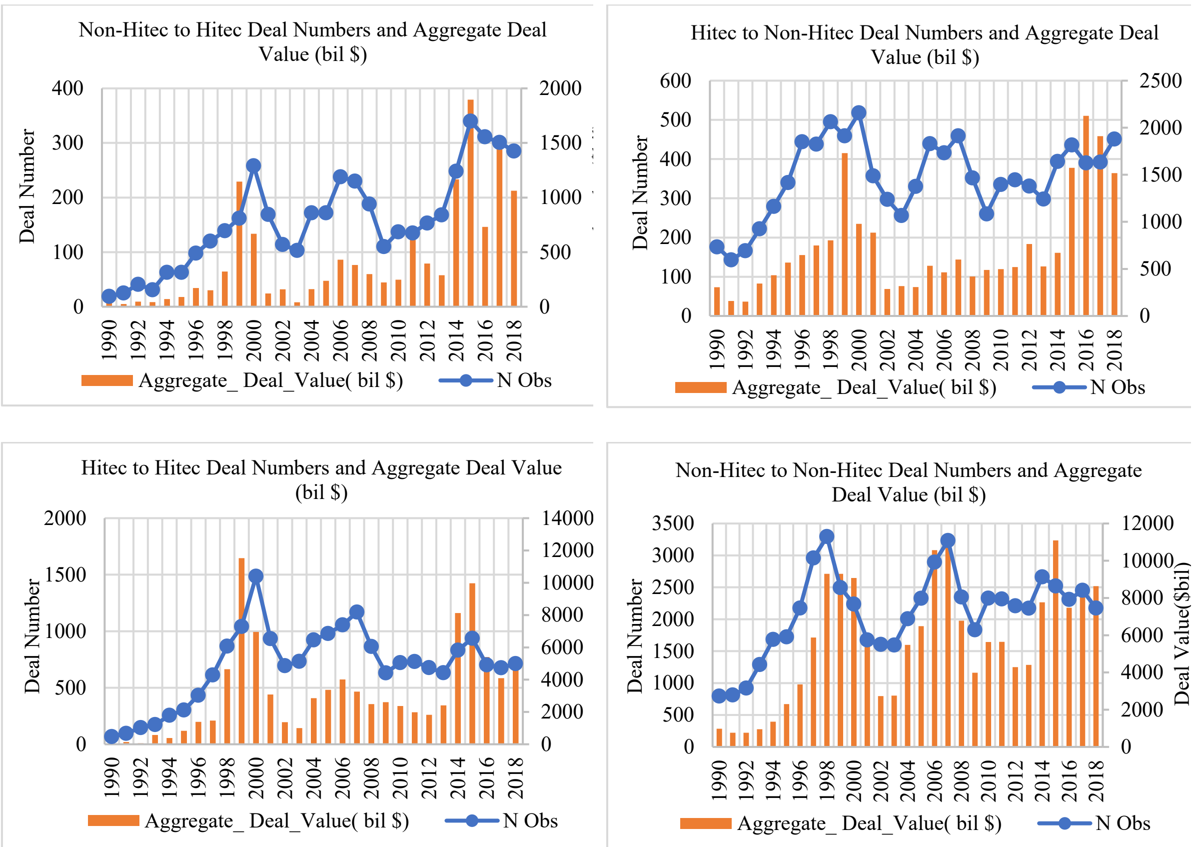

Figure 4.2 The Area Charts of Four Technology Deal Types

This figure exhibits the proportion of each technology deal type on the whole M&A market by deal number and deal value during 1990-2018, respectively, where the sample is described in Table 4.1.

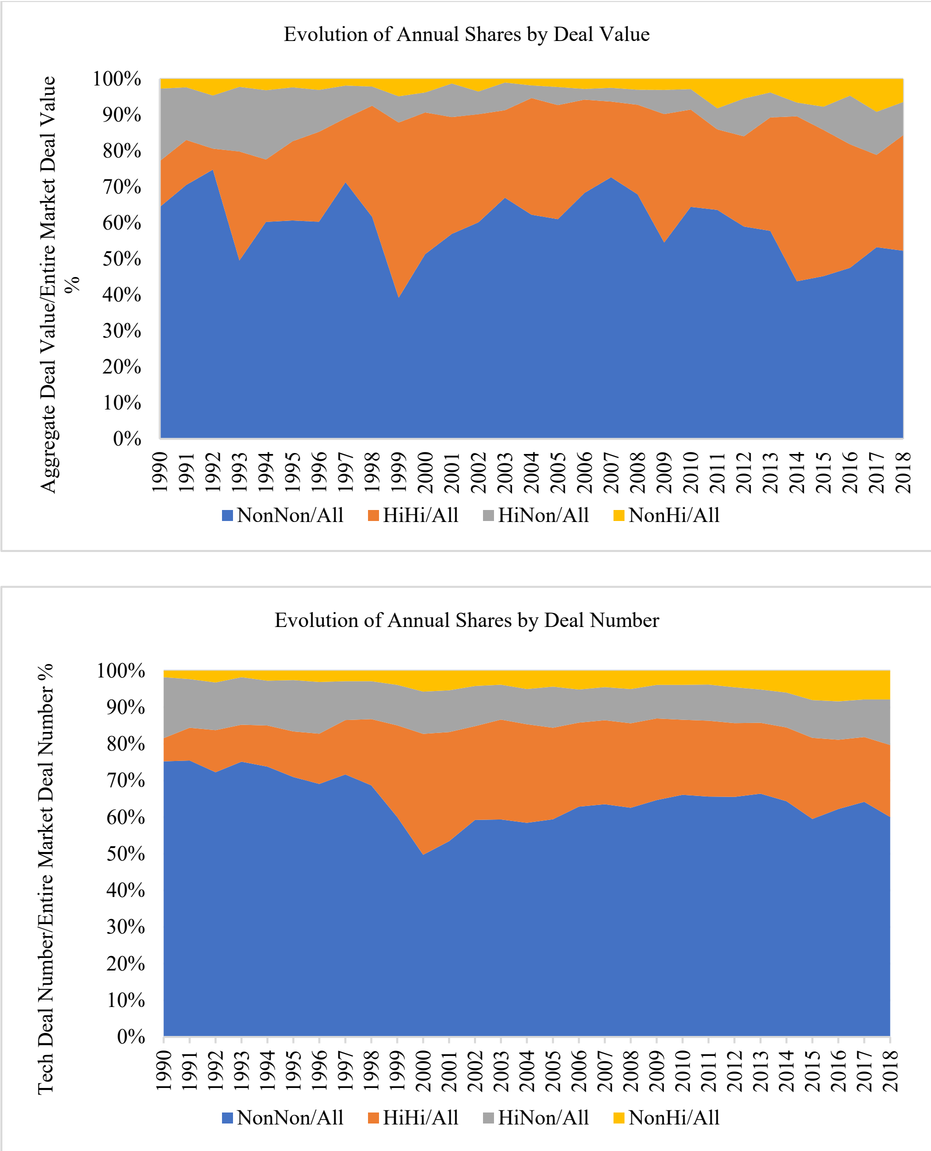

Table 4.4 Summary Statistics

The table presents means, medians, and sample size for the bidder and deal characteristics of the primary sample described in Table 4.1, including 95,935 deals undertaken by public bidders, of which 12,847 deals are on public targets, and 83,088 deals are on private firms, segregated into different technology deal types. Column (1) shows statistics for all sample deals, and Columns (2) to (5) present summary statistics for four different types of technology deals, respectively. Column (6) indicates the technologically distant deals, and Column (7) reports differences between *Hi-Non* & *Non-Hi* deals and the rest. Panel A indicates private target deal characteristics, and Panel B is private target deal characteristics. The symbols *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively. The definition of all variables is in the Appendix C.

		All	***Hi-Non***	***Non-Hi***	***Hi-Hi***	***Non-Non***	***Hi-Non& Non-Hi***	**Difference**
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Public Targets								
Deal Value($mil)	mean	1,781.09	1,613.72	1,778.91	2,791.16	1,445.52	1,676.56	-123.82***
	median	186.61	211.16	186.66	268.01	161.66	203.00	17.48
	n	12,847	855	525	3,024	8443	1,380	
Size ($mil)	mean	8,280.21	8,923.74	6,251.05	15,461.17	5,704.07	7,888.59	-438.45
	median	1,029.57	1,363.74	898.70	1,744.89	866.14	1,163.91	88.15
	n	11,507	753	476	2,763	7,515	1,229	
Target Size ($mil)	mean	1,190.39	924.68	1,060.93	1,448.59	1,112.50	980.63	-235.50**
	median	167.24	168.00	125.89	179.91	166.73	144.59	25.56*
	n	8,243	531	370	2,264	5,078	901	
Relative Size%	mean	51.19	49.01	72.33	40.46	54.01	58.04	7.67**
	median	24.04	18.16	24.07	18.41	27.39	20.46	-3.97
	n	11,507	753	476	2,763	7,515	1,229	
Book-to-Market	mean	0.73	0.57	0.61	0.47	0.85	0.58	-0.17***
	median	0.56	0.43	0.44	0.37	0.67	0.43	-0.15***
	n	9,854	651	398	2,364	6,441	1,049	
Leverage	mean	1.05	0.88	0.89	0.65	1.23	0.88	-0.19***
	median	0.51	0.42	0.48	0.26	0.64	0.44	-0.07***
	n	10,697	699	425	2,564	7,009	2,235	
Hostile %	mean	7.00	7.37	7.24	5.59	7.33	7.32	0.45
	n	12,847	855	525	3,024	8,443	1,380	
Tender %	mean	25.66	28.89	29.33	27.11	24.57	29.06	3.81***
	n	12,847	855	525	3,024	8,443	1,380	
All Stock %	mean	39.09	34.27	36.57	36.11	40.80	35.14	-4.42***
	n	12,847	855	525	3,024	8,443	1,380	
All Cash %	mean	27.51	32.98	35.62	35.25	23.68	34.00	7.26***
	n	12,847	855	525	3,024	8,443	1,380	
Incl. Stock %	mean	58.63	51.35	50.48	53.77	61.61	51.01	-8.53***
	n	12,847	855	525	3,024	8,443	1,380	
Cross-border %	mean	21.27	22.00	28.19	25.99	19.07	24.35	3.45***
	n	12,847	855	525	3,024	8,443	1,380	
Competing Bid%	mean	8.24	8.77	5.90	8.23	8.34	7.68	0.63
	n	12,847	855	525	3,024	8,443	1,380	
Synergy Proxy %	mean	12.91	9.60	14.48	16.07	12.01	11.45	-1.63*
	n	1,2847	855	525-	3,024-	8,443-	1,380	
Hi-Non & Non-Hi%	mean	10.74						
	n	12,847						
Hi-Non%	mean	6.66						
	n	12,847						
Non-Hi%	mean	4.10						
	n	12,847						
Hi-Hi%	mean	23.54						
	n	12,847						
Non-Non%	mean	65.72						
	n	12,847						
Panel B: Private Targets								
Deal Value($mil)	mean	164.32	142.01	145.14	194.46	159.99	142.96	-25.47***

	median	27.80	23.23	23.59	25.45	30.11	23.32	-5.51***
	n	83,088	9,365	4,068	17,058	52,597	13,433	
Size ($mil)	mean	2,096.61	2,125.98	1,672.66	2,855.31	1,867.80	1,989.87	-127.27
	median	333.40	294.81	230.61	351.04	340.666	273.43	-75.94***
	n	73,975	8,350	3,583	15,571	46,471	11,933	
Relative Size%	mean	39.06	36.63	68.46	27.66	41.05	46.18	8.49***
	median	9.08	7.85	12.00	7.65	9.72	8.89	-0.23
	n	73,975	8,350	3,583	15,571	46,471	11,933	
Book-to-Market	mean	0.74	0.61	0.66	0.52	0.84	0.63	-0.13***
	median	0.56	0.45	0.47	0.40	0.65	0.46	-0.12***
	n	59,753	6,830	2,883	12,551	37,489	9,713	
Leverage	mean	0.86	0.70	0.76	0.51	1.01	0.72	-0.16***
	median	0.41	0.31	0.33	0.12	0.54	0.31	-0.12***
	n	66,200	7,440	3,041	13,984	41,735	10,481	
Hostile %	mean	0.79	0.08	0.05	0.05	0.09	0.07	-0.01
	n	83,088	9,365	4,068	17,058	52,597	13,433	
Tender %	mean	0.26	0.23	0.10	0.09	0.33	0.19	-0.07*
	n	83,088	9,365	4,068	17,058	52,597	13,433	
100% Stock %	mean	11.00	12.44	16.03	14.44	9.07	13.53	3.14***
	n	83,088	9,365	4,068	17,058	525,97	13,433	
100% Cash %	mean	23.52	25.10	19.89	24.87	23.08	23.51	0.01
	n	83,088	9,365	4,068	17,058	52,597	13,433	
Incl. Stock %	mean	27.97	30.00	36.11	36.12	24.35	31.80	4.57***
	n	8,088	9,365	4,068	17,058	52,597	13,433	
Cross-border %	mean	26.43	27.88	24.14	31.22	23.79	26.75	0.38*
	n	83,088	9,365	4,068	17,058	52,597	13,433	
Competing Bid%	mean	0.295	0.22	0.15	0.23	0.34	0.20	-0.11**
	n	83,088	9,365	4,068	17,058	52,597	13,433	
Synergy Proxy %	mean	5.93	6.47	8.43	8.15	4.91	7.06	1.36***
	n	83,088	9,365	4,068	17,058	52,597	13,433	
Hi-Non & Non-Hi%	mean	16.17				-		
	n	83,088						
Hi-Non%	mean	11.27						
	n	83,088						
Non-Hi%	mean	4.90						
	n	83,088						
Hi-Hi%	mean	20.53						
	n	83,088						
Non-Non%	mean	63.30						
	n	83,088						

Table 4.5 Univariate Tests of Acquirers' Stock Return Performance around the Deal and Operating Performance Changes

This table reports the mean and median of the acquirer's three-day cumulative abnormal return in percentage (Panel A), ACAR, and operating performance changes in percentage (Panel B), % ΔROA (*- 1, + i*) (*i =1,2,3*), by target public status and technology deal group. *Year - 1* is the last fiscal year before the deal announcement. Year+*i* is the *i*th fiscal year after the announcement, where *i* equals to 1, 2 or 3. T-tests are used for means and Wilcoxon tests for medians of ACARs and ROA changes (%). The variables are defined in the Appendix C. The ***, **, and * are used to denote statistical significance at 1%, 5%, and 10% levels, respectively.

Target listed Status		***Technology Deal Type***					
		All	***Hi-Non***	***Non-Hi***	***Hi-Hi***	***Non-Non***	***Hi-Non& Non-Hi***
Panel A: 3-day % *ACAR*							
(1) All Targets	mean	1.58***	2.01***	2.69***	1.49***	1.45***	2.22***
	median	0.56***	0.77***	0.75***	0.71***	0.48***	0.76***
	n	79,455	8,520	3,778	17,064	50,093	12298
(2) Public Targets	mean	-0.42	-0.28	0.05	-1.06	-0.23	-0.16
	median	-0.43	-0.33	-0.09	-0.70	-0.38	-0.24
	n	11,075	728	451	2,681	7,215	1179
(3) Private Targets	mean	1.90***	2.23***	3.05***	1.96***	1.73***	2.47***
	median	0.71***	0.85***	0.91***	0.97***	0.61***	0.87***
	n	68,380	7,792	3,327	14,383	42,878	11,119
(4) (3) – (2)	mean	2.32***	2.51***	3.00***	3.02***	1.96***	2.63***
	median	1.14***	1.18***	1.00***	1.67***	0.99***	1.11***
Panel B: %Δ*ROA*							
(1) Public Targets							
ΔROA (-1, +1)	mean	-2.55	-1.30	-0.67	-4.44	-2.07	
	median	-4.59	-4.91	-4.06	-9.37	-3.52	
	n	10,137	681	402	2,501	6,553	
ΔROA (-1, +2)	mean	-2.79	-1.95	-0.70	-4.86	-2.22	
	median	-4.47	-4.90	-3.92	-9.44	-3.35	
	n	9411	650	365	2,320	6,076	
ΔROA (-1, +3)	mean	-3.14	-3.48	-1.49	-5.28	-2.39	
	median	-4.46	-4.89	-4.04	-9.52	-3.24	
	n	8,676	596	331	2,130	5,619	
(2) Private Targets							
ΔROA (-1, +1)	mean	0.046	0.75**	7.26***	-0.06	-0.60	
	median	-5.61	-6.12	-4.04	-8.86	-4.86	
	n	62,809	7,180	2,998	13,474	39,157	
ΔROA (-1, +2)	mean	-0.40	0.027	6.02***	-0.75	-0.83	
	median	-5.53	-6.08	-4.21	-8.94	-4.74	
	n	57,346	6,518	2,637	12,167	36,024	
ΔROA (-1, +3)	mean	-0.74	-0.52	5.59***	-1.28	-1.04	
	median	-5.49	-6.15	-4.18	-9.05	-4.63	
	n	51,535	5,902	2,306	10,827	32,500	
(3) (2) – (1)							
ΔROA (-1, +1)	mean	2.59***	2.05*	7.93***	4.38***	1.47***	
	median	-1.02***	-1.21**	0.02	0.51**	-1.34***	
ΔROA (-1, +2)	mean	2.39***	1.98*	6.72***	4.11***	1.39***	
	median	-1.06***	-1.18**	-0.29	0.50**	-1.39***	
ΔROA (-1, +3)	mean	2.41***	2.96**	7.07***	4.00***	1.35***	
	median	-1.03***	-1.26**	-0.14	0.47*	-1.39***	

Table 4.6 Acquirer Stock Returns Regression Analysis

The table reports multivariate regression coefficient estimates of the acquirer's three-day cumulative abnormal return (ACAR%) on technology dummy, acquirer, and deal characteristics. The technology dummy variable takes the value of 1 if the deal was in the specific technology deal type and 0 otherwise. Panel A shows the results for all the 63,373 deals with available information. Panel B and Panel C present estimates for deals with private and public targets, respectively. All regressions are controlled by the year and country-fixed effects. The sample criteria are described in Table 4.1. Definitions of the variables are explained in the Appendix C. The *, **, and *** denote statistical significance levels of 10%, 5%, and 1% respectively.

3-day *ACARs* (%)	**Panel A: All targets**					**Panel B: Private targets**					**Panel C: Public targets**				
	Hi-Non	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non& Non-Hi*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non& Non-Hi*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non& Non-Hi*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Technology dummy	0.223***	0.503***	-0.016	-0.194**	0.336***	0.211**	0.454***	0.000	-0.197**	0.309***	-0.028	0.322	-0.584**	0.430**	0.114
	(0.008)	(0.006)	(0.869)	(0.033)	(0.000)	(0.029)	(0.002)	(0.998)	(0.042)	(0.001)	(0.894)	(0.342)	(0.011)	(0.036)	(0.598)
Log(Size)	-0.419***	-0.418***	-0.420***	-0.416***	-0.417***	-0.423***	-0.423***	-0.424***	-0.421***	-0.422***	-0.359***	-0.359***	-0.356***	-0.357***	-0.359***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	1.083***	1.076***	1.082***	1.085***	1.080***	1.189***	1.185***	1.189***	1.193***	1.187***	0.206	0.201	0.202	0.212	0.203
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.317)	(0.330)	(0.330)	(0.307)	(0.323)
Book-to-Market	-0.194***	-0.197***	-0.201***	-0.177***	-0.189***	-0.181***	-0.185***	-0.187***	-0.165***	-0.177**	-0.157	-0.152	-0.219*	-0.217	-0.153
	(0.009)	(0.008)	(0.003)	(0.007)	(0.010)	(0.010)	(0.009)	(0.005)	(0.010)	(0.012)	(0.240)	(0.250)	(0.085)	(0.103)	(0.256)
Hostile	-0.379	-0.380	-0.379	-0.378	-0.381	-0.658	-0.647	-0.655	-0.667	-0.655	-0.261	-0.260	-0.277	-0.274	-0.260
	(0.103)	(0.102)	(0.104)	(0.105)	(0.102)	(0.571)	(0.576)	(0.573)	(0.564)	(0.573)	(0.260)	(0.259)	(0.235)	(0.242)	(0.260)
Tender	0.690***	0.686***	0.695***	0.676***	0.683***	0.177	0.181	0.181	0.182	0.176	-0.096	-0.098	-0.069	-0.070	-0.098
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.803)	(0.798)	(0.799)	(0.797)	(0.804)	(0.535)	(0.526)	(0.659)	(0.657)	(0.527)
Private target	2.227***	2.237***	2.237***	2.227***	2.221***										
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)										
Payment incl. stock	0.310**	0.309**	0.311**	0.298**	0.309**	0.785***	0.784***	0.786***	0.768***	0.783***	-2.054***	-2.047***	-2.075***	-2.086***	-2.048***
	(0.034)	(0.033)	(0.033)	(0.040)	(0.034)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	0.325***	0.330***	0.331***	0.311***	0.323***	0.265**	0.270***	0.270**	0.250**	0.263**	0.091	0.088	0.114	0.113	0.089
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)	(0.010)	(0.012)	(0.019)	(0.012)	(0.727)	(0.734)	(0.660)	(0.659)	(0.732)
Competing bidder	-0.028	-0.019	-0.025	-0.026	-0.025	0.598	0.598	0.597	0.600	0.599	0.079	0.084	0.083	0.080	0.079
	(0.905)	(0.935)	(0.914)	(0.909)	(0.914)	(0.256)	(0.256)	(0.258)	(0.257)	(0.255)	(0.773)	(0.760)	(0.764)	(0.770)	(0.773)
Leverage	-0.023	-0.023	-0.025	-0.016	-0.021	-0.050**	-0.051**	-0.052**	-0.043*	-0.049**	0.127**	0.128**	0.105*	0.108*	0.128**
	(0.298)	(0.278)	(0.254)	(0.481)	(0.327)	(0.044)	(0.039)	(0.036)	(0.083)	(0.048)	(0.046)	(0.046)	(0.082)	(0.069)	(0.045)
Synergy dummy	0.566***	0.563***	0.567***	0.555***	0.563***	0.814***	0.812***	0.816***	0.802***	0.811***	-0.142	-0.142	-0.128	-0.135	-0.141
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.631)	(0.630)	(0.663)	(0.645)	(0.633)
Constant	0.456***	0.479***	0.471***	0.664***	0.452***	2.695***	2.727***	2.720***	2.903***	2.688***	7.750*	7.738*	7.796*	7.426*	7.726*
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	63,373	63,373	63,373	63,373	63,373	54,065	54,065	54,065	54,065	54,065	9,308	9,308	9,308	9,308	9,308
Adj. $\boldsymbol{R}^2$ (%)	5.60	5.61	5.59	5.61	5.62	5.42	5.43	5.42	5.43	5.44	5.27	5.27	5.37	5.33	5.27

Table 4.7 Acquirers Return Regressions with Three and Four Technology Dummies

The table presents OLS regressions of ACAR on technology deal indicators and other control variables. The technology deal indicator is a dummy equal to one if the acquirer and target are in the corresponding technology industry. Panel A is all deals satisfying the criteria in Table 4.1, Panel B is the unlisted target deals, and Panel C deals with listed targets. Models (1), (3), and (5) are regressions with three technology dummies and the constant. Models (2), (4), and (6) include four technology type indicators without constants. Symbols *, **, *** denote statistical significance at the 1%, 5%, and 10% levels. All variables' definitions are provided in the Appendix C.

3-day *ACARs* (%)	Panel A: All targets		Panel B: Private targets		Panel C: Public targets	
	(1)	(2)	(3)	(4)	(5)	(6)
Hi-Non-tech dummy	0.273***	0.736	0.263**	-0.258	-0.201	7.624
	(0.004)	(0.862)	(0.015)	(0.972)	(0.371)	(0.012)
Non-Hi-tech dummy	0.553***	1.017	0.509**	-0.012	0.129	7.953
	(0.004)	(0.810)	(0.014)	(0.999)	(0.724)	(0.009)
Hi-Hi-tech dummy	0.068	0.531	0.083	-0.438	-0.598**	7.226
	(0.533)	(0.900)	(0.471)	(0.952)	(0.014)	(0.017)
Non-Non-tech dummy		0.463		-0.521		7.824
		(0.913)		(0.943)		(0.010)
Log (Size)	-0.416***	-0.416***	-0.421***	-0.421***	-0.356***	-0.356
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	1.079***	1.079***	1.187***	1.187***	0.201	0.201
	(0.000)	(0.000)	(0.000)	(0.000)	(0.333)	(0.065)
Book-to-Market	-0.184***	-0.184***	-0.171***	-0.171***	-0.223*	-0.223
	(0.005)	(0.000)	(0.007)	(0.000)	(0.091)	(0.065)
Hostile	-0.380	-0.380	-0.656	-0.656	-0.278	-0.278
	(0.102)	0.197	(0.570)	(0.561)	(0.234)	(0.359)
Tender	0.676***	0.676***	0.178	0.178	-0.067	-0.067
	(0.001)	(0.000)	(0.801)	(0.782)	(0.669)	(0.727)
Private target	2.224***	2.224***				
	(0.000)	(0.000)				
Payment incl. stock	0.305**	0.305***	0.776***	0.776***	-2.078***	-2.078
	(0.036)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	0.319***	0.319***	0.258**	0.258***	0.115	0.115
	(0.001)	(0.000)	(0.016)	(0.001)	(0.657)	(0.590)
Competing bidder	-0.022	-0.022	0.600	0.600	0.087	0.087
	(0.924)	(0.932)	(0.255)	(0.338)	(0.752)	(0.752)
Leverage	-0.019	-0.019	-0.046*	-0.046**	0.104*	0.104
	(0.390)	(0.328)	(0.065)	(0.031)	(0.079)	(0.021)
Synergy dummy	0.559***	0.559***	0.805***	0.805***	-0.130	-0.130
	(0.003)	(0.000)	(0.000)	(0.000)	(0.657)	(0.568)
Constant	0.463***	No	2.699***	No	7.824*	No
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	63,373	63,373	54,065	54,065	9,308	9,308
Adj. R^2 (%)	5.62	8.89	5.44	10.41	5.37	5.94

Table 4.8 Mechanisms of Acquirers' Return of Technologically Distant Deals

The table presents the mechanisms analysis of why the technologically distant deals (*Non-Hi* and *Hi-Non*) significantly and positively affect the acquirer's short-term returns. Panel A reports the cash flow volatility of firms, which is calculated as a standard deviation of operating cashflows since the prior seven years scaled by the mean of these operating cashflows. The sample is split into high and low cash flow volatility according to the median of the year-country pair. Panel B displays Tobin's Q in explaining the positive relationship between technologically distant deals and acquisition performance. Tobin's Q is the market value of total assets over the book value of total assets. We categorise and separate firms into growth and value firms using Tobin's Q. When the firm's Tobin's Q is above the year and country's median, it is a growth firm; otherwise, it is a value firm. Panel C shows the economic policy uncertainty (EPU), explaining the higher return for technologically distant acquisitions. EPU is defined as the average economic policy uncertainty of a firm's country by each year obtained from the national and global EPU index. We split the sample into high-EPU firms and low-EPU firms. The technologically distant deal indicator is the *HiNon-NonHi* dummy, equal to one if the acquirer and target are in the corresponding technology industry. Symbols *, **, *** denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables' definitions are provided in Appendix C.

3-day *ACARs* (%)	**Panel A: Cash flow volatility**		**Panel B: Tobin's Q**		**Panel C: EPU**	
	(1) High	*(2) Low*	*(3) Growth*	*(4) Value*	*(5) High*	*(6) Low*
HiNon-NonHi dummy	0.092	0.339***	0.289*	0.339***	0.197*	0.340***
	(0.445)	(0.000)	(0.063)	(0.004)	(0.057)	(0.000)
Log (Size)	-0.253**	-0.426***	-0.384***	-0.460***	-0.322***	-0.421***
	(0.030)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Relative size	0.430	1.090***	1.094***	1.056***	1.741**	1.066***
	(0.436)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)
Book-to-Market	0.048	-0.174**	-0.172	-0.140*	-0.627*	-0.177**
	(0.918)	(0.016)	(0.520)	(0.055)	(0.062)	(0.012)
Hostile	0.780	-0.565**	-0.234	-0.472	1.189**	-0.498**
	(0.239)	(0.029)	(0.337)	(0.252)	(0.031)	(0.036)
Tender	1.268***	0.567***	0.727***	0.605**	1.353**	0.670***
	(0.004)	(0.006)	(0.008)	(0.028)	(0.013)	(0.001)
Public target	-1.980***	-2.212***	-2.253***	-2.229***	-1.714**	-2.260***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.000)
Payment incl. stock	-0.862***	0.356**	0.066	0.572***	-0.659	0.354**
	(0.009)	(0.020)	(0.685)	(0.001)	(0.215)	(0.019)
Cross-border	-0.164	0.339***	0.240**	0.329**	0.011	0.338***
	(0.518)	(0.001)	(0.016)	(0.034)	(0.968)	(0.001)
Competing bidder	0.187	-0.011	-0.245	0.259	-0.136	-0.011
	(0.852)	(0.965)	(0.478)	(0.376)	(0.906)	(0.962)
Leverage	0.115	-0.021	-0.008	-0.054	-0.049	-0.021
	(0.125)	(0.346)	(0.786)	(0.110)	(0.459)	(0.369)
Synergy dummy	0.408	0.594***	0.447	0.668***	1.128***	0.460**
	(0.148)	(0.005)	(0.114)	(0.000)	(0.001)	(0.017)
Constant	6.247	3.104	0.827	4.198***	2.237**	3.074***
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	29,710	30.975	32,525	30,848	21,921	25,452
Adj. R^2 (%)	0.041	0.054	0.052	0.060	0.039	0.055

Table 4.9 Operating Performance Changes Around Takeover Multivariate Regressions Private Targets vs. Public Targets

The table reports cross-sectional regression estimates of operating performance changes before and after the M&As. The dependent variable, ΔROA (-1, + *i*) (*i* =1,2,3), is the change in return on assets adjusted by the industry average between the post-announcement and pre-announcement. Year-*1* is the last fiscal year prior to the deal announcement. Year +*i* is the *i* year post the announcement. Panel A shows the estimates of ΔROA (-1, +1), panel B reports the results of ΔROA (-1, +2), and panel C is on the ΔROA (-1, +3). The regressions are controlled with year and country-fixed effects. *P*-values are presented below regression estimates. All variables are described in the Appendix C. Symbols *, **, and *** correspond to statistical significance levels at 10%, 5%, and 1%, respectively.

Panel A: % Δ*ROA (-1, +1)*								
	(1) Private targets				*(2) Public targets*			
	Hi-Non	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*
Technology dummy	-0.709**	2.435***	-2.234***	1.444***	-0.028	1.256	-2.043***	1.462***
	(0.018)	(0.000)	(0.000)	(0.000)	(0.969)	(0.177)	(0.000)	(0.000)
Log (Size)	-3.684***	-3.673***	-3.705***	-3.709***	-2.843***	-2.843***	-2.835***	-2.839***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	2.788***	2.768***	2.731***	2.762***	1.135***	1.123***	1.119***	1.147***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-market	-3.668***	-3.637***	-3.825***	-3.808***	-1.996***	-1.980***	-2.212***	-2.197***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hostile	2.433	2.452	2.569	2.526	-0.485	-0.491	-0.553	-0.532
	(0.481)	(0.478)	(0.457)	(0.465)	(0.508)	(0.502)	(0.450)	(0.468)
Tender	1.517	1.496	1.458	1.509	-1.334***	-1.340***	-1.242***	-1.244***
	(0.444)	(0.451)	(0.462)	(0.447)	(0.004)	(0.004)	(0.007)	(0.007)
Payment incl. stock	4.645***	4.628***	4.815***	4.771***	1.678***	1.703***	1.602***	1.563***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	3.876***	3.861***	4.035***	4.007***	2.668***	2.662***	2.741***	2.737***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Competing bidder	1.026	1.034	1.039	1.025	-0.887	-0.871	-0.879	-0.883
	(0.584)	(0.581)	(0.579)	(0.584)	(0.183)	(0.190)	(0.186)	(0.184)
Leverage	0.371***	0.380***	0.298***	0.312***	0.653***	0.656***	0.577***	0.588***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Synergy dummy	-1.701***	-1.730***	-1.588***	-1.606***	-1.579***	-1.580***	-1.524***	-1.558***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.006)	(0.005)
Constant	25.816	-1.289	-1.465	-2.688	17.991**	17.983**	18.034**	16.763**
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	54,274	54,274	54,274	54,274	9,135	9,135	9,135	9,135
Adj. R^2 (%)	15.81	15.85	15.93	15.88	14.84	14.86	15.04	14.96

Panel B: % Δ*ROA (-1, +2)*								
	(1) Private targets				*(2) Public targets*			
	Hi-Non	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*
Technology dummy	-0.743**	2.188***	-2.339***	1.593***	-0.299	1.144	-2.154***	1.671***
	(0.016)	(0.000)	(0.000)	(0.000)	(0.683)	(0.230)	(0.000)	(0.000)
Log (Size)	-3.620***	-3.610***	-3.643***	-3.647***	-2.737***	-2.737***	-2.727***	-2.731***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	2.905***	2.887***	2.843***	2.875***	1.146***	1.135***	1.131***	1.157***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-market	-3.570***	-3.539***	-3.735***	-3.726***	-2.006***	-1.984***	-2.231***	-2.235***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hostile	2.475	2.479	2.609	2.585	-0.530	-0.534	-0.606	-0.588
	(0.486)	(0.485)	(0.463)	(0.467)	(0.473)	(0.470)	(0.412)	(0.426)
Tender	1.494	1.471	1.416	1.479	-1.315***	-1.324***	-1.227***	-1.218***
	(0.452)	(0.459)	(0.476)	(0.456)	(0.005)	(0.005)	(0.009)	(0.009)
Payment incl. stock	4.381***	4.364***	4.560***	4.521***	1.625***	1.651***	1.552***	1.506***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	3.938***	3.923***	4.100***	4.080***	2.837***	2.833***	2.903***	2.905***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Competing bidder	0.946	0.945	0.941	0.942	-0.734	-0.727	-0.746	-0.739
	(0.618)	(0.618)	(0.619)	(0.619)	(0.274)	(0.278)	(0.265)	(0.270)
Leverage	0.403***	0.412***	0.326***	0.338***	0.635***	0.640***	0.555***	0.559***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Synergy dummy	-1.917***	-1.947***	-1.794***	-1.806***	-1.304***	-1.300***	-1.226***	-1.269***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.020)	(0.029)	(0.023)
Constant	3.876	3.922	3.626	2.141	20.090**	20.035**	20.145**	18.701**
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	49,754	49,754	49,754	49,754	8,498	8,498	8,498	8,498
Adj. R^2 (%)	15.97	16.00	16.10	16.05	14.83	14.85	15.06	14.99

Panel C: % Δ*ROA (-1, +3)*

	(1) Private targets				*(2) Public targets*			
	Hi-Non	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*
Technology dummy	-0.810**	2.454***	-2.532***	1.712***	-0.425	1.337	-2.200***	1.716***
	(0.012)	(0.000)	(0.000)	(0.000)	(0.561)	(0.160)	(0.000)	(0.000)
Log (Size)	-3.567***	-3.557***	-3.592***	-3.596***	-2.565***	-2.566***	-2.554***	-2.556***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	2.767***	2.750***	2.701***	2.733***	1.330***	1.315***	1.310***	1.341***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-market	-3.527***	-3.494***	-3.703***	-3.692***	-1.660***	-1.635***	-1.884***	-1.885***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hostile	3.542	3.523	3.715	3.708	-0.807	-0.810	-0.873	-0.855
	(0.350)	(0.352)	(0.326)	(0.328)	(0.269)	(0.267)	(0.232)	(0.242)
Tender	1.370	1.339	1.260	1.346	-1.326***	-1.342***	-1.242***	-1.226***
	(0.499)	(0.509)	(0.534)	(0.506)	(0.004)	(0.004)	(0.008)	(0.009)
Payment incl. stock	4.347***	4.323***	4.536***	4.499***	1.592***	1.624***	1.535***	1.485***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	3.972***	3.956***	4.144***	4.123***	2.890***	2.887***	2.954***	2.956***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Competing bidder	0.661	0.657	0.653	0.654	-1.080	-1.077	-1.098*	-1.084
	(0.735)	(0.736)	(0.738)	(0.737)	(0.106)	(0.107)	(0.100)	(0.104)
Leverage	0.444***	0.453***	0.358***	0.373***	0.604***	0.612***	0.525***	0.523***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Synergy dummy	-1.862***	-1.892***	-1.731***	-1.743***	-1.361***	-1.358***	-1.287***	-1.321***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.016)	(0.022)	(0.019)
Constant	17.959	17.614	17.638	16.695	18.425**	18.372**	18.471**	16.965**
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,849	44,849	44,849	44,849	7,844	7,844	7,844	7,844
Adj. R^2 (%)	15.78	15.81	15.93	15.87	15.55	15.57	15.80	15.74

Table 4.10 Propensity Score Matching of ACARs

The table reports the acquisition gain differences by comparing the three-day acquirer % ACAR of *Non-Hi* deals or *Hi-Non* with other deals using a propensity score matching estimator, conditional on the target's listed status. Panel A reports logit estimation results where the dependent variable equals one if the deal is in the *Non-Hi* or the *Hi-Non* type and zero otherwise. Panel B presents ACAR for the *Non-Hi* or the *Hi-Non* deals (Treated group) and propensity score-matched firms in other deals (Control group). The difference is the % ACAR of treated sample minus control sample. Symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. All variables are defined in the Appendix C.

Panel A: Probit estimation

	(1) Private targets		*(2) Public targets*	
	Non-Hi	*Hi-Non*	*Non-Hi*	*Hi-Non*
Leverage	0.001	-0.013	-0.041	0.033
	(0.972)	(0.348)	(0.492)	(0.380)
Liquidity	-0.012	-0.014***	-0.061	-0.036*
	(0.115)	(0.006)	(0.116)	(0.100)
Cash to total assets	0.011	0.498***	-1.068**	0.148
	(0.948)	(0.000)	(0.045)	(0.662)
Tobin's q	0.001**	0.000	-0.003	-0.004
	(0.013)	(0.678)	(0.748)	(0.440)
Relative size	0.128***	-0.008	0.170**	0.009
	(0.000)	(0.703)	(0.024)	(0.901)
Log (Size)	0.001	0.006	0.011	-0.016
	(0.523)	(0.533)	(0.755)	(0.549)
Acquirer nation	-0.002***	0.003***	0.003*	0.010***
	(0.000)	(0.000)	(0.086)	(0.000)
Pre-BHR	-0.032	-0.001	0.036	0.010
	(0.166)	(0.561)	(0.215)	(0.408)
Post-BHR	-0.098***	0.018	-0.085	-0.025
	(0.005)	(0.400)	(0.266)	(0.522)
Cross border	-0.313***	0.007	0.188	-0.018
	(0.000)	(0.847)	(0.219)	(0.885)
Constant	-2.748	-2.231	-3.216	-3.159
N	31,460	31,460	5,327	5,327
Adj. $\boldsymbol{R^2}$ (%)	0.78	0.39	2.02	1.43

Panel B: Propensity score matching of private target deals

			One-to-one	*5 Nearest*	*30 Nearest*	*50 Nearest*	*Radius Caliper*	*Gaussian Kernel*
Non-Hi								
3-day	Treated	mean	2.885	2.885	2.885	2.885	2.885	2.885
ACARs	Control	mean	1.987	2.241	2.255	2.299	2.192	1.973
	Difference		0.898***	0.644***	0.630***	0.586**	0.693***	0.912***
Hi-Non								
3-day	Treated	mean	2.026	2.026	2.026	2.026	2.026	2.026
ACARs	Control	mean	1.778	1.921	1.935	1.952	1.920	1.981
	Difference		0.248	0.106	0.091	0.074	0.107	0.045

Panel C: Propensity score matching of public target deals

			One-to-one	*5 Nearest*	*30 Nearest*	*50 Nearest*	*Radius Caliper*	*Gaussian Kernel*
Non-Hi								
3-day	Treated	mean	0.172	0.172	0.172	0.172	0.172	0.172
ACARs	Control	mean	-0.535	-0.413	-0.503	-0.535	-0.522	-0.519
	Difference		0.708	0.585	0.676	0.707	0.695	0.692
Hi-Non								
3-day								
ACARs	Treated	mean	-0.430	-0.430	-0.430	-0.430	-0.430	-0.430
	Control	mean	-0.679	-0.454	-0.483	-0.526	-0.598	-0.594
	Difference		0.249	0.024	0.053	0.096	0.168	0.164

Table 4.11 Propensity Score Estimation of Changes in ROAs

The table reports the acquisition gain differences by comparing the changes in operating performance of *Non-Hi* deals with other deals using a propensity score matching estimator, conditional on the listed status on the target. Panel A reports logit estimation results where the dependent variable equals one if the deal is in the *Non-Hi* type and zero otherwise. Panel B presents changes in operating performance for the *Non-Hi* deals (Treated group) and propensity score-matched firms in other deals (Control group). The difference is the ΔROA (-1, + *i*) (*i* =1,2,3) of treated sample minus control sample. Symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. All variables are defined in the Appendix C.

Panel A: Probit estimation						
	(1) Private targets			*(2) Public targets*		
	ΔROA (-1,+1)	*ΔROA (-1,+2)*	*ΔROA (-1,+3)*	*ΔROA (-1,+1)*	*ΔROA (-1,+2)*	*ΔROA (-1,+3)*
Leverage	-0.041**	-0.040**	-0.048**	-0.031	-0.090	-0.188**
	(0.030)	(0.046)	(0.027)	(0.506)	(0.121)	(0.015)
Liquidity	-0.016**	-0.018***	-0.022***	-0.074**	-0.092**	-0.103**
	(0.014)	(0.009)	(0.003)	(0.028)	(0.018)	(0.017)
Cash to total assets	0.155	0.155	0.203	-0.278	-0.291	-0.275
	(0.260)	(0.291)	(0.193)	(0.537)	(0.546)	(0.589)
Tobin's q	0.001**	0.001**	0.002***	-0.002	-0.001	0.000
	(0.026)	(0.028)	(0.002)	(0.700)	(0.888)	(0.933)
Relative size	0.109***	0.116***	0.108***	0.080	0.056	0.100
	(0.000)	(0.000)	(0.000)	(0.272)	(0.481)	(0.209)
Log (Size)	0.011	0.006	-0.002	0.000	0.005	0.019
	(0.382)	(0.647)	(0.889)	(0.987)	(0.877)	(0.579)
ΔROA pre (-2, -1)	0.102	0.117	0.094	-0.233	-0.349	-0.525
	(0.277)	(0.238)	(0.376)	(0.586)	(0.482)	(0.349)
ROA pre-industry-adj.	-0.102	-0.117	-0.094	0.232	0.350	0.525
	(0.269)	(0.234)	(0.371)	(0.584)	(0.479)	(0.346)
FF10 acquirer	0.109***	0.105***	0.106***	0.102***	0.113***	0.113***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquirer nation	-0.003***	-0.003***	-0.003***	0.005***	0.005***	0.004**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.005)	(0.019)
Constant	-3.341***	-3.310***	-3.286***	-3.759***	-3.767***	-3.772***
N	42,373	38,770	35,012	6,473	6,020	5,550
Adj. R^2 (%)	1.21	1.22	1.29	1.85	2.14	2.34

Panel B: Propensity score matching of private target deals								
			One-to-one	*5 Nearest*	*30 Nearest*	*50 Nearest*	*Radius Caliper*	*Gaussian Kernel*
ΔROA (-1,+1)	Treated	mean	0.691	0.691	0.691	0.691	0.691	0.691
	Control	mean	-2.189	-0.914	-0.782	-0.818	-1.366	-2.686
	Difference		2.881***	1.606**	1.473**	1.510**	2.058***	3.377***
ΔROA (-1,+2)	Treated	mean	0.398	0.398	0.398	0.398	0.398	0.398
	Control	mean	-1.432	-1.127	-0.947	-0.953	-1.566	-2.667
	Difference		1.830**	1.526**	1.345**	1.352**	1.964***	3.065***
ΔROA (-1,+3)	Treated	mean	0.445	0.445	0.445	0.445	0.445	0.445
	Control	mean	-0.999	-0.997	-1.093	-1.155	-1.585	-2.933
	Difference		1.445*	1.442*	1.538**	1.601**	2.031***	3.378***

Panel C: Propensity score matching of public target deals								
			One-to-one	*5 Nearest*	*30 Nearest*	*50 Nearest*	*Radius Caliper*	*Gaussian Kernel*
ΔROA (-1,+1)	Treated	mean	-3.021	-3.021	-3.021	-3.021	-3.021	-3.021
	Control	mean	-6.274	-5.214	-5.172	-5.109	-5.236	-5.192
	Difference		3.253**	2.193*	2.151**	2.088*	2.215**	2.171**
ΔROA (-1,+2)	Treated	mean	-3.491	-3.491	-3.491	-3.491	-3.491	-3.491
	Control	mean	-6.476	-6.129	-5.428	-5.361	-5.727	-5.443
	Difference		2.985**	2.639**	1.937*	1.870*	2.236**	1.952*
ΔROA (-1,+3)	Treated	mean	-3.696	-3.696	-3.696	-3.696	-3.696	-3.696
	Control	mean	-7.173	-5.974	-6.141	-5.953	-6.109	-5.724
	Difference		3.477**	2.277*	2.445**	2.257**	2.412**	2.028*

Table 4.12 Acquirer Stock Returns Regression Analysis 1990-2008 vs. 2009-2018

The table reports multivariate regression coefficient estimates of the acquirer's three-day cumulative abnormal return (ACAR%) on technology dummy, acquirer, and deal characteristics. The technology dummy variable takes the value of 1 if the deal was in the specific technology deal type and 0 otherwise. Panel A shows the results for all 38,082 deals with available information during the 1990-2008 period. Panel B presents estimates for deals in 2009-2018. All regressions are controlled by the year and country-fixed effects. The sample criteria are described in Table 4.1. Definitions of the variables are explained in the Appendix C. The *, **, and *** denote statistical significance levels of 10%, 5%, and 1%, respectively.

Three-day *ACAR %*								
	Panel A: 1990-2008				*Panel B: 2009-2018*			
	Hi-Non	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*
Technology dummy	0.323***	0.345*	-0.158*	-0.098	0.275*	0.581***	0.158	-0.385***
	(0.007)	(0.078)	(0.098)	(0.235)	(0.083)	(0.005)	(0.192)	(0.000)
Log (Size)	-0.482***	-0.483***	-0.485***	-0.482***	-0.478***	-0.480***	-0.479***	-0.476***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	0.951***	0.950***	0.948***	0.953***	1.112***	1.103***	1.113***	1.113***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-market	-0.154***	-0.162***	-0.178***	-0.151***	-0.296***	-0.299***	-0.290***	-0.263***
	(0.008)	(0.005)	(0.002)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)
Hostile	-1.230***	-1.238***	-1.235***	-1.234***	-0.438	-0.429	-0.437	-0.433
	(0.000)	(0.000)	(0.000)	(0.000)	(0.433)	(0.442)	(0.434)	(0.438)
Tender	-0.775***	-0.784***	-0.770***	-0.783***	-0.633*	-0.649**	-0.667**	-0.703**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.053)	(0.047)	(0.042)	(0.031)
Private target	0.303***	0.307***	0.313***	0.303***	0.203**	0.196**	0.196*	0.170*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.042)	(0.050)	(0.051)	(0.090)
Payment incl. stock	-0.390***	-0.390***	-0.378***	-0.398***	0.308***	0.300**	0.299**	0.299**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.011)	(0.011)	(0.011)
Cross-border	0.369***	0.378***	0.390***	0.368***	0.373***	0.376***	0.364***	0.341***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.002)	(0.004)
Competing bidder	-0.476	-0.470	-0.473	-0.473	-0.754	-0.748	-0.767	-0.768
	(0.107)	(0.112)	(0.109)	(0.110)	(0.126)	(0.128)	(0.119)	(0.118)
Leverage	-0.020	-0.023	-0.029	-0.018	-0.029	-0.029	-0.026	-0.017
	(0.393)	(0.337)	(0.222)	(0.447)	(0.378)	(0.377)	(0.436)	(0.607)
Synergy dummy	-0.205	-0.206	-0.198	-0.212	0.605***	0.600***	0.599***	0.582***
	(0.291)	(0.289)	(0.309)	(0.276)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.181	2.215	2.205	2.309	5.414***	5.432***	5.423***	5.719***
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	38,082	38,082	38,082	38,082	25,291	25,291	25,291	25,291
Adj. $\boldsymbol{R^2}$ (%)	3.96	3.95	3.94	3.94	5.88	5.90	5.88	5.92

Table 4.13 Operating Performance Changes After Takeover Multivariate Regressions for 1990-2008 vs. 2009-2018

The table reports cross-sectional regression estimates of operating performance changes before and after the M&A deal. The dependent variable, ΔROA (-1, + *i*) (*i* =1,2,3), is the change in return on assets adjusted by the industry average between the post-announcement and pre-announcement. *Year-1* is the last fiscal year prior to the deal announcement. *Year+i* is the i^{th} year post the announcement. Panel A shows the estimates of ΔROA (-1, +1), Panel B reports the results of ΔROA (-1, +2), and Panel C is on the ΔROA (-1, +3). The regressions are controlled with year and country-fixed effects. *P*-values are presented below regression estimates. All variables are described in the Appendix C. Symbols *, **, and *** correspond to statistical significance levels at 10%, 5%, and 1%, respectively.

Panel A: *ΔROA (-1, +1) %*								
	(1)1990-2008				*(2)2009-2018*			
	Hi-Non	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*
Technology dummy	-1.011***	2.054***	-1.982***	1.593***	0.453	2.969***	-1.460***	0.106
	(0.002)	(0.000)	(0.000)	(0.000)	(0.346)	(0.000)	(0.000)	(0.740)
Log (Size)	-2.939***	-2.928***	-2.953***	-2.962***	-4.579***	-4.582***	-4.587***	-4.583***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	2.743***	2.726***	2.696***	2.720***	2.072***	2.035***	2.049***	2.070***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-market	-2.501***	-2.456***	-2.653***	-2.677***	-4.731***	-4.728***	-4.844***	-4.751***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hostile	-1.005	-1.020	-0.993	-0.994	-0.045	-0.014	-0.052	-0.042
	(0.291)	(0.285)	(0.297)	(0.297)	(0.980)	(0.994)	(0.976)	(0.981)
Tender	-0.529	-0.562	-0.435	-0.432	0.289	0.228	0.532	0.298
	(0.283)	(0.255)	(0.377)	(0.381)	(0.773)	(0.819)	(0.595)	(0.766)
Private target	-1.274***	-1.296***	-1.231***	-1.214***	-2.199***	-2.253***	-2.101***	-2.184***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payment incl. stock	3.483***	3.486***	3.639***	3.605***	5.467***	5.448***	5.494***	5.460***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	3.049***	3.018***	3.166***	3.185***	5.009***	5.013***	5.129***	5.025***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Competing bidder	-0.901	-0.895	-0.916	-0.914	-1.144	-1.106	-1.059	-1.149
	(0.272)	(0.275)	(0.263)	(0.265)	(0.448)	(0.463)	(0.482)	(0.446)
Leverage	0.634***	0.645***	0.564***	0.564***	-0.056	-0.054	-0.100	-0.062
	(0.000)	(0.000)	(0.000)	(0.000)	(0.574)	(0.589)	(0.323)	(0.537)
Synergy dummy	-0.857	-0.847	-0.737	-0.771	-2.150***	-2.181***	-2.075***	-2.141***
	(0.109)	(0.113)	(0.168)	(0.149)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	26.303	26.251	28.290	25.994	19.972***	20.114***	20.252***	19.948***
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	37,722	37,722	37,722	37,722	25,687	25,687	25,687	25,687
Adj. R^2 (%)	11.50	11.52	11.61	11.60	20.20	20.26	20.24	20.20
Panel B: *ΔROA (-1, +2) %*								
	(1)1990-2008				*(2)2009-2018*			
	Hi-Non	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*
Technology dummy	-1.145***	1.771***	-2.116***	1.802***	0.661	2.801***	-1.488***	0.098
	(0.001)	(0.001)	(0.000)	(0.000)	(0.204)	(0.000)	(0.000)	(0.775)
Log (Size)	-2.875***	-2.864***	-2.889***	-2.900***	-4.576***	-4.582***	-4.587***	-4.582***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	2.741***	2.728***	2.693***	2.715***	2.233***	2.198***	2.208***	2.231***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-market	-2.448***	-2.401***	-2.609***	-2.647***	-4.715***	-4.714***	-4.834***	-4.738***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hostile	-1.057	-1.063	-1.043	-1.047	-0.225	-0.180	-0.230	-0.221
	(0.265)	(0.262)	(0.271)	(0.269)	(0.906)	(0.925)	(0.904)	(0.907)
Tender	-0.400	-0.430	-0.302	-0.289	0.207	0.158	0.452	0.212
	(0.420)	(0.387)	(0.543)	(0.561)	(0.842)	(0.880)	(0.665)	(0.839)
Private target	-1.409***	-1.431***	-1.361***	-1.339***	-2.346***	-2.391***	-2.243***	-2.329***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payment incl. stock	3.310***	3.314***	3.477***	3.448***	5.207***	5.182***	5.232***	5.198***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	3.117***	3.083***	3.240***	3.270***	5.143***	5.160***	5.265***	5.162***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Competing bidder	-0.904	-0.907	-0.930	-0.919	-0.605	-0.579	-0.539	-0.617
	(0.269)	(0.268)	(0.255)	(0.261)	(0.707)	(0.718)	(0.737)	(0.701)
Leverage	0.679***	0.691***	0.606***	0.601***	-0.114	-0.112	-0.159	-0.121
	(0.000)	(0.000)	(0.000)	(0.000)	(0.292)	(0.300)	(0.145)	(0.267)
Synergy dummy	-0.962*	-0.950*	-0.822	-0.859	-2.228***	-2.259***	-2.147***	-2.218***
	(0.073)	(0.077)	(0.126)	(0.110)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	15.130	15.060	-9.637	-11.551	20.386***	20.548***	20.691***	20.390***
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	35,851	35,851	35,851	35,851	22,401	22,401	22,401	22,401
Adj. R^2 (%)	11.63	11.63	11.76	11.75	20.79	20.85	20.83	20.79

Panel C: *ΔROA (-1, +3) %*

	(1)1990-2008				*(2)2009-2018*			
	Hi-Non	*Non-Hi*	*Hi-Hi*	*Non-Non*	*Hi-Non*	*Non-Hi*	*Hi-Hi*	*Non-Non*
Technology dummy	-1.139***	1.868***	-2.426***	1.998***	0.576	3.272***	-1.359***	-0.063
	(0.001)	(0.001)	(0.000)	(0.000)	(0.308)	(0.000)	(0.002)	(0.866)
Log (Size)	-2.825***	-2.815***	-2.841***	-2.852***	-4.547***	-4.552***	-4.557***	-4.551***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	2.475***	2.461***	2.420***	2.446***	2.206***	2.170***	2.183***	2.205***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-market	-2.295***	-2.247***	-2.479***	-2.516***	-4.837***	-4.831***	-4.943***	-4.842***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hostile	-0.843	-0.852	-0.826	-0.829	-1.547	-1.471	-1.526	-1.538
	(0.380)	(0.375)	(0.389)	(0.387)	(0.445)	(0.467)	(0.451)	(0.447)
Tender	-0.456	-0.492	-0.347	-0.331	0.051	-0.024	0.262	0.029
	(0.364)	(0.327)	(0.489)	(0.510)	(0.964)	(0.983)	(0.815)	(0.979)
Private target	-1.564***	-1.587***	-1.514***	-1.491***	-2.259***	-2.313***	-2.168***	-2.257***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payment incl. stock	3.263***	3.267***	3.453***	3.414***	5.364***	5.329***	5.386***	5.355***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	3.156***	3.121***	3.295***	3.326***	5.238***	5.264***	5.353***	5.243***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Competing bidder	-0.745	-0.747	-0.775	-0.764	-1.852	-1.836	-1.789	-1.865
	(0.366)	(0.365)	(0.347)	(0.354)	(0.294)	(0.298)	(0.311)	(0.291)
Leverage	0.694***	0.705***	0.607***	0.606***	-0.098	-0.095	-0.139	-0.099
	(0.000)	(0.000)	(0.000)	(0.000)	(0.418)	(0.432)	(0.252)	(0.416)
Synergy dummy	-0.722	-0.712	-0.573	-0.613	-2.356***	-2.385***	-2.279***	-2.355***
	(0.182)	(0.189)	(0.290)	(0.257)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	18.892	15.152	14.960	13.124	21.661***	21.764***	21.823***	21.747***
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	33,606	33,606	33,606	33,606	19,087	19,087	19,087	19,087
Adj. R^2 (%)	11.48	11.48	11.66	11.64	21.08	21.15	21.11	21.07

Table 4.14 Synergy Gains

The table reports multivariate regression coefficient estimates of the synergy gains for four different technology deal types. The synergy gains are calculated as the sum of the weighted average combined three-day CARs of the acquirer and target, where the weight depends on the market value of the acquirer and target one month before the announcement. The technology dummy variable takes the value of 1 if the deal was in the specific technology deal type and 0 otherwise. All regressions are controlled by year- and country-fixed effects. Definitions of the variables are explained in the Appendix C. The *, **, and *** denote statistical significance levels of 10%, 5%, and 1%, respectively.

% Synergy Gains	***Hi-Non*** *(1)*	***Non-Hi*** *(2)*	***Hi-Hi*** *(3)*	***Non-Non*** *(4)*
Technology dummy	0.270	0.231	-0.934***	0.686***
	(0.480)	(0.577)	(0.001)	(0.008)
Log (Size)	-0.299***	-0.299***	-0.303***	-0.304***
	(0.000)	(0.000)	(0.000)	(0.000)
Relative size	1.398***	1.396***	1.381***	1.401***
	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-Market	0.158	0.157	0.047	0.052
	(0.438)	(0.436)	(0.817)	(0.794)
Hostile	1.136***	1.138***	1.112***	1.117***
	(0.002)	(0.002)	(0.003)	(0.003)
Tender	0.358	0.359	0.405	0.401
	(0.141)	(0.143)	(0.093)	(0.094)
Payment incl. stock	-1.834***	-1.836***	-1.884***	-1.901***
	(0.000)	(0.000)	(0.000)	(0.000)
Cross-border	0.356**	0.354**	0.402**	0.393**
	(0.041)	(0.042)	(0.023)	(0.027)
Competing bidder	0.028	0.034	0.028	0.022
	(0.937)	(0.923)	(0.938)	(0.950)
Leverage	0.085	0.084	0.049	0.055
	(0.128)	(0.130)	(0.364)	(0.295)
Synergy dummy	0.432	0.430	0.452*	0.440
	(0.122)	(0.121)	(0.099)	(0.109)
Constant	-5.989	-5.929	-5.798	-6.418
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	6,459	6,459	6,459	6,459
Adj. R^2 (%)	6.72	6.72	6.98	6.88

Appendix C. Variable Definitions and Constructions (Essay Three)

Panel A: Variable Definitions	
Variable	**Definition**
Dependent variables	
% ACAR	Acquirer cumulative abnormal returns in the 3-day event window around the acquisition announcement day (-1, +1). The abnormal returns are calculated by the market model. The model parameters are estimated with 200 trading days, starting 215 trading days and ending 15 trading days prior to the announcement. The Worldscope's country market index return is employed as the market benchmark return.
% ∆ ROA (- 1, + *i*)	Changes in operating performance in percentage format are the acquirer's ROA ($t + i$) minus ROA ($t - 1$), where year t is the deal announcement year, and i equals 1, 2, and 3 (1 year, 2 years, and 3-years following the deal announcement). ROA is defined as net income before extraordinary items scaled by total assets at the end of the fiscal year. Then, ROA in year t is adjusted by the mean of this ratio for companies in the same Fama-French 10 industry.
Firm and deal characteristics	
Deal Value ($mil)	Value of deal from Thomson Financial SDC with inflation-adjusted in the 2018-dollar term.
Size ($mil)	Acquirer market value 30-days prior to the announcement in millions of dollar terms.
Log (Size)	The nature logarithm of the acquirer's market value one month before the announcement.
Target Size($mil)	Target market value 30-days prior to the announcement in millions of dollar terms.
Relative Size	Deal value scaled by acquirer market value one month prior to the deal announcement)
Book-to-Market	Acquirer total book value of equity over market value at the last fiscal year-end prior to the announcement.
Leverage	(Acquirer's long-term debt + short-term debt)$_{t-1}$/ (Common equity)$_{t-1}$
Private Target	Dummy variable if the target is a private firm, it equals one, zero otherwise.
Hostile	Dummy variable takes one for deals defined as hostile or unsolicited, zero otherwise
Tender	Dummy, one for tender offers, zero otherwise.
All Cash	Dummy variable that takes the value of 1 if the deals use 100% cash for the deal.
All Stock	Dummy variable that equals 1 for deals when the deal is made with pure stock payment.
Incl. Stock	Dummy takes the value of one when deals include a percentage of the stock payment, 0 otherwise.
Cross-border	Dummy variable takes one if the acquirer and the target are not from the same country.
Competing Bidders	Competing bidder, dummy variable takes the value of 1 if the deal has competitors bidding against the acquirer, zero otherwise.
Liquidity	Current ratio of the acquirer, the ratio of total current assets to total current liabilities at the year-end of the fiscal year t-1.
Cash flow volatility	Standard deviation of operating cashflows since the prior seven years scaled by the mean of these operating cashflows.
EPU	Economic policy uncertainty, the average of 12 months of economic policy uncertainty in the acquirer's country.
Synergy	Dummy variable takes one if the acquisition purpose in the deal announcement states synergy gains, with the code 'SYN' in the Deal Purpose Code in SDC, zero otherwise.
Tobin's q	The ratio of acquirer market value scaled by the book value of total assets in the last available end of the fiscal year prior to the announcement.
Pre-BHR	Acquirers buy-and-hold return calculated over 3 years (36 months) prior to the deal announcement.
Post-BHR	Acquirer 3 years (36 months) buy-and-hold abnormal return after the deal announcement.
∆ROA pre (-2, -1)	The operating performance change of the previous year before the deal. It is the acquirer's changes of return on assets one year before the last year-end of the fiscal year prior to the deal announcement. The mean industry-

	adjusted ROA at *t-1* minus the ROA at *t-2*, where *t* is the deal year.
ROA pre-industry adjusted.	Return on asset of the acquirer at the end of fiscal year *t-1* minus the average of ROA in the same Fama-French 10 industry at year *t-1*.
Technology dummy	
Hi-Hi	Tech dummy variable, 1 if the acquirer and target are both hi-tech firms, 0 otherwise.
Hi-Non	Tech dummy variable, 1 if the acquirer is a hi-tech firm and the target is a non-high-tech firm, 0 otherwise.
Non-Hi	Tech dummy variable, 1 if the acquirer does not belong to the hi-tech industry and the target is a hi-tech company, zero otherwise.
Non-Non	Tech dummy variable, 1 if the acquirer and target are both non-high-tech firms, 0 otherwise.
Hi-Non & *Non-Hi*	Tech dummy variable, equals one if the acquirer is in hi-tech and the target is not a hi-tech firm, or the acquirer is classified as non-high-tech with a hi-tech target, 0 otherwise.

Panel B: Technology Classification

Classification	Description
SDC Industry	Thomson SDC industry code. It classifies the high-tech industry of the acquirer (AHTECH) and target (THTECH) if its business line involves high technology areas based on SIC codes, NAIC codes, and overall firm business description, consisting of much more detail on business industry classification than only using the Standard Industrial Classification (SIC) codes. It constitutes computers & peripherals, e-commerce & B2B, electronics, hardware, internet infrastructure, internet software & services, semiconductors, software, biotechnology, chemicals, pharmaceuticals, communications, and other high technology.
FF10 Industry	Using the Fama-French 10 industry portfolios to categorize the acquirers and target industries based on SIC codes. The Hi-technology industry includes computers, software, and electronic equipment.
Macro Industry	Thomson Financial SDC proprietary macro-level industry. There exist 13 macro-level industry classifications covering more than 86 mid-level industry categories. The thirteen-macro industry includes consumer products and services, consumer staples, energy and power, financials, government and agencies, healthcare, high technology, industrials, materials, media and entertainment, real estate, retail, and telecommunications.
Primary Business Industry	The SDC code for industry classification of a firm's primary business. It defines biotechnology, computers & computer equipment, electronics, communications, and all other high technology as the primary high-tech industry (AHITECHP for acquirers and THITECHP for targets).
Ultimate Parent Industry	The ultimate parent industry code on SDC describes the high technology industry as the firm's ultimate parent primary business.

Panel C: Details of SDC High Technology Industries

SDC High Technology	Detail
Biotech and Health Care	Artificial organs/limbs
	Drug delivery systems
	General medical instruments/supplements
	General pharmacies
	Genetically engineered products human）
	Health care services
	In-vitro diagnostic products
	Lab equipment
	Medical imaging systems
	Medical lasers
	Medical monitoring systems
	Medical chemicals
	Nuclear medicines
	Nuclear chemicals (excluding medicals)
	Other biotechnology
	Over-the-counter drugs

	Rehabilitation equipment
	Surgical instruments/equipment
	Vaccines/specialty drugs
Communications	Alarm systems
	Cellular communications
	Data comms (excluding networking）
	Facsimile equipment
	Internet services and software
	Messaging systems
	Microwaves communications
	Other telecommunications equipment
	Satellite communications
	Satellite (non-communications)
	Telephone interconnect equipment
	Telecommunications equipment
Computer Hardware	CAD/CAM/CAE/graphics systems
	CD-ROM drives
	Disk drives
	Mainframes and supercomputers
	Microcomputers (PCs)
	Modems
	Monitors/terminals
	Networking systems (LAN, WAN）
	Other computer systems
	Other peripherals
	Portable computers
	Printers
	Scanning devices
	Turnkey systems
	Workstations
Computer Software & Service	Applications software (business)
	Applications software (home）
	Communication/network software
	Computer consulting services
	Database software/programming
	Data-processing services
	Desktop publishing
	Operating systems
	Other computer-related services
	Other software (including games)
	Programming services
	Utilities/file management software
Electronics	Precision or measuring test equipment
	Printed circuit boards
	Process control systems
	Search, detection, navigation
	Semiconductors
	Superconductors
	Other electronics
Other	Advanced manufacturing systems
	Advanced materials
	Defence-related technology
	Lasers
	Propulsion systems
	Research and development firm
	Robotics
	Other

5. Conclusions

5.1 Conclusions

This thesis discusses three different research questions on M&A—the effect of political ideology divergence between the CEO and board room, climate change uncertainty on M&A deal likelihood, deal process and deal performance, and the success and failure of technology acquisitions—in three separate essays.

The main focus of the first study is to explore the effect of political ideology divergence (*PID*) within the top management team, particularly between the CEO and board of directors, on M&A decisions and associated likely impact. The analysis finds that *PID* between CEO and board is positively linked with firms' acquisition likelihood and this effect remains consistent after considering alternative measures of *PID*, different identification strategies, and a battery of robustness checks. The channel analysis shows that the *PID* within top management might introduce complexities, and significantly influence CEOs' risk-taking disposition. Specifically, overconfident CEOs, founder CEOs, and CEOs with higher pay for payment sensitivity, plausibly prefer riskier pursuits that make them more inclined to acquisitions than others with similar levels of *PID*. In addition, this chapter exhibits that higher *PID* firms generate better long-term stock and operating performance. These firms experience increased board meeting frequency, higher institutional ownership, and greater proportions of independent directors. This analysis suggests that although ideological divergence might bring challenges to cohesive decision-making for firms, such divergence within the team could introduce various perspectives, leading to more rigorous debates and timely communications and can facilitate thorough analysis of investment opportunities.

The second study aims to analyse the effect of climate change exposure on acquisition likelihood. This chapter reveals that firm-level climate change exposure negatively impacts firms' inclination to engage in M&As in the global context. The negative relationship remains significant even after addressing potential endogeneity concerns and various robust tests. This study finds that the negative effect is more pronounced when firms have higher cost of external financing, higher financial constraints, operates in pro-cyclical industries, and investor confidence is low. Furthermore, this analysis shows the repercussions of climate change exposure on the M&A process and post-acquisition performance, highlighting challenges such as reduced deal completion probability, extended deal durations, and suboptimal short-term stock returns and operating performance. These findings underscore that firms that proactively consider climate risks in their strategic planning will be better positioned to navigate the threats and opportunities in light of global climate change challenges.

The final study discusses the performance of technology M&As. This study differentiates deal types into technologically distant and technologically similar deals based on the technology status of acquirers and targets. The findings show that technology-distant deals generate significantly higher short-term stock returns, especially for acquisitions with private targets. In contrast, pure technology deals (high-tech acquirers and high-tech targets) have the lowest announcement period returns for shareholders. This chapter then demonstrates that non-tech bidders experience the most improved operating performance after acquiring high-technology targets relative to all other technology related deals, such as non-technology bidders acquiring non-technology targets, high-technology acquirers acquiring high-technology and non-technology targets. In contrast, this positive effect on operating performance does not exist when high-tech bidders engage in technologically distant deals. The differences in post-deal long-term operating performance highlight substantial distinctions in the integration process between high- and low-tech systems. The empirical results highlight the pivotal role of evolving technology in disrupting and shifting traditional corporations and creating superior value for shareholders by transforming business models and providing emerging opportunities.

Overall, the three studies offer insights into factors affecting M&As and their corresponding performance. Collectively, these studies underscore the importance of political ideology divergence, environmental considerations, and technological compatibility in M&A strategies and outcomes.

5.2 Future Research

Future research could improve this thesis in several aspects.

Chapter 2 provides evidence of the relationship between political ideology divergence (*PID*) and acquisition likelihood. Further research can explore the effect of *PID* on different corporate strategies, such as *PID* and voluntary disclosure. The extent and nature of voluntary disclosure can significantly impact a company’s reputation, investor relations, and market perception (Holland, 1998; Francis et al., 2008; Tsang et al., 2019). It is a key aspect of corporate transparency and governance. Empirical analysis could involve studying the effect of *PID* on the level and nature of voluntary disclosures at the firm level. The study could further explore whether companies with greater *PID* have a different extent of information asymmetry, and how this, in turn, affects their disclosure practices. Understanding this relationship can provide insights into how corporate governance impacts a company's approach to transparency and information sharing, and it could also have implications for stakeholders who seek to understand the underlying factors influencing a company's disclosure practices (Raffournier, 1995; Zeng et al., 2012; Shehata, 2014). Second, additional analysis can be conducted to figure out how political ideology divergence among various entities involved in corporate governance and management influences business practices and outcomes. This includes exploring *PID* between the acquirer firm top management team and target top management team, between the CEO or board and the auditors, and between the CEO or board and the analysts, and between fund managers and party in power as ideological differences could influence negotiation strategies, regulatory environment, economic policies valuation, integration plans, interpretation of financial information, and ultimately the success of corporate decisions.

Chapter 3 shows that climate change exposure negatively affects acquisition likelihood and deal completion probability. First, further study could help understand why and how the three components of aggregate climate change exposure, i.e., the physical, regulatory, and opportunity climate change exposure, affect M&A decisions differently. Each component represents a different dimension of how climate change affects businesses. Analysing the distinct nature of each component is crucial because they require different strategic responses and have varied implications for risk assessment, valuation, and integration planning in M&A. This research would contribute to a more nuanced understanding of how climate change is reshaping the corporate landscape, especially strategic decisions such as M&As. Second, additional analysis to figure out that whether firms that perform well in terms of Environmental, Social, and Governance (ESG) factors, and those that are more transparent in disclosing their ESG actions, tend to have better performance in their M&A activities when they face increasing climate change exposures. This is based on the hypothesis that firms with superior ESG performance might be better equipped to manage climate change risks, discussing whether the ways for firms to develop and improve their ESG strategies could enhance their investment strategies and M&A outcomes in an environment increasingly affected by climate change.

Chapter 4 reveals that non-tech acquirers making deals with high-tech targets are extremely profitable, reflecting the transformative role of technology assets and the importance of complementary resources. There exist some issues that have not been extensively investigated. For instance, the factors that drive firms to acquire technology assets, such as economic shocks, industry productivity and competition, firm market power, concentration, and competitiveness warrant attention. In addition, the mechanisms behind the success of technologically distant deals, particularly on how firms become technically efficient or how private acquirers perform in technology M&As, particularly on the motivation and performance of special purpose acquisition companies (SPAC) would be interesting to investigate. Also, the difference between the technology merger wave and other merger waves, and the comparison of the performance of firms getting ahead of the curve to the firms that are the late movers in the technology merger wave are very pertinent questions to ask. A whole raft of questions still remains unanswered.

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