Essays on environmental factors and corporate investment behaviours in China

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ABSTRACT

This thesis contains three essays. We mainly explore the impact of environmental factors on the corporate investment decisions and behaviours of listed firms in China. In the first essay, we investigate the impact of air pollution on corporate mergers and acquisitions (M&As) for acquiring firms based on their headquarters' location. We find that air pollution decreases local firms' M&A activities, and this result continues to hold after controlling for endogeneity and conducting a series of robustness tests. Our analysis indicates that this is achieved through its adverse effects on firms' operational conditions, specifically by reducing net operating cash flow and increasing environmental expenditures. Additionally, we discover that the adverse effect of air pollution on M&As is impacted by external stakeholders; specifically, it is more significant for firms with limited access to external resources and firms located in regions with higher levels of environmental awareness. Conversely, firms with greater government subsidies and stronger financial health and growth opportunities are better able to mitigate these adverse effects. Our results also reveal that acquirers in high-pollution areas tend to prefer stock-based payment methods, take longer to complete acquisitions, generate less shareholder wealth and bring negative market reaction, as well as suffer from declining performance in the long-term. This research provides a comprehensive insight into the real effects of air pollution on corporate M&A activities.

The second essay examines the impact of air pollution on corporate innovation investment, utilizing a novel measure of adjusted air pollution exposure that accounts for variations in exposure levels and the severity of local air pollution. This measure is calculated by multiplying a firm's absolute sensitivity to air pollution (AQI exposure) by the city-level Air Quality Index (AQI), thereby capturing firms' heterogeneous exposure to local air pollution and the degree of local air pollution. The findings indicate a significant negative relationship between adjusted

air pollution exposure and corporate innovation investment. This relationship remains robust after addressing endogeneity concerns and performing a series of robustness checks. Furthermore, the negative effect of air pollution exposure is found to be mediated through reduced net operating cash flows and increased debt financing costs. However, state ownership appears to mitigate these adverse impacts. The negative influence is more pronounced in firms that disclose environmental information, exhibit low managerial risk tolerance, operate in non-polluting industries, are located in more developed and less polluted regions, or the sub-samples after the signing of the 2015 Paris Agreement. This research highlights the critical role of adjusted air pollution exposure in shaping corporate innovation investment in China.

The third essay estimates how corporate innovation investment responds to climate policy uncertainty. The findings show that climate policy uncertainty positively contributes to corporate innovation investment, and this finding remains robust after addressing endogeneity concerns and conducting a series of robustness checks. Furthermore, we find that stringent government environmental regulation serves as a potential mechanism, compelling firms to adopt cleaner production and increase their investment in innovation. In addition, this positive relationship for firms with higher government subsidies is stronger and for firms with higher allocation of fixed assets disappears. We also find that firms with fewer connections to the government are more sensitive to climate policy uncertainty and they tend to increase their investment in innovation to mitigate the uncertainty. Furthermore, when firms invest more in innovation during periods of high policy uncertainty, their long-term performance and firm value are likely to improve. Overall, this research underscores the critical role that climate policy uncertainty plays in shaping corporate innovation investment in China.

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CHAPTER ONE INTRODUCTION

1.1. Introduction

China has experienced an explosive economic expansion over the past few decades, but this expansion has brought significant environmental degradation, raising widespread public concerns (Li, Dong, Luan, & Wang, 2020). Early research primarily focuses on the effects of environmental factors on public health and overall economic growth (Bakian et al., 2015; Genc, Zadeoglulari, Fuss, & Genc, 2012; Yao, Li, Smyth, & Zhang, 2022). Over time, environmental challenges—especially air pollution and climate change—have become crucial considerations in corporate investment decisions due to their direct impact on financial performance, operational risks, and long-term sustainability (Ardia, Bluteau, Boudt, & Inghelbrecht, 2023; Dong, Fisman, Wang, & Xu, 2021; Huang, Xu, & Yu, 2020; Mbanyele & Muchenje, 2022; Wang, Dai, & Kong, 2021). As a result, companies are increasingly focusing on how these environmental factors shape corporate strategies, investment decisions, and shareholder expectations.

The intention of this thesis is to explore the impact of environmental factors on corporate decision-making within the context of China's evolving economic landscape. It comprises three core studies that address how specific environmental challenges and measures—air pollution, adjusted air pollution exposure, and climate policy uncertainty—impact different aspects of risky and long-term corporate investment behaviours, including mergers and acquisitions (M&As) and innovation strategies. These two areas are crucial for firms to sustain long-term competitiveness, enabling firms to secure growth opportunities and adapt to changing environmental and regulatory pressures (Alexandridis, Antypas, & Travlos, 2017; Kemp & Pontoglio, 2011). Through analysing the effects of environmental challenges on these investment strategies, the thesis provides insights into how firms navigate and integrate environmental risks into investment decision-making processes.

The first essay focuses on city-level environmental risk, specifically air pollution, examining its effects on M&As, focusing on the operational pressures that high pollution levels place on firms. It explores how air pollution raises environmental awareness among external stakeholders, prompting their negative responses that restrict firms' cash flow and increase environmental costs, which, in turn, impacts their M&A decisions. The second essay refines the analysis of air pollution effects from the city level to the combination of the city and the firm-level perspective and focuses on corporate innovation. Using an adjusted measure of air pollution exposure, it examines how varying degrees of pollution exposure directly faced by firms influence their investment in innovation. Findings indicate that higher exposure to pollution can hinder innovation due to constrained cash flow and elevated debt financing costs, although state ownership appears to alleviate some of these pressures. The third essay explores climate policy uncertainty as a forward-looking environmental risk, analysing how it drives firms to prioritize innovation investments in response to fluctuating regulatory expectations. The study underscores that stringent government environmental regulations act as a driving force, compelling firms to adopt cleaner production and increase innovation investments, which ultimately enhance long-term performance and firm value.

As the world's second-largest economy and largest transition economy (Allen, Qian, & Qian, 2005; Prasad & Rajan, 2006), China's rapid economic expansion, combined with intensifying environmental challenges and evolving regulations, offers a compelling context for examining how environmental pressures influence corporate strategies and investment decisions. First, as the world's largest emitter of carbon dioxide, accounting for 30.6% of global greenhouse gas emissions in 2020, China faces severe environmental challenges, including high levels of air pollution and greenhouse gas emissions (Friedlingstein et al., 2022)[1]. Second, since 2012, the Chinese government has attached great importance to environmental governance, stressed the principle of sustainable development, and introduced a series of policies to adjust the economic structure (CBRC, 2014B)[2]. Third, China has experienced rapid economic development since the 1980s. Mergers and acquisitions and corporate innovation have become essential for maintaining firms' long-term competitiveness. These investment strategies help companies pursue growth opportunities and respond effectively to evolving environmental and regulatory demands, ensuring resilience in a dynamic economic landscape (Alexandridis et al., 2017; Kemp & Pontoglio, 2011). Thus, the Chinese market is ideal for examining the impacts of environmental factors on corporate behaviours or investments.

The next three sections of this chapter provide an overview of each of the three essays, detailing their contributions to the current literature. Section Five outlines the research outputs achieved during the doctoral studies, while the final section presents the overall structure of the thesis.

1.2. Essay one

This essay investigates the impact of air pollution, a critical environmental factor, on M&As within listed firms in China. Specifically, it explores the extent to which air pollution affects M&A decisions and performance, aiming to address an empirical question surrounding the likelihood and determinants of M&A activity in this context. Using a sample that includes 22,327 firm-year observations of 3,564 listed firms in mainland China from 2010 to 2020, we find that air pollution is negatively related to the likelihood of corporate M&As. The results still remain after a series of robustness tests and addressing the endogeneity concerns using a

[1] According to the 2020 data, the second-largest emitter of carbon dioxide is the United States, accounting for 13.42% of global emissions, followed by the European Union (27 countries) at 7.48%. The data can be accessed on the website at: https://ourworldindata.org/co2-emissions.
[2] China Banking Regulatory Commission (CBRC), 2014b. Available at: http://www.cbrc.gov.cn/EngdocView.do?docID= C5AE0DDAFB3E43DF85DC12DD6840244A

two-stage least squares (2SLS) instrumental variable (IV) approach and Propensity Score Matching (PSM) approach. We then examine the channels by which air pollution affects M&A activities, grounded in resource-based theory[3] and find that air pollution raises environmental awareness among external stakeholders and triggers negative responses from firms' external stakeholders, resulting in firms' resource constraints and operational inefficiencies that limit their capacity to engage in activities such as M&As.

Furthermore, our cross-sectional analysis highlights that the adverse effect of air pollution on M&As is impacted by external stakeholders. Specifically, it is more significant for firms with limited access to external resources, such as bank loans and trade credit, as well as for firms located in regions with higher environmental awareness, including more developed and less polluted areas. Additionally, our analysis indicates that firms receiving higher government subsidies and those with stronger financial positions and growth opportunities are better positioned to mitigate the adverse effects of air pollution on their M&A activities. Finally, we present evidence that acquirers in heavily polluted regions tend to favour stock-based payments, experience longer acquisition processes, generate less shareholder wealth and bring negative market reaction, and face declining long-term performance.

Essay one first contributes to the literature by highlighting how air pollution influences corporate policies and activities, specifically in M&As. While much research examines the public health and psychological impacts of air pollution, and some studies address its effects on stock performance, operational efficiency, and corporate policy decisions (Ai & Tan, 2020), our work provides novel insights into the adverse effects of air pollution on M&A activity. To

[3] More details in the Chapter 2. Resource-Based Theory is widely applied to analyse investment decisions, including mergers and acquisitions (M&As). In M&As, firms often aim to acquire specific resources from the target company, whether in the form of new technology, human talent, or market access, thereby enhancing their resource portfolio and strengthening competitive positioning. However, resource constraints—such as limited financial resources, environmental liabilities, or operational inefficiencies—can hinder a firm's ability to undertake or benefit from such investments (Hart, 1995; Kozlenkova, Samaha, & Palmatier, 2014).

our knowledge, this is the first study to examine this connection, thereby complementing the emerging literature on the implications of climate change and environmental conditions for firms' broader business strategies (Amran, Ooi, Wong, & Hashim, 2016). Second, our study also supports the resource-based theory (RBT), in contrast to previous research that primarily examines the relationship between air pollution and firm investment activities through the lens of human capital theory (Jie, Massa, Zhang, & Zhang, 2021; Tan & Yan, 2021; Xue, Zhang, & Zhao, 2021). We argue that a firm's financial resources serve as a crucial transmission channel for its investment activities, particularly in the context of M&As. Third, our findings have significant policy implications. While existing literature typically emphasizes the urgent need to manage air pollution from a public health perspective, our results indicate that air pollution negatively impacts M&A activities, a vital mechanism for asset reallocation that influences capital markets (Andrade & Stafford, 2004; Jovanovic & Rousseau, 2008; Martynova & Renneboog, 2008). This highlights the necessity for policymakers to focus on environmental issues, as reducing air pollution can yield broader economic benefits, enhancing firm-level investment efficiency and increasing shareholder value.

1.3. Essay two

This essay investigates the impact of a novel measure -- firm's adjusted air pollution exposure on its innovation investment in mainland China from 2010 to 2022. Adjusted air pollution exposure is measured by multiplying a firm's absolute sensitivity to air pollution (AQI exposure) by the city-level Air Quality Index (AQI), capturing both the firms' heterogeneous exposure to local air pollution and the extent of local air pollution. In line with methodologies from Baker, Bloom, and Davis (2016), Bali, Brown, and Tang (2017), and Brogaard and Detzel (2015), we construct AQI exposure by using Fama-French three factors to estimate rolling regressions of each firm's excess return on the market, size, value, and the air pollution anomaly risk[4]. This allows us to capture a firm's sensitivity to fluctuations in abnormal air pollution.

Our study is related to two theories. The strategic growth option theory suggests that enterprises may act immediately to invest in innovation activities to secure their market share when they face uncertainty (Kulatilaka & Perotti, 1998; Tajaddini & Gholipour, 2021). This aligns with Weeds (2002), who finds that uncertainty may promote investment in valuable growth opportunities to gain a competitive advantage. In contrast, real options theory argues that uncertainty increases the value of waiting, as firms can avoid sunk costs by deferring risky investments (Bulan, 2005; Chen, Lee, & Zeng, 2019; Gulen & Ion, 2016). Supporting this view, Pastor and Veronesi (2012) find that a rise in uncertainty decreases investment for the firms, while Kelly, Pástor, and Veronesi (2016) similarly conclude that investment tends to decline under heightened uncertainty.

To contribute to the ongoing debate, this chapter investigates how the adjusted air pollution exposure affects innovation investment in Chinese listed firms. Furthermore, we also consider the output of innovation and examine the impacts of the adjusted air pollution exposure on patent applications. This chapter examines the impact of adjusted air pollution exposure of the firm on its corporate innovation investment using a sample that includes 16,952 firm-year observations of 3,197 listed firms in mainland China from 2010 to 2022. Our findings indicate a negative relationship between adjusted air pollution exposure and corporate innovation investment. Economically, this relationship is significant: a one standard deviation increase in adjusted air pollution exposure corresponds to a 1.94% decrease in corporate innovation investment. After performing a series of robustness checks and endogeneity tests, the result still holds, including double-clustering robust standard errors by firm and year, incorporating

[4] More details about the air pollution anomaly construction are described in Section 3.3.2.2., Chapter 3.

firm fixed effects, using alternative measures of adjusted air pollution exposure and corporate innovation, controlling for macroeconomic uncertainty, and applying Propensity Score Matching (PSM) approach. Our mediation analysis results support that reduced corporate net operating cash flow and increased financing costs are important channels through which adjusted air pollution exposure affects corporate innovation investment. Furthermore, we also perform a battery of additional analyses. Our findings suggest that firm-specific factors, such as environmental information disclosure, managerial risk tolerance, and industry classification (polluting vs. non-polluting sectors), as well as external factors like regional development levels and local pollution intensity, shape the relationship between adjusted air pollution exposure and innovation investment. We also find that the negative impact of adjusted air pollution exposure on innovation investment becomes more pronounced following the signing of the 2015 Paris Agreement.

We make the following contributions to the literature. First, using publicly accessible air pollution and trading data, we construct a unique firm-level measure of adjusted air pollution exposure, which captures both city-level air quality index and firm-level air pollution exposure. We find that firms in locations with low air pollution have higher sensitivity to air pollution, which shows the importance of combining both firm exposure and air pollution level when measuring the total effect of air pollution exposure. Second, our work provides evidence that firms' adjusted exposure to air pollution negatively impacts corporate innovation investment. While previous research has utilized city-level air quality indices to examine the impact of air pollution on corporate innovation (Tan & Yan, 2021; Wang, Xing, Yu, & Dai, 2021), the question of whether and how firms' heterogeneous exposure to air pollution influences innovation has not been thoroughly explored. This work is among the first to investigate the effect of adjusted air pollution exposure on firms' decision-making processes. Third, we find additional channels in which firms with higher adjusted air pollution exposure reduce innovation investment through increased firm's financial distress, supporting the real options theory. Previous studies find that the city-level air quality index is negatively associated with corporate innovation (Tan & Yan, 2021; Wang et al., 2021). Their findings align with human capital theory, which suggests that health concerns arising from air pollution drive away talented executives and contribute to the lower effectiveness of firm decisions, diminishing the effectiveness of firm decisions and leading to reduced innovation in polluted regions. In contrast to their city-level focus, our study provides firm-level evidence supporting the real options theory of investment irreversibility, showing that firms with higher adjusted air pollution exposure decrease innovation investment in response to heightened uncertainty.

1.4. Essay three

Essay three examines how corporate innovation investment responds to climate policy uncertainty in Chinese listed firms. In recent decades, extreme weather changes and abnormal climate events, such as global warming, rising sea levels, cyclones, and forest fires, have become increasingly severe and posed unprecedented challenges to global sustainability, prompting governments worldwide to adopt diverse policy measures aimed at mitigating greenhouse gas emissions and promoting sustainable practices (IPCC, 2021). Particularly, since the signing of the 2015 Paris Agreement, an increasing number of countries have transformed their development strategies and implemented a series of climate policies, committed to reducing emissions voluntarily, and achieving the common vision of creating a "zero-carbon society" with "net zero emissions". However, these policies associated with climate change vary over time, and future government policies are largely unpredictable and change with political turnover and shifting policy preferences (Lee & Cho, 2023; Zhu, Zhang, Ren, & Wang, 2023). For example, Trump's decision to withdraw from the Paris Agreement, increasing the degree of uncertainty of climate policies.

We use the Chinese climate policy uncertainty (CPU) index created by Lee and Cho (2023) and R&D expenditure as our measure of innovation This study investigates the effect of climate policy uncertainty on corporate innovation investment that includes 16,952 firm-year observations of 3,197 listed firms in mainland China from 2010 to 2022. We find that climate policy uncertainty positively contributes to corporate innovation investment. The results are also economically significant: a one standard deviation increase in climate policy uncertainty corresponds to an 8.80% rise in corporate innovation investment. After conducting a series of robustness checks and endogeneity tests, including the application of the Generalized Method of Moments (GMM) and the use of an instrumental variable (IV) approach, the results remain robust and consistent. Our analysis further reveals that stringent government environmental regulation serves as a potential mechanism, compelling firms to adopt cleaner production practices and increasing their investment in innovation, as seen with policies like the low-carbon pilot city initiative and the signing of the 2015 Paris Agreement. We further find that firms who have fewer connections with government such as non-SOEs and non-political connections are more sensitive to the climate policy uncertainty and invest more in innovation to mitigate the climate policy uncertainty. Moreover, the positive relationship is stronger for firms receiving substantial government subsidies, while it diminishes for firms with higher allocations of fixed assets. We finally examine the impact of climate policy uncertainty on long-term firm performance and firm value. Analysing the interaction between CPU and R&D investment with future Tobin's Q and ROA, we find that this positive relationship boosts long-term performance and firm value, which shows that innovation investment improved by the climate policy uncertainty will bring the positive market expectations for firms.

Our findings are closely related to Bai, Du, Xu, and Abbas (2023), Zhu et al. (2023), and Liu, Chen, Cao, and Wen (2024), who also report a significant positive relationship between climate policy uncertainty and corporate innovation investment. Our work differentiates itself from existing literature by using a climate policy uncertainty (CPU) index specifically tailored to the Chinese context, as developed by Lee and Cho (2023). This index offers several unique contributions. First, it captures climate policy uncertainty in China by leveraging information about China contained in tweets from users worldwide, not just in China. Tweets posted by global users could be a better source of measuring uncertainty than newspapers in China which are subject to strong media censorship (Shao, 2018; Xu & Albert, 2014) that could lead to the under- or over-statement of uncertainty. Second, this method contrasts with prior research that predominantly relies on US data, thus providing a unique perspective that captures the specific context of the Chinese climate policy. Given that climate policies and their associated uncertainties vary significantly across countries, our approach offers a more accurate reflection of China's policy environment. Third, Lee and Cho (2023) also demonstrate that Chinese climate uncertainty indices are not predicted by the US climate-related indices, while the US indices are well predicted by Chinese climate uncertainty indices. This evidence highlights that our used indices reflect China-specific information about climate uncertainty. Moreover, the ability of Chinese indices to predict US climate-related indices underscores China's critical role in global climate uncertainty, which is reasonable considering that China is the world's largest emitter of carbon dioxide. In addition, in comparison with Liu et al. (2024), we focus on innovation inputs in our work rather than outputs (patents), as CPU comes from tweets, which is very current and short-lived information. Its impact on innovation outputs will be very indirect.

Essay three makes several contributions to the literature. First, to our best knowledge, we are the first work to use the Chinese Climate Policy Uncertainty (CPU) index to investigate the relationship between climate policy uncertainty and corporate innovation investment, contributing to the existing literature on climate policy uncertainty. While prior studies have largely relied on the US CPU[5] index, yielding mixed results, our study provides a new perspective by incorporating the Chinese CPU and revealing additional insights beyond the US context. Second, our empirical evidence demonstrates that climate policy uncertainty can drive firms to adjust their development and innovation strategies. Investing in innovation during uncertain policy periods allows firms to better adapt to the policy uncertainty, leading to improved long-term performance and enhanced firm value. Third, we uncover the role of stringent government environmental regulation as a mechanism through which climate policy uncertainty influences corporate innovation strategies. The research findings may help to create more flexible and effective climate policies that enhance corporate innovation.

1.5. Research output from PhD study

Essay one: Air pollution and mergers and acquisitions: Evidence from China (with the new title as "High stakes in hazy skies: How air pollution impacts M&A decisions in China")

- Presented at the School of Economics and Finance Seminar, Massey University, New Zealand, 2023
- Presented at the European Financial Management Association (EFMA) Conference, Cardiff University, UK, 2023
- Presented at the China Accounting and Finance Conference (CAFC), Zhongnan University of Economics and Law, China, 2025

Essay two: Adjusted air pollution exposure and corporate innovation investment: Evidence from China

- Liu, J., Chi, J., Kabir, M. H., & Hafeez, B. (2025). Adjusted air pollution exposure and corporate innovation investment: Evidence from China. *International Review of*

[5] More details about this type of literature reviews are showed in Section 4.1., Chapter 4.

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- Presented at the School of Economics and Finance Seminar, Massey University, New Zealand, 2024
- Presented at the International Review of Finance 25th Anniversary Conference, HK, China, 2024

Essay three: Climate policy uncertainty and corporate innovation investment: Evidence from China

- Presented at the International Corporate Governance Conference (ICGC), Cardiff University, UK, 2024
- Presented at the Massey Sustainable Finance Conference (MSFC), Massey University, New Zealand, 2024
- Presented at the International Symposium for the Advancement of Financial Economics (ISAFE), Gubei Watertown Resort Area, Beijing, China, 2025

1.6. Structure of the thesis

The structure of the thesis is organized as follows. Chapter 2 presents the first essay, which investigates the impact of air pollution on mergers and acquisitions for Chinese listed firm. Chapter 3 discusses the second essay, which studies the influence of adjusted air pollution exposure on corporate innovation investment in China. Chapter 4 presents the third essay, which examines how corporate innovation investment responds to climate policy uncertainty in China. Chapter 5 concludes the thesis by outlining the main findings and implications of each of the three essays and adds a discussion about the future research on environmental factors and firm's investment behaviours.

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[1] Refer to the Massey University Publishing and Authorship guidelines (OneMassey for staff, Stream for students) and/ or Contributor Roles Taxonomy (CRediT) guidelines for guidance.

CHAPTER TWO ESSAY ONE

High stakes in hazy skies: How air pollution impacts M&A decisions in China

Abstract

This chapter investigates the impact of air pollution on corporate mergers and acquisitions (M&As) for acquiring firms based on their headquarters location. Using a sample of Chinese listed firms, we find that air pollution decreases local firms' M&A activities, and this result continues to hold after alleviating for endogeneity and conducting a series of robustness tests. The mechanism tests show that the adverse effects are due to the reduction of net operating cash flow and increasing environmental expenditures. The main findings are more significant for firms with limited access to external resources and firms located in regions with higher levels of environmental awareness. Moreover, we show that firms receiving higher government subsidies and exhibiting strong financial health are more capable of alleviating this negative impact. Finally, we also provide evidence that acquirers in heavy air pollution cities prefer to use stock-based payment, take longer to complete acquisitions, create less shareholder wealth, bring negative market reactions, and suffer from declining performance in the long term.

Key words: mergers and acquisitions, air pollution, external stakeholders, resource constraints, operational inefficiencies

JEL code: G34, G18, Q53, Q56

2.1. Introduction

A growing body of research highlights the wide-ranging impacts of air pollution on human health, economic development, and corporate operations. Medical experts have documented the adverse effects of pollution on physical health, such as respiratory and cardiovascular issues. Psychologists have emphasized the adverse mental health effects on individuals living in highly polluted environments, while economists have pointed to significant economic drawbacks, noting how pollution disrupts productivity and imposes financial burdens on individuals, firms, and the broader economy (Jung et al., 2018)[6]. These studies underscore pollution's extensive reach and implications for public health, psychological well-being, and economic stability.

An emerging body of research highlights the adverse effects of air pollution on firm operations and decision-making in corporate policies and activities. Studies have shown, for example, that pollution worsens debt financing costs (Tan et al., 2022), increases equity offering discounts (Han et al., 2022), reduces corporate innovation (Tan & Yan, 2021), and encourages more conservative accounting practices (Wu et al., 2022), among others. Resource-based theory (RBT) is a strategic management framework that explains how a firm's internal resources and capabilities can create a sustainable competitive advantage (Barney et al., 2021). Resource-based theory is widely applied to analyse investment decisions, including mergers and acquisitions (M&As). In M&As, firms often aim to acquire specific resources from the target company, whether in the form of new technology, human talent, or market access, thereby enhancing their resource portfolio and strengthening competitive positioning. However, resource constraints—such as limited financial resources, environmental liabilities, or operational inefficiencies—can hinder a firm's ability to undertake or benefit from such

[6] For instance, Jung et al. (2018) put the risk of air pollution into three distinct categories to firms: (1) physical damage to operations caused by worsening environmental conditions; (2) loss of financial viability due to increasingly restrictive climate policy; and (3) costs of litigation and reputational damage due to potential breach of climate policy.

investments (Hart, 1995; Kozlenkova, Samaha, & Palmatier, 2014). Air pollution triggers responses from external stakeholders[7], resulting in firms' resource constraints and operational inefficiencies that limit their capacity to engage in activities such as mergers and acquisitions (M&As).

Limited research addresses the effects of air pollution on mergers and acquisitions (M&As) despite M&As being major corporate investment decisions crucial for firm development and capital reallocation (Gokkaya et al., 2021). While internal factors like managers' overconfidence (Goel & Thakor, 2010), compensation structures (Yim, 2013), managers' networks and social ties (Fracassi, 2017; Wu, 2011), board composition (Huang & Kisgen, 2013), ownership structure (Bauguess & Stegemoller, 2008), and corporate policies/cultures/types/values are well-documented drivers of M&A decisions (Bonaime et al., 2018; Shleifer & Vishny, 2003; Teerikangas & Very, 2006; Zhang, 2022). External factors have received growing attention. Recent studies explore how macro-level factors such as the business cycle (Maksimovic & Phillips, 2001), political dynamics (Yang et al., 2022), and geographical distance between the bidder and target firms (Li et al., 2022) significantly shape M&A activity. This shift highlights the importance of understanding both internal and external influences on M&A outcomes, including the potential impact of environmental factors like air pollution.

The reasons for exploring M&A and air pollution are multifold. First, air pollution poses a significant environmental challenge for developing countries like China and India, where rapid economic growth often correlates with increased pollution levels (WHO, 2021). While

[7] Since 2012, the Chinese government has prioritized environmental governance, advancing sustainable development policies aimed at economic restructuring (CBRC, 2014B). Regulations from both central and local authorities have led firms to either limit production or increase environmental spending to mitigate pollution. This often results in lower operating revenues (Tan et al., 2021; Tan & Yan, 2021), and financial institutions have also tightened credit terms for firms in high-pollution areas to minimize credit risk, further constraining external financing (Tan et al., 2022; Tan et al., 2021).

economic development might cause pollution, particularly in emerging markets, how pollution impacts corporate decision-making processes or activities at the firm level is less clear. Addressing this issue holds academic value and has important normative implications for policy and business practice. Second, the Chinese government has prioritized environmental governance, advancing sustainable development policies aimed at economic restructuring since 2012 (CBRC, 2014B)[8]. Regulations from central and local authorities have led firms to limit production or increase environmental spending to mitigate pollution. This often results in lower operating revenues (Tan et al., 2021; Tan & Yan, 2021), and financial institutions have also tightened credit terms for firms in high-pollution areas to minimize credit risk, further constraining external financing (Tan et al., 2022; Tan et al., 2021). Exploring how these policy measures impact corporate M&A activities is thus highly relevant. Finally, China has provided daily, city-level air pollution data, offering quantifiable and accessible metrics on air quality across the country since 2000. This availability enables a comprehensive assessment of how air pollution influences firm behaviour and strategic decisions, such as M&A activities, across varied geographic and economic contexts.

Using a sample that includes 22,327 firm-year observations of 3,564 listed firms in mainland China from 2010 to 2020, we investigate the influence of air pollution, a critical environmental factor, on merger and acquisition (M&A) activities within listed firms in China. Specifically, it explores how air pollution affects M&A decisions and performance, aiming to address an empirical question surrounding the likelihood and determinants of M&A activity in this context. We utilize the annual city-level air quality index (AQI) as a proxy for air pollution (Dong et al., 2021; Wang et al., 2021). We match air pollution levels with M&A data for both target and acquiring firms based on the location of the firm headquarters. Based on the firm headquarters

[8] China Banking Regulatory Commission (CBRC), 2014b, No. 40 Document General Office of the China Banking Regulatory Commission, Options on Green Credit Implementation. Available at: http://www.cbrc.gov.cn/EngdocView.do?docID= C5AE0DDAFB3E43DF85DC12DD6840244A

location, we match the air pollution data and the M&A sample, both targets and acquirers. This matching assumes that the headquarters location generally reflects the primary concentration of a firm's facilities and operations (Bai et al., 2021).

We find that air pollution is negatively related to corporate M&As. The results survived after a series of robustness tests and alleviating the endogeneity using a two-stage least squares (2SLS) instrumental variable (IV) approach and Propensity Score Matching (PSM) approach. Our findings indicate that the negative impact of air pollution on M&A activities operates through its deteriorating effects on firms' operational inefficiencies, notably by reducing net operating cash flow and elevating environmental expenditures, grounded in resource-based theory. These results align with prior research that financial constraints generate negative cash flow shocks and may lead to under-investment (Bond & Van Reenen, 2007; Carpenter & Guariglia, 2008; Guariglia & Yang, 2016), higher environmental governance costs result in many firms prefer to hold more cash and decrease investment activities (Tan et al., 2021; Tan & Yan, 2021).

We further examine the heterogeneity impact of air pollution on M&As. The findings suggest that the negative influence of air pollution on M&A activities is especially significant for firms with limited access to external financing sources, such as bank loans and trade credit, and for firms located in regions with higher environmental awareness, including more developed and less polluted areas. Additionally, our analysis indicates that firms receiving higher government subsidies and those with more substantial financial positions—such as low default risk and a high Tobin's Q—are better positioned to mitigate the adverse effects of air pollution on their M&A activities. Finally, we present evidence of a negative association between air pollution levels in acquirer regions and the likelihood of cash-based payment in M&A transactions, alongside a positive association with stock-based payment. This aligns with our channel analysis, suggesting that firms in high-pollution areas often encounter resource constraints and operational inefficiencies, favouring stock issuance as a financing method in M&A deals. Additionally, we observe that acquirers from areas with high pollution levels require longer to finalize acquisitions. Evaluating shareholder value through two-day cumulative average abnormal returns (CAAR) before M&A announcements, we find a negative relationship between air pollution and acquirer shareholder value, and this means that markets perceive the event as unfavourable. Our analysis further reveals that air pollution adversely affects acquirers' long-term performance in the years following M&A transactions.

Our paper makes several contributions. First, we provide the first piece of empirical evidence about how local air pollution affects local firms' M&A activities, supporting the resource-based theory, in contrast to previous research that primarily examines the relationship between air pollution and firm investment activities through the lens of human capital theory (Jie et al., 2021; Tan & Yan, 2021; Xue et al., 2021). We argue that a firm's financial resources are a crucial transmission channel for its investment activities, particularly in mergers and acquisitions (M&As). Second, we contribute to the literature by highlighting how air pollution influences corporate policies and activities, specifically mergers and acquisitions (M&As). While much research examines the public health and psychological impacts of air pollution, and some studies address its effects on stock performance, operational efficiency, and corporate policy decisions (Ai & Tan, 2020), our work provides novel insights into the adverse effects of air pollution on M&A activity. To the best of our knowledge, this is the first study to examine this connection, complementing the emerging literature on the implications of climate change and environmental conditions for firms' broader business strategies (Amran et al., 2016). Third, our findings carry significant policy implications. While existing literature typically emphasizes the urgent need to manage air pollution from a public health perspective, our results indicate that air pollution negatively impacts M&A activities, a vital mechanism for asset reallocation that influences capital markets (Andrade & Stafford, 2004; Jovanovic & Rousseau, 2008; Martynova & Renneboog, 2008). This insight highlights the necessity for policymakers to focus on environmental issues, as reducing air pollution can yield broader economic benefits, enhancing firm-level investment efficiency and increasing shareholder value. Mitigating air pollution could catalyse economic growth through corporate M&A activities.

The chapter is structured as follows. We review the background and literature on air pollution and M&As and propose the hypotheses in Section 2.2. We then describe the dataset, variable construction, and descriptive statistics in Section 2.3. We present and discuss our main results and report some robustness tests in Section 2.4, and we conclude in Section 2.5.

2.2. Literature review

2.2.1. Merger and acquisitions

M&As are among the most important events in a company's lifecycle and significantly impact the firm's operations and activities. They are considered one of the business strategies for enriched financial performance and growth (Anthony, 2017; Sahu & Agarwal, 2017). M&A transactions enable firms to perform business diversification (Levine, 2017), foreign market entry (Xu, 2017), accessing resources (Ahuja & Katila, 2001), deliberate learning (Zollo & Singh, 2004) and reinforcing market power (Hossain, 2021).

Research on the determinants of M&As has grown significantly since the 1970s, with numerous studies exploring the internal and external factors influencing acquirers' motivations for M&A activities (DePamphilis, 2019; Feldman & Hernandez, 2021; Fuller & Pusateri, 2018). Internal factors, in particular, have been closely examined, beginning with the characteristics and preferences of CEOs and managers. For instance, CEOs' overconfidence and narcissism (Goel & Thakor, 2010), CEOs' compensation contracts (Yim, 2013), top managers' and directors' networks and social ties (Fracassi, 2017; Wu, 2011). Corporate characteristics represent another significant category of internal determinants. These include the composition of boards (Huang & Kisgen, 2013), ownership structures (Bauguess & Stegemoller, 2008), corporate policies (Bonaime et al., 2018), corporate cultures between targets and bidders (Teerikangas & Very, 2006), corporate types (Zhang, 2022), and corporate values (Shleifer & Vishny, 2003).

Recent research has increasingly concentrated on external factors that influence M&A activity, particularly focusing on political influence (Yang et al., 2022), geographical distance between bidder and target (Li et al., 2022), and the business cycle (Maksimovic & Phillips, 2001). For example, Brockman, Rui, and Zou (2013) conduct a study across 22 countries, demonstrating that politically connected firms engage in more M&As than their unconnected counterparts, especially in contexts with low corruption and strong legal frameworks. Geographical distance also emerges as a key external determinant, as Uysal, Kedia, and Panchapagesan (2008) find that acquisitions are more likely when the bidder and target firms are located in closer proximity to one another. Maksimovic and Phillips (2001) find reporting an active market for corporate assets during economic expansion, with close to seven percent of plants changing ownership annually through mergers, acquisitions, and asset sales during peak periods.

The current literature on factors influencing corporate M&A activity has largely emphasized entity-level determinants, such as characteristics of firms, governmental policies, and market dynamics. In contrast, relatively few studies have examined the role of natural environmental factors, such as air pollution, in shaping M&A decisions. This gap underscores the need for further research into how environmental issues, including air pollution, may impact corporate M&A behaviours and strategies.

2.2.2. The impact of air pollution

Air pollution is one of the heaviest environmental risks worldwide, killing an estimated seven million people yearly (WHO 2022). WHO data show that almost 99% of the global population breathes air that exceeds WHO guideline limits containing high levels of pollutants, with low- and middle-income countries suffering from the highest exposures (WHO 2022). Early studies on air pollution have primarily focused on its effects on individual health and psychological factors, such as mood and sentiment (Bakian et al., 2015; Chen, Ebenstein, Greenstone, & Li, 2013; Graff Zivin & Neidell, 2013). More recently, research has increasingly explored the relationship between air pollution and broader macroeconomic activities (Chay & Greenstone, 2005; Chen et al., 2013; Ebenstein et al., 2015; Ebenstein, Fan, Greenstone, He, & Zhou, 2017). At the firm level, financial economists have begun extending this area of inquiry, examining how air pollution affects corporate accounting, financial policies, investment strategies, and overall business activities.

Several studies focus on the effects of air pollution on the firm's accounting policies, financial report quality, and internal control quality. For example, Wu et al. (2022) find that increased air pollution induces firms to follow more conservative accounting practices and utilize more conservative estimates in their reporting. Liu, Yang, Liu, and Liu (2019) and Hu, Xue, and Liu (2022) find that firms' internal control quality and financial reporting quality are significantly and negatively associated with the severity of air pollution in their home cities. Another strand of literature focuses on the impacts of air pollution on corporate capital structure and corporate financing. Liu, Wu, and Chan (2021) show that firms respond to increased air pollution by using more capital and less labour to remain competitive. Tan, Tan, and Chan (2021) establish that air pollution in the firms' operating environment increases the cost of debt financing. Hu and Chang (2022) find that firms in cities with poor air quality pay lower amounts of cash dividends than those in cities with better air quality because those firms increase environment expenditures on anti-pollution measurements, such as purchasing and installing environmentally friendly and efficient equipment, keeping more cash holdings, but these firms face more uncertainty about future earnings. Gan, Li, and Jiang (2022) find that start-up firms suffering severe air pollution receive less investment from venture capital and experience a lower probability of being financed by venture capitalists. Furthermore, Wang et al. (2021) highlight that air pollution is an important noneconomic factor driving firms' human capital and employee treatment strategy. They find that firms in air pollution areas enhance employee treatment through monetary compensation, safety security, and career training.

A body of literature details how air pollution affects firms' decisions and policies. Broadly, two theories regarding the impact of air pollution on firms' performance and their decisions have been forwarded. The environmental stress theory suggests that environmental stressors, such as radiation, physical structure, non-ergonomic furniture, natural disasters, pollution, illnesses, and climate change, significantly affect the health and sentiments of individuals and social groups (Lazarus & Cohen, 1977). This theory has been tied to the human capital effect to determine whether the environment stresses out people, impacting the decision-making process. Air pollution induces negative moods and risk-aversion behaviours among investors, leading to a negative relationship between air pollution and stock returns (Levy & Yagil, 2011). Dong et al. (2021) show that analysts experiencing severe air pollution within a firm's operating environment during visits to the firm produce lower subsequent earnings forecasts. Tan, Tan, et al. (2021) find that air pollution drives a pessimistic mood and/or weakens the cognitive ability of management, leading to poor operation and an increase in precautionary needs for more cash due to pollution abatement or decreased availability of bank loans. Tan and Yan (2021) and Wang et al. (2021) find that air pollution adversely affects the psychology of the executives, affecting decision-making poorly regarding innovation, which ultimately reduces corporate innovation and investment. He and Lin (2022) also find a similar adverse impact on managers' moods that reduces firms' investment efficiency.

The resource-based theory suggests that firms' resources are rare and challenging for other firms to duplicate. It is important for a firm to use its internal resources and capabilities to create sustainable competitive advantage (Peteraf, 1993; Wernerfelt, 1984). However, air pollution can degrade these resources, introducing financial and operational challenges. For example, Tan, Tan, et al. (2021) find that firms in high-air-pollution cities are subject to higher financial constraints and operating risks than those in low-air-pollution cities. Similarly, Zhang, Tan, and Chan (2021) report that initial public offerings (IPOs) for firms in high-pollution regions are underpriced, reflecting increased investor risk perception. In addition, air pollution can significantly hinder corporate innovation, as pollution-related costs and constrained financial resources limit firms' ability to invest in growth opportunities (Tan & Yan, 2021). Collectively, firms in severely polluted cities face higher crash risk, restricted financial conditions, and greater environmental expenditure burdens, further eroding resources needed for sustained competitiveness (Tan, Tan, & Chan, 2021).

2.2.3. Hypothesis development

While prior research has established that air pollution can influence firm performance and decision-making, no studies have yet examined the effects of air pollution on M&A decisions or market reactions to such transactions. Understanding why air pollution might impact M&A activities is essential. On the one hand, according to the resource-based theory, firms in areas with severe air pollution often encounter operating difficulties and financing challenges (Tan et al., 2022; Tan et al., 2021), which can lead to shifts in corporate policies and more conservative decision-making (Liu et al., 2021; Tan et al., 2021; Tan & Yan, 2021). Air pollution also brings reactions from external stakeholders that ultimately impact firm operations. Governments frequently implement environmental regulations to manage air pollution, with local authorities sometimes employing administrative measures to restrict firm operations under political pressure (Tan et al., 2021; Tan & Yan, 2021). While these restrictions improved air quality (He et al., 2016; Ma & Takeuchi, 2020), they also disrupted business operations. Similarly, banks and supply chain partners respond to heightened air pollution levels. Wang et al. (2021) find that banks impose stricter credit terms on firms located in highly polluted cities due to the increased credit risk, thereby creating additional external financing challenges. Liu et al. (2020) find that when consumers prefer low-carbon products, competition among manufacturers incentivizes firms to invest in environmentally friendly technologies. Tan et al. (2021) further document that firms in severely polluted cities have reduced trade credit access.

As a result, firms located in cities with severe air pollution face tighter financial conditions, strict environmental regulations, and higher environmental investments due to external stakeholders' reactions to poor air quality. From a resource-based theory, firms in highly polluted areas may have resource constraints limiting their capacity to engage in mergers and acquisitions (M&As). For example, Tan et al. (2021) find that firms in high-air-pollution cities spend more money to comply with environmental regulations and invest in environmental investment. Additionally, Tan & Yan (2021) find that air pollution reduces corporate innovation investment because it drains financial resources, constraining firms even more and increasing environmental governance costs. Consequently, we expect that air pollution is negatively associated with corporate M&A activities, given the financial and operational challenges due to the external stakeholders reacting to poor air quality. Thus, we propose the following hypotheses:

Hypothesis 1a (*H1a*): Air pollution positively impacts corporate M&A activities.

Conversely, firms in areas with severe air pollution often encounter operating difficulties and financing challenges (Tan et al., 2022; Tan, Zhang, et al., 2021), which can lead to shifts in corporate policies and more conservative decision-making (Liu et al., 2021; Tan, Tan, et al., 2021; Tan & Yan, 2021). Air pollution brings reaction from external stakeholders of firms that ultimately impacts firm operations. To manage air pollution, governments frequently implement environmental regulations, with local authorities sometimes employing administrative measures to restrict firm operations under political pressure (Tan, Zhang, et al., 2021; Tan & Yan, 2021). A notable example is the 2008 Beijing Olympics, where, to significantly reduce air pollution, the Beijing municipal government removed 60,000 taxis and buses by the end of 2007 and relocated 200 factories. In July 2008, the central government further suspended production in Beijing and surrounding areas, temporarily halting thermal power plants. While these measures improved air quality (He, Fan, & Zhou, 2016; Ma & Takeuchi, 2020), they also disrupted business operations.

Similarly, heightened air pollution levels might elicit negative responses from banks and supply chain partners, reflecting the growing environmental awareness and concern among external stakeholders. For instance, Wang, Xiong, Mirza, Shao, and Yue (2021) find that banks impose stricter credit terms on firms located in highly polluted cities, due to the increased credit risk, thereby creating additional external financing challenges. Tan, Zhang, et al. (2021) find that suppliers change their trade credit strategy to grant less trade credit to their customers located in cities with severe air pollution. Liu, Ke, and Tian (2020) further find that when consumers demonstrate a preference for low-carbon products, competition among manufacturers incentivizes firms to invest in environmentally friendly technologies.

As a result, firms located in cities with severe air pollution face tighter financial conditions, strict environmental regulations, and higher environmental investments due to external stakeholders react to poor air quality (Tan et al., 2022; Tan, Zhang, et al., 2021). Under a resource-based perspective, firms located in highly polluted areas may have resource constraints that limit their capacity to engage in activities such as mergers and acquisitions (M&As). For example, Tan, Tan, et al. (2021) find that firms in high-air-pollution cities spend more money to comply with environmental regulations and invest in environmental investment. Additionally, Tan and Yan (2021) find that air pollution reduces corporate innovation investment because it drains financial resources, constraining firms even more and increasing environmental governance costs. Consequently, we expect that air pollution is negatively associated with corporate M&A activities, given the financial and operational challenges due to the external stakeholders reacting to poor air quality. Thus, we propose the following hypotheses:

Hypothesis 1b (*H1b*): Air pollution negatively impacts corporate M&A activities.

2.3. Data and methodology

2.3.1. Sample selection and data sources

The initial sample consists of all acquiring firms with all A-shares listed on China's two mainland stock exchanges, the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The data on M&A announcements data and transaction-related party details, stock returns, company locations, and the firm's financial information are obtained from the China Stock Market and Accounting Research (CSMAR) database. We hand collect some of the missing target firms' locations from Google Engine. Following Erel, Liao, and Weisbach (2012) and Nguyen, Phan, and Simpson (2020), we exclude Leveraged Buyouts (LBOs), spinoffs, recapitalizations, self-tender offers, exchange offers, repurchases, partial equity stake purchases, acquisitions of remaining interest, and privatizations, as well as deals disclosed with less than 1 million RMB. Moreover, we exclude firms from the financial industry. We require the firms to take over the control of the targets and exclude gradual acquisitions. Then, we merge the M&A and CSMAR data to retain firm-year observations and form the full sample. The matching process results in a final sample containing 22,327 firm-year observations and 3,564 listed acquiring firms located in 31 provincial-level regions in mainland China from 2010 to 2020[9].

[9] In our sample, all target firms are non-listed firms in China.

The provincial distribution of M&As by acquirers from 2010 to 2020 is shown in *Fig. 2.1*. The majority of mergers and acquisitions take place in the southern provinces, particularly in these developed and coastal regions. We provide the number of M&A deals over the sample period, distributed by year and by industry using the industry classification of listed companies issued by China Securities Regulatory Commission (CSRC) in 2012 in Appendix A.2. In panel A, we find that the annual number of M&A deals increased over the period 2010–2016. We notice a sharp increase in acquisitions in 2015 and 2016, with 18.44% and 15.62% of the acquisitions in our sample. In Panel B, we find that industries that experience a high frequency of M&As include computer equipment, information technology service, chemicals and allied products, electronic and other electrical equipment, and medicine manufacturing.

[Insert Figure 2.1. here]

2.3.2. Air pollution variables

We utilize the annual city-level air quality index (AQI) as a proxy for air pollution (Dong et al., 2021; Wang et al., 2021). For each city in China, we first obtain the monthly air quality index (AQI) between 2013 and 2020 from the CSMAR database. We then calculate the annual average AQI of each acquirer's city (AAQI) and target firms' city (TAQI). The AQI is constructed based on the levels of six atmospheric pollutants: sulfur dioxide ($\mathrm{SO_2}$), nitrogen dioxide ($\mathrm{NO_2}$), suspended particulates smaller than 10 μm in aero- dynamic diameter ($\mathrm{PM_{10}}$), suspended particulates smaller than 2.5 μm in aerodynamic diameter ($\mathrm{PM_{2.5}}$), carbon monoxide (CO), and ozone ($\mathrm{O_3}$). Before 2013, the Chinese government monitored only $\mathrm{SO_2}$, $\mathrm{NO_2}$, and $\mathrm{PM_{10}}$, which were used to construct the air pollution index (API) and served as a summary measure of air quality. While the API and AQI are not directly comparable, they are highly correlated (Zheng, Cao, & Singh, 2014). Similar to Dong et al. (2021), we use the API index before 2013 and the AQI index after 2013 in our sample. For notational simplicity, we refer to both as AQI in what follows[10]. For a small number of cities, the AQI index is not available from CSMAR. We fill in some of the missing data from the Qingyue Open Environment Data Center website, which collects pollution data from local governments[11]. We divide AQI by 1000 for the ease of interpretation of the regression coefficients following (Dong et al., 2021). We match the AQI data to both target and acquiring firms based on the location of their headquarters. This approach assumes that firms' headquarters typically represent the primary concentration of their operations and facilities (Bai et al., 2021), thereby providing a reasonable basis for associating air pollution level with firm-level activities.

The Ministry of Environmental Protection of China (MEPC) distinguishes among six categories of AQI: I-excellent (AQI ≤50), II-good (50 < AQI ≤100), III- lightly polluted (100 < AQI ≤150), IV-moderately polluted (150 < AQI ≤200), V-heavily polluted (200 < AQI ≤300) and VI-severely polluted (AQI > 300)[12]. A high AQI implies relatively worse air pollution. *Fig. 2.2.* presents the average air quality index for each province from 2010 to 2020. It is evident that the northern provinces experience higher levels of air pollution than the southern provinces. Appendix A.3. presents summary data on air pollution for each city. The five regions with the highest levels of pollution are Hebei, Henan, Xinjiang, Tianjin, and Shanxi, all located in the north of China. The five regions with the lowest levels of pollution are Hainan, Tibet, Fujian, Yunnan, and Guangdong, all located in the country's south.

[Insert Figure 2.2. here]

2.3.3. Baseline model

We examine the effect of air pollution on firm acquisitions using the following logit model:

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[10] We do a robustness check using pure AQI from 2013 to 2020. Our baseline results still hold.
[11] The Qingyue Open Environment Data Center (https://data.epmap.org) is an organization which compiles environmental data from government sources and provides them freely to the public in standard data formats.
[12] The same six classifications were used both pre- and post-2014, though based on only three pollutants in the earlier period (Dong et al., 2021).

$$M\&A\ dummy_{i,t} = \alpha_0 + \beta_1 \times AQI/1000_{i,t} + \gamma \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \qquad (2.1)$$

where the M&A dummy is an indicator variable that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t*, and 0 otherwise. Air pollution is measured by the level of air quality index (*AQI*) of the city in which firm *i*'s headquarter is located. Following some M&A literature reviews, we control for several firm characteristics related to firm acquisitiveness, including firm size (*Size*), firm age (*Age*), leverage ratio (*Leverage*), return on assets (*ROA*), growth rate of sales (*Growth*), the ratio of the book value to the market value of assets (*BM*), cash holding (*CH/at*), capital expenditure ratio (*Capex/at*), the top five major shareholding (*Top5*), independent directors' ratio (*IndepR*), number of board members (*BoardSize*), *Dual*, *INST*, state-owned enterprise (*SOE*) and polluting industries (*Polluter*) (Dong, Hirshleifer, Richardson, & Teoh, 2006; Faccio & Masulis, 2005; Phan, 2014; Erel et al., 2012; Nguyen et al., 2020). The definitions of the variables are provided in Appendix A.1. All continuous variables are winsorized at the top and bottom 1% to mitigate the concern of outliers. Following Yang et al. (2022), we further control for the natural logarithm of the province GDP growth rate and province GDP per capita in our partial analysis since corporate M&As might be correlated with local economic conditions. We additionally control for industry and year fixed effects as well as cluster the standard errors at the firm level.

2.4. Empirical results

2.4.1. Descriptive statistics

We report the summary statistics of the full sample and the M&A subsample in Panels A and B, respectively, of Table 2.1. The full sample includes 22,327 firm-year observations of 3,564 firms, while the M&A subsample consists of 3,541 firm-year observations comprising 1,600 firms. The mean and median of *M&A* are 0.120 and 0.000, respectively, and the mean and median of the average air pollution (*AQI*) are 0.082 and 0.079, respectively. The mean and median of the acquirer's AQI, *AAQI* (target's AQI, *TAQI*) in the M&A subsample are 0.083 (0.085) and 0.081 (0.082), respectively. These align with previous studies, such as Li, Massa, Zhang, and Zhang (2021). In terms of the control variables, the average firm size is 22.14, the average return on assets is 3.80%, and the average leverage ratio is 42%. Approximately 28% of the CEOs in our sample are also chairmen, and the top five major shareholders on average hold 55% of firm stocks. The average board size consists of approximately 8 (log=2.10) members, 38% of whom are independent directors, which is consistent with China Securities Regulatory Commission (CSRC) requirements on board independence. The mean of the State-owned enterprises (*SOEs*) is 0.353, indicating that 35.3% of the observations in our sample are SOEs. The descriptive statistics of other variables also align with prior studies (Bonaime et al., 2018; Yang et al., 2022). We report the correlation coefficients among variables in Appendix A.4. The correlation coefficients among variables are smaller than 0.6, indicating that the multi-collinearity issue is not a severe concern.

[Insert Table 2.1. here]

Following Nguyen et al. (2020), we divide the cities in two ways (quartile and bisection) based on the median level of AQI in each year. The univariate results presented in Table 2.2. provide preliminary evidence that firms headquartered in areas with higher levels of air pollution conduct fewer M&A activities. For instance, when our sample is divided into high and low-quartile subsamples based on the quartile level of air quality index, we find that the mean acquisitiveness for firms located in cities with high air quality index is 3.78% lower than their firms located in cities with low air quality index. And when our sample is divided into high and low two subsamples based on the median level of air quality index, we find that the mean acquisitiveness for firms located in cities with high air quality index is 1.38%, which is lower than their counterparts (Panels A and B in Table 2.2.).

[Insert Table 2.2. here]

2.4.2. Baseline results

We conduct logit model regression, controlling for industry and year fixed effects as well as cluster the standard errors at the firm level, to examine the impact of air pollution on M&A activities. Columns 1-2 of Table 2.3. report the M&A logit model results. The coefficients of air pollution are negative (-6.009 and -4.323) and highly significant at 1% level. These results indicate that firms headquartered in more air pollution areas are less likely to pursue M&As. We further control for the natural logarithm of the province GDP per capita and province GDP growth rate in the model and report the results in Column 3 of Table 2.3. We find that the coefficient of air pollution remains negative (-4.249) and statistically significant at the 1% level. Using the coefficient estimates of air pollution in Column 3, we illustrate the economic significance of the effect of air pollution, holding other variables constant at their sample means: a 1-standard-deviation increase in air pollution above its sample mean is associated with 11.47% ($0.027 \times -4.249 = -0.1147$) decrease in acquisition probability[13]. These estimates indicate a statistically and economically significant impact of air pollution on M&A activities.

The coefficients on the control variables are generally consistent with those reported in relevant studies (Li, Lu, & Lo, 2019; Nguyen et al., 2020; Renneboog & Vansteenkiste, 2019). For example, the coefficient on *BM* is negative and significant at the 1% level, suggesting that firms with lower market value are less likely to invest in M&A activities; the coefficient on *Growth* is positive and significant at the 1% level, suggesting that firms with higher growth and profitability prefer to invest in M&A activities. In addition, the coefficients on *CapEx/at* is significantly negative, indicating that investment in fixed assets reduces M&A activities. Overall, the results in Table 2.3. support our *H1b* that air pollution has a negative impact on

[13] Here, the number of 0.027 can be found in Table 2.1, which is the standard deviation of the air pollution variable.

M&A activities.

[Insert Table 2.3. here]

2.4.3. Endogeneity tests

Our baseline regression results may suffer from potential endogeneity issues, such as omitted variables and sample selection bias. In this context, several plausible omitted variables could jointly influence both local air quality and firms' M&A activity—for example, unobserved managerial ability, corporate governance quality, or firm-specific strategic orientations. We also consider possible forms of sample selection bias, such as the exclusion of firms with incomplete pollution data and the restriction to firms that engage in M&A. These factors may cause our estimation sample to deviate from the broader firm population and potentially bias the results. To mitigate these issues, we employ two strategies: (1) an instrumental variable (IV) approach and (2) a quasi-experimental design based on propensity score matching.

2.4.3.1. Instrumental variable (IV) approach

We first explore exogenous variations of air pollution, building on knowledge obtained from the atmospheric environment literature. Following existing studies (Arceo, Hanna, & Oliva, 2016; Chen, Oliva, & Zhang, 2022), we introduce thermal inversions as the exogenous instrument variable (IV) for air pollution. A valid instrument should satisfy two conditions. First, the instrument should be strongly correlated with air pollution. Second, the instrument should not directly affect firms' M&A activities. Thermal inversions are a common exogenous meteorological phenomenon that leads to high concentrations of air pollutants near the ground level, thereby inducing severe air pollution[14]. Therefore, thermal inversions should be

[14] The underlying mechanism behind thermal inversions is as follows. Under normal conditions, temperature decreases as altitude increases. Given that air moves from hot to cool regions, air pollutants can circulate vertically, thereby decreasing air pollution concentrations near the ground. However, under certain meteorological circumstances (Arceo et al., 2016), the temperature of a layer of air above the ground can be higher than that at low altitudes, which leads to an inversion in the temperature/height gradient of thermal inversion. When this

positively correlated with local air pollution and satisfy the relevant condition. Moreover, no existing theories or empirical evidence suggest that thermal inversions drive firms' M&A activities. Thus, thermal inversions should also satisfy the exclusion condition and serve as an appropriate instrument for local air pollution measures.

The city-annual level inversion intensity is constructed with the following steps: (1) Inversion data from the National Aeronautics and Space Administration (NASA) [15] includes air temperatures in 42 vertical layers from 110 meters to 36,000 meters every six hours. If the temperature of the second layer above the ground is higher than that of the first layer, there is a thermal inversion, otherwise there is no thermal inversion; (2) Obtain the temperature of the first layer (110m) and the second layer (320m) above the ground at 4-time points of each grid in a day, and calculate their daily average; (3) Calculate the annual thermal inversion of each city, using the temperature in the second layer (320 m) minus the temperature in the first layer (110 m). If the difference is positive, then thermal inversions exist, and the dummy variable Thermal_Inversion_Dummy equals one. However, if the difference is negative, then such a condition is normal, and Thermal_Inversion_Dummy equals zero.

We use the two-stage least square (2SLS) panel regression. In the first stage, we regress air pollution on the instrumental variable, along with the set of control variables. In the second stage, we re-run the regression of *Eq. (2.1)* but use the fitted value of air pollution as the explanatory variable. Relevant results are reported in Table 2.4. Column (1) reports the results of the first-stage regression. The coefficient on *Thermal_Inversion_Dummy* is positive and significant at the 1% level, indicating that the chosen instrumental variable is valid. Moreover, the first-stage F-statistic is high (*F-statistic* = 32.02), and LM-statistic is statistically significant,

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condition occurs, air pollutants are trapped near the ground level, thereby leading to high air pollution concentrations (Chen et al., 2022).

[15] Specially at: https://disc.gsfc.nasa.gov/datasets/M2I6NPANA_5.12.4/summary.

showing that the instrumental variable is not weak. The Sargan-Hansen statistic is insignificant, indicating that the IV model is not overidentified. Column (2) reports the results of the second-stage regression. The explanatory variable is the fitted value of air pollution (*Air pollution_Fitted*). The coefficient of *Air pollution_Fitted* is negatively and significantly related to *M&A* at the 1% level, suggesting that our main results are not influenced by potential endogeneity concerns such as omitted variables and reverse causality.

$$AQI\ pollution_{i,t} = \alpha_0 + \alpha_1 \times Thermal\_Inversion\_Dummy_{i,t} + \alpha_2 \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (2.2)$$

$$M\&A\ dummy_{i,t} = \beta_0 + \beta_1 \times AQI\ \widehat{pollution}_{i,t} + \beta_2 \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (2.3)$$

[Insert Table 2.4. here]

2.4.3.2. Quasi-experiment with propensity score matching

To substantiate the observed effects of air pollution on M&A activities, we introduce the quasi-experiment of the "Qinling-Huai River policy". As Chen et al. (2013) and Li et al. (2019) noted, the Huai River splits China into northern and southern parts, and China's central government provides free winter heating only in cities north of the Huai River. Because the centralized winter heating system rests on inefficient coal-based hot water boilers, it leads to substantial energy loss and releases significant air pollutants. Such policy has unintended consequences worsening air quality in northern regions and creating a discontinuity in AQI for cities across the two sides of the Huai River (Lepori, 2016). Thus, there may be observable differences between cities where firms are headquartered with and without central free heating. We use the propensity score matching approach to resolve this issue.

The results from the pre-matched logistic model are presented in column (1), Panel A of Table 2.5. Then, by applying the one-to-one nearest-neighbour propensity score approach, each headquarter city with free heating is matched with the most similar firm that headquarter city without free heating. To improve the matching accuracy, we exclude the pairs with a propensity score difference larger than 1%. We conduct two diagnostic tests to ensure matching accuracy. First, we re-conduct the logistic analysis using the propensity score-matched sample. The results are reported in column (2), Panel A of Table 2.5. All the coefficients on independent variables in the post-matched logistic model become much smaller and insignificant, suggesting no observable difference between treatment and control after matching. Second, we compare each of the characteristics of firms with and without free heating using *t*-tests. The pre-matched *t*-test results are reported in Panel B of Table 2.5., which reveals that firms are significantly different in their characteristics depending on whether they have free heating. The post-matched *t*-test results are reported in Panel C of Table 2.5., which show no significant difference between firms with and without free heating in the propensity score-matched sample.

Using the propensity score-matched sample, we re-estimate the baseline regression controlling for industry and year-fixed effects. The results reported in Panel D of Table 2.5. show that the coefficients on air pollution remain negative and statistically significant at 1% level. In general, the propensity score matching results confirm that the results of Table 2.3. are robust.

In addition, because industry characteristics play a critical role in shaping both M&A activity and pollution exposure, we further refine our PSM design by adopting a within-industry matching strategy. Specifically, we restrict treated firms to be matched only with control firms from the same industry, thereby enhancing comparability. As a robustness check, we also implement an industry-stratified PSM approach, in which propensity scores are estimated separately within each industry stratum. These refinements reduce concerns about cross-industry mismatches and strengthen the credibility of our identification strategy. The results, reported in Appendix A.6, indicate that the coefficients on air pollution remain negative and statistically significant at the 1% level.

[Insert Table 2.5. here]

2.4.4. Channel tests of operational conditions

As detailed in the hypothesis section, air pollution brings responses from external stakeholders, which can lead to tighter financial conditions and operational challenges for firms. Consequently, we anticipate that firms located in areas with severe air pollution will have fewer resources available to support M&A activities. To assess this, we utilize net operating cash flow (*CF*) and the firm's environmental investment (*En-Investment*) as indicators of operational conditions. We employ a two-stage least squares (2SLS) approach to examine the proposed relationships.

In the first stage, we examine whether severe air pollution is associated with lower net operating cash flow and higher environmental investment. The predicted values from the first-stage regressions are then used as the independent variable in the second-stage analysis. Results of the 2SLS channel regressions are shown in Table 2.6. From column (1), we observe a negative and significant (at the 5% significance level) relationship between air pollution and *CF*, indicating that severe air pollution is related to lower net operating cash flow. From column (3), we observe air pollution is positively associated with *En-Investment* with statistical significance at the 5% level, indicating that air pollution is associated with higher environmental investment. As expected, the coefficients of both fitted values predicted in the first-stage are negative and significant with M&A at the 10% and 1% levels across columns (2) and (4). Therefore, the results support our assumption that air pollution decreases a firm's M&A activities by negatively impacting operating conditions and reducing available resources. This indicates that poor operating conditions and resource constraints serve as significant channels through which air pollution influences M&A activities.

$$CF_{i,t} = \alpha_0 + \alpha_1 \times AQI\ pollution_{i,t} + \alpha_2 \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \tag{2.4}$$

$$M\&A\ dummy_{i,t} = \beta_0 + \beta_1 \times \widehat{CF_{i,t}} + \beta_2 \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (2.5)$$

$$En\_Investment_{i,t} = \alpha_0 + \alpha_1 \times AQI\ pollution_{i,t} + \alpha_2 \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t}$$

(2.6)

$$M\&A\ dummy_{i,t} = \beta_0 + \beta_1 \times \widehat{En\_Investment_{i,t}} + \beta_2 \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t}$$

(2.7)

[Insert Table 2.6. here]

2.4.5. Cross-sectional tests

The baseline results indicate a negative relationship between air pollution and M&A activities. Furthermore, we find that air pollution increases a firm's exposure to operational risks, as well as environmental expenditures. To further investigate this effect, we conduct a cross-sectional analysis based on our hypothesis regarding the influence of air pollution on external stakeholders, exploring how the impact of air pollution on M&A activity differs between firms with high versus low access to external financial resources or between firms operating in regions with differing levels of environmental awareness.

2.4.5.1. External resource accessibility

To examine the effect of air pollution on corporate M&As according to external resources accessibility, we divide the sample based on two critical external sources: bank loans (from a bank perspective) and trade credit (from a supplier perspective). The sample is divided into two groups—low and high—based on the median values of these two variables. Firms can use bank loans and trade credit to meet their financing needs. Bank loans are the major and important source of external financing for firms. However, in emerging markets, formal financing, such as bank loans, is often limited due to capital market constraints. As a result, trade credit—funds owed to suppliers—serves as an informal form of financing within the supply chain (Jiang & Zeng, 2014; Tan, Zhang, et al., 2021). These two channels are critical external financing sources for firms. However, prior research has shown that air pollution is negatively related to these funding sources (Li, Zhang, & Zeng, 2019; Tan, Tan, et al., 2021; Tan, Zhang, et al., 2021). Thus, we hypothesize that the negative relationship between air pollution and M&As is pronounced in these firms that have fewer bank loans and lower trade credit.

We present the findings in Table 2.7. Across the columns (1) and (3), the coefficients for air pollution remain consistently negative and significant at the 1% levels within the low-bank-loan and low-trade-credit subsamples. *Chow*-tests confirm that the coefficients differ significantly among these two subsamples. These findings suggest that when firms have limited access to external funding—whether in the form of bank loans or trade credit—the negative effect of air pollution on their M&A activity becomes more pronounced.

[Insert Table 2.7. here]

2.4.5.2. Environmental awareness

To analyze the impact of air pollution on corporate M&As in relation to environmental awareness levels, we categorize the sample based on the economic development and the pollution levels of the provinces where the firms are headquartered. The province economic development is measured by the Fan-Gang index[16], which classifies provinces as either well-developed or less-developed, depending on whether the Fan-Gang index for the acquirer's headquarters province is above the sample median. Additionally, we consider the air pollution levels in the acquirer's province, distinguishing between more-polluted and less-polluted regions based on whether the acquirer's Air Quality Index (AQI) exceeds the sample median.

Bao and Liu (2022) find that environmental awareness is higher in developed provinces,

[16] Fan-Gang index, also known as the marketization index, is an index system that measures the relative progress of marketization in provinces, autonomous regions, and municipalities across the country in the form of indexes. The larger the index, the higher the degree of marketization. The data is from the China Market Index Database.

particularly in southern regions, where governments are more proactive in addressing air pollution. According to Huang, Ding, and Failler (2022), increased governmental focus on environmental issues supports pollution reduction through green development and industrial upgrading, although this trend is generally more evident in developed regions. White and Hunter (2009) find that that balancing environmental quality with economic growth remains a significant challenge in less developed areas. Additionally, due to the Qinling-Huai River policy[17], air quality in southern provinces is generally better than in northern ones. Consequently, we expect firms in well-developed, less polluted provinces to exhibit greater environmental awareness. This suggests that the impact of air pollution on M&A activities may be more pronounced for firms located in these more developed and cleaner regions.

The regression results are reported in Table 2.8. Across the columns (1) and (3), the coefficients for air pollution remain consistently negative and significant at the 1% levels within the well-developed provinces and less-polluted provinces. The findings are consistent with our conjectures.

[Insert Table 2.8. here]

2.4.6. Moderating effects

Our findings thus far support the hypothesis that air pollution is negatively associated with corporate M&As. The results further indicate that this negative effect is more pronounced among firms with limited access to bank loans and lower trade credit, as well as those located in more developed, less polluted regions. To investigate factors that may help mitigate this negative effect, we introduce additional variables relevant to M&A activity, including

[17] The Huai River splits China into northern and southern parts, and China's central government provides free winter heating only in cities north of the Huai River. Because the centralized winter heating system rests on the use of inefficiently coal-based hot water boilers, which leads to substantial energy loss and releases a significant amount of air pollutants. This policy has unintentionally worsened air quality in northern regions, creating a discontinuity in terms of AQI for cities across the two sides of the Huai River (Lepori, 2016; Li et al., 2021).

government support and indicators of firm's own financial health. These factors include government subsidies (*Subsidy*), firm's default risk (*DD_KMV*)[18], and indicators of potential profitability and future growth (*Tobin's Q*).

Government subsidies play a critical role not only in corporate financing but also in shaping firms' investment decisions (Li, Zhang, Lee, & Li, 2021). Government support through subsidies has provided firms with sufficient funds, reduced the financing pressure faced by firms, and thus enhanced the enthusiasm of companies to carry out long-term activities (Dewenter & Malatesta, 2001). Beyond external financial support like government subsidies, a firm's own financial health also serves as a key factor in mitigating the adverse effects of air pollution on M&A activities. Firms with low default risk are generally better positioned to engage in acquisitions, as their strong financial standing can enhance their credibility and provide greater access to favourable financing options (Harford, 1999; Renneboog & Vansteenkiste, 2019). Moreover, Tobin's Q is a widely used indicator in M&A strategies, influencing both acquirers' and targets' decisions. Firms with high Tobin's Q, often reflecting robust growth potential, may pursue M&As as a strategic approach to maximize or leverage expected market growth (Chen, Sun, Tang, & Wu, 2011; Renneboog & Vansteenkiste, 2019).

This section discusses how government subsidies (*Subsidy*), firm's default risk (*DD_KMV*), and Tobin's Q act as moderating variables in the relationship between air pollution and corporate M&A activities. The regression results are reported in Table 2.9. We find that the regression coefficient of the interaction term (*AQI×Subsidy*) is significantly positive at the 5% level, suggesting that government subsidies help firms offset the negative effects of air pollution on M&A activity. Additionally, the interaction terms (*AQI×DD_KMV*) and

[18] The Distance-to-Default (DD) KMV model, is a credit risk assessment framework developed by KMV Corporation (now part of Moody's Analytics). The model is based on Merton's structural model of credit risk Merton model (1974) and assesses a firm's probability of default by analysing its equity value, volatility, and liabilities. Higher DD means a larger Distance to Default indicates a lower probability of default.

(*AQI×Tobin's Q*) show significantly positive coefficients at the 5% and 1% levels, respectively. This indicates that firms with robust financial health and growth opportunities, as indicated by low default risk and high Tobin's Q, are more capable of alleviating the negative impact of air pollution on corporate M&A activities.

[Insert Table 2.9. here]

2.4.7. Robustness checks

We conduct a series of robustness checks to validate our findings. First, we introduce additional fixed effects, alternative model with high-frequency fixed effects, and seasonal effects to verify our results. In Panel A of Table 2.10., we add the province-level fixed effect into our baseline model in *Eq. (2.1)*. The coefficient estimates in Panel A are negative and significant at the 10% levels across all columns. In Panel B, we run the relationship between air pollution and M&As using the lead-lag model, where the *t+1* year M&A dummy variable is regressed on *t*-year AQI with all controls along with the firm, industry, province, and year fixed effects. The coefficients in panel B are still negative and significant at the 5% and 10% levels across all columns. The findings support our baseline results.

Moreover, according to the Qinling-Huai River policy, China's central government provides free winter heating from November through the following March. As the centralized winter heating system rests on inefficiently coal-based hot water boilers, free winter heating would cause air pollution in winter worse than in other seasons. To check whether there are differential effects in winter and non-winter seasons, we calculate the monthly average AQI during the free winter heating periods (November to March) and other periods (April to October) for the city where the firm headquarter is located. The coefficient estimates reported in Panel C vary from -2.955 to -4.601 for the variable $Air\ pollution_{Nov\text{-}Mar}$, and from -3.692 to -6.367 for $Air\ pollution_{Apr\text{-}Oct}$, depending on the model, and they are still significant at least at 5% level. This implied that our baseline results are robust and not driven by the winter season.

[Insert Table 2.10. here]

We further assess the robustness of our baseline results by employing alternative measurements for both dependent and independent variables and adjusting the sample period. In Panel A of Table 2.11., we replace the M&A dummy variable in *Eq. (2.1)* with the actual expense value paid by acquirers, yielding a statistically significant negative coefficient for AQI, even after incorporating all control variables and fixed effects. Panels B and C examine alternative proxies for air pollution: in Panel B, we use the natural logarithm of the annual average level of $PM_{2.5}$ and AQI change in each acquiring firm's city, as reported by CSMAR; in Panel C, we employ the natural logarithm of the annual average AQI. Findings from both panels indicate that the coefficient estimates for $PM_{2.5}$ and Log AQI remain negative and statistically significant at the 1% level with all controls and fixed effects in place, further substantiating our baseline results.

Finally, since AQI data is available from 2013, and our sample starts from 2010, we have included the API index before 2013 and the AQI index after 2013 to construct our measure of air quality following Dong et al. (2021) in our baseline regression. To ensure that the API index does not drive our results, we run the baseline regression using only AQI for the sample period from 2013 to 2020. The coefficient estimates in Panel D are all significantly negative at the 1% level. After using all controls and fixed effect, the coefficient of AQI is -4.057, which is closer to our baseline estimate.

[Insert Table 2.11. here]

2.4.8. Further analysis

Until now, the results have presented whether and how air pollution affects M&A decisions. In this section, we further investigate the implications of air pollution on various aspects of

M&A activities, including the choice of payment methods, the duration of deal completion, the creation of shareholder wealth and market reaction, and the long-term performance of firms following the completion of these mergers and acquisitions. This comprehensive analysis aims to interpret the broader impact of environmental factors on corporate strategies and outcomes in the context of M&A activities.

2.4.8.1. Air pollution and M&A payments

The selection of the payment method in mergers and acquisitions (M&A) is a critical component of the deal structure, influencing both the financial outcomes for the parties involved and the risk management strategies of the firms (Faccio & Masulis, 2005; Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003). Ray (2022) and DePamphilis (2019) outline two primary payment methods in M&A transactions: cash-based and stock-based. The cash payment approach is simple and straightforward, involving either acquirer's internal cash reserves or funds raised through debt. However, Tan, Tan, et al. (2021) and Tan, Zhang, et al. (2021) further suggest that firms in higher air pollution areas are hard to access to the bank loans and trade credit. The stock payment method involves the acquirer issuing equity shares to the target, allowing both firms to share risks and outcomes of the M&A (Alshwer, Sibilkov, & Zaiats, 2011; Faccio & Masulis, 2005). According to the financial constraints hypothesis (Alshwer et al., 2011; Faccio & Masulis, 2005), firms with financially constrained are more likely to use the stock payment method in an M&A deal.

These findings lead us to anticipate that acquirers located in areas with high air pollution may be more likely to choose stock over cash as a means of payment in acquisition deals. We use the following logit model to examine the relationship between air pollution and payment method:

$Cash\ dummy_{i,j} = \alpha + \beta \times AAQI/1000_{i,t} + \gamma \times TAQI/1000_{i,t} + \lambda \times Controls_{i,t} + Year +$

$$Industry + \varepsilon_{i,j,t} \quad (2.8)$$

$$Stock\ dummy_{i,j} = \alpha + \beta \times AAQI/1000_{i,t} + \gamma \times TAQI/1000_{i,t} + \lambda \times Controls_{i,t} + Year + Industry + \varepsilon_{i,j,t} \quad (2.9)$$

where the cash (stock) dummy is an indicator variable that takes a value of 1 if the payment for M&A deal *j* of firm *i* is entirely in cash (stock) and 0 otherwise. AAQI (TAQI) is the level of air pollution in the acquirer (target) headquarter city. Following previous studies and baseline model (Dong et al., 2006; Faccio & Masulis, 2005; Phan, 2014), we further control for some important deal characteristics such as *Deal ratio*, *Diversifying dummy*, *Cross-city dummy, Intellectual property dummy*. The variables used are detailed in Appendix A.1.

Table 2.12. presents the results of the payment method regression. Our analysis shows that higher air pollution levels in an acquirer's area are significantly associated with a lower likelihood of cash payment and a higher likelihood of stock payment. These findings remain robust even after including four additional control variables: *Deal ratio, Diversifying dummy, Cross-city dummy*, and *Intellectual property dummy*. This supports our hypothesis that high air pollution imposes resource constraints on firms due to reduced operating cash flow and increased environmental investments, leading firms to favour stock over cash as a payment method in acquisitions.

[Insert Table 2.12. here]

2.4.8.2. Air pollution and completion days

In this section, we investigate the impact of air pollution on the duration of mergers and acquisitions (M&As). Previous research on M&As has predominantly concentrated on motivations for the transactions, realization of synergies, stock price implications, and post-merger integration. However, limited attention has been given to fundamental factors influencing the time interval between acquisition announcements and their eventual completion, such as deal duration and completion time (Luypaert & De Maeseneire, 2015; Thompson & Kim, 2020). Understanding how air pollution affects this timeline is crucial, as it may introduce operational uncertainties and financial constraints that prolong the M&A process.

Ekelund, Ford, and Thornton (2001) find that more complex deals result in longer completion times. For example, stock offers require much more administrative burden than cash transactions. Similar to tender offers, mergers frequently take longer to complete than tender offers since shareholders must approve the deal. Hostile bids take longer because target shareholders must be convinced of the deal's appeal, while potential acquirers may also need to fend off any takeover defense mechanisms. Likewise, acquisitions of large companies are likely to increase deal complexity, given that they consist of multiple business units and are better armed to resist a hostile bid. Luypaert and De Maeseneire (2015) find that deal complexity critically affects the time to completion. A lengthier acquisition duration characterizes stock offers, deal hostility, mergers, and larger deals. This demonstrates that the complexity of the deal itself causes longer completion durations. We explore whether air pollution, as an external factor, has any bearing on how quickly M&A agreements are reached. Given the established negative association between air pollution and both M&A announcements and cash payments, along with the resource constraints imposed on firms operating in polluted environments, we anticipate a significantly positive relationship between air pollution levels and the number of days required to complete M&A transactions. This hypothesis aligns with previous studies that suggest environmental factors can hinder operational efficiency and prolong negotiation processes (Luypaert & De Maeseneire, 2015; Thompson & Kim, 2020).

The results reported in Table 2.13. indicate that, on average, the level of air pollution in an acquirer area is positively related to the completion days of M&A deals, this means that M&A

deals take longer to complete in regions with higher levels of air pollution for acquirers. The results are also robust when we add four variables related to the M&A characteristics (*Deal ratio, Diversifying dummy, Intellectual property dummy, and Cross-city dummy*) as controls. Furthermore, the time required to complete an acquisition is influenced by the chosen payment method, whether cash or stock. We also incorporate payment methods (cash/stock) in our regression analysis of time-to-completion, and our findings remain consistent. Thus, confirm that firms take longer to complete acquisitions as a result of air pollution.

[Insert Table 2.13. here]

2.4.8.3. Air pollution and M&A performance

In this section, we examine, first, whether air pollution affects shareholder wealth of acquiring firms around the announcements of M&As, and second, the long-term firm performance after the M&A deals. To check the wealth effect, we calculate the acquiring firms' Cumulative Average abnormal returns (CAARs). CAARs around the merger announcement periods provide a clean estimation of the market's reception of the news announcement and the underlying wealth effects (Rahayu & Wardana, 2021). We expect the level of air pollution in an acquirer headquarter city to be negatively related to its shareholder wealth due to the resource constraints associated with air pollution.

Panels A and B of Table 2.14. report the Average Abnormal Return (AAR) and CAAR summary statistics for acquiring firms. Using the CSI300 index returns as the market returns, we estimate the market model to calculate the two-day CARs of the acquiring firms. The length of the estimation window covers 250 trading days before each M&A announcement event (Meyer, Gremler, & Hogreve, 2014). The event date refers to the announcement date of each M&A. We delete multiple M&As for each firm within 250 trading days and only keep the earliest one. The means of the average abnormal returns (AARs) up to five days before and after the announcement event reported in Panel A are significantly different from zero. Similarly, the means of CAARs reported in Panel B for different windows ranging from [-5, 0] to [-5, +5] are statistically significantly different from zero. Panel C reports the regression results of the cumulative average abnormal return (CAAR) in the [-1, 0] window on AAQI and TAQI. The CAAR [-1, 0] window reflects immediate market reactions, where day -1 captures investor anticipation prior to the announcement, while day 0 represents the official disclosure. The coefficient for the AAQI is negative and statistically significant ($p < 0.05$), aligning with our hypothesis that the market interprets the event negatively. Furthermore, the economic implications are notable: a one-standard deviation increase in the AAQI above its sample mean is associated with a decrease of 22 basis points (0.22%) in acquirer shareholder value, holding other variables constant at their sample means.

Since air pollution poses resource constraints for firms, potentially increasing their operational and financial risks. This, in turn, may adversely affect their long-term performance and necessitate adjustments in their policies and behaviours (Liu et al., 2021; Tan, Tan et al., 2021; Tan & Yan, 2021). To assess long-term performance, we conduct regressions of return on assets (*ROA*) and growth rates (*Growth*) of acquiring firms one-year post-M&A on the AAQI, TAQI, and various firm and deal characteristics. The findings, presented in Panels A and B of Table 2.15., indicate that the coefficient estimates for the AAQI are negative and statistically significant at the 5% level across all columns. These results suggest that air pollution has a detrimental effect on the long-term performance of acquiring firms.

$$ROA_{i,t+1} = \alpha_0 + \alpha_1 \times AAQI_{i,t} + \alpha_2 \times TAQI_{i,t} + \alpha_3 \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (2.10)$$

$$Growth_{i,t+1} = \beta_0 + \beta_1 \times AAQI_{i,t} + \beta_2 \times TAQI_{i,t} + \beta_3 \times Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (2.11)$$

[Insert Table 2.14. here]

[Insert Table 2.15. here]

2.5. Conclusion

This study investigates the impact of air pollution on corporate mergers and acquisitions (M&As) for acquiring firms based on their headquarters location. Using a comprehensive sample of Chinese listing firms, we find that air pollution negatively impacts the M&A activities of local firms. This finding remains robust after addressing endogeneity and conducting a series of robustness tests. The study suggests that air pollution primarily affects M&A activity through adverse operational impacts, including decreased net operating cash flow and increased environmental expenditures. Furthermore, the analysis reveals that the negative impact of air pollution is more pronounced for firms with limited access to external resources and higher levels of environmental awareness. Moreover, firms receiving substantial government subsidies and exhibiting strong financial health are better able to mitigate the adverse effects of air pollution on their M&A activities. Our results also reveal that acquirers in heavily polluted regions tend to favour stock-based payments, experience longer acquisition processes, generate less shareholder wealth and bring negative market reaction, and face declining long-term performance.

Overall, our findings suggest the importance of air pollution as a significant non-economic determinant of corporate M&A activity. This study not only contributes to the literature on the intersection of environmental factors and M&As but also highlights key policy implications for developing countries like China. Beyond safeguarding public health, effective air pollution management is essential to foster economic development and facilitate corporate M&As. Our study insights the importance for firms and local governments to increase their awareness of the economic impacts associated with air pollution and calls for more attention and action from regulators and firms to better protect the environment in our modern society.

2.6. Tables and figures

Figure 2.1. Provincial distribution of M&As by acquirers from 2010 to 2020

Figure 2.2. Average air quality index among provinces between 2010 and 2020

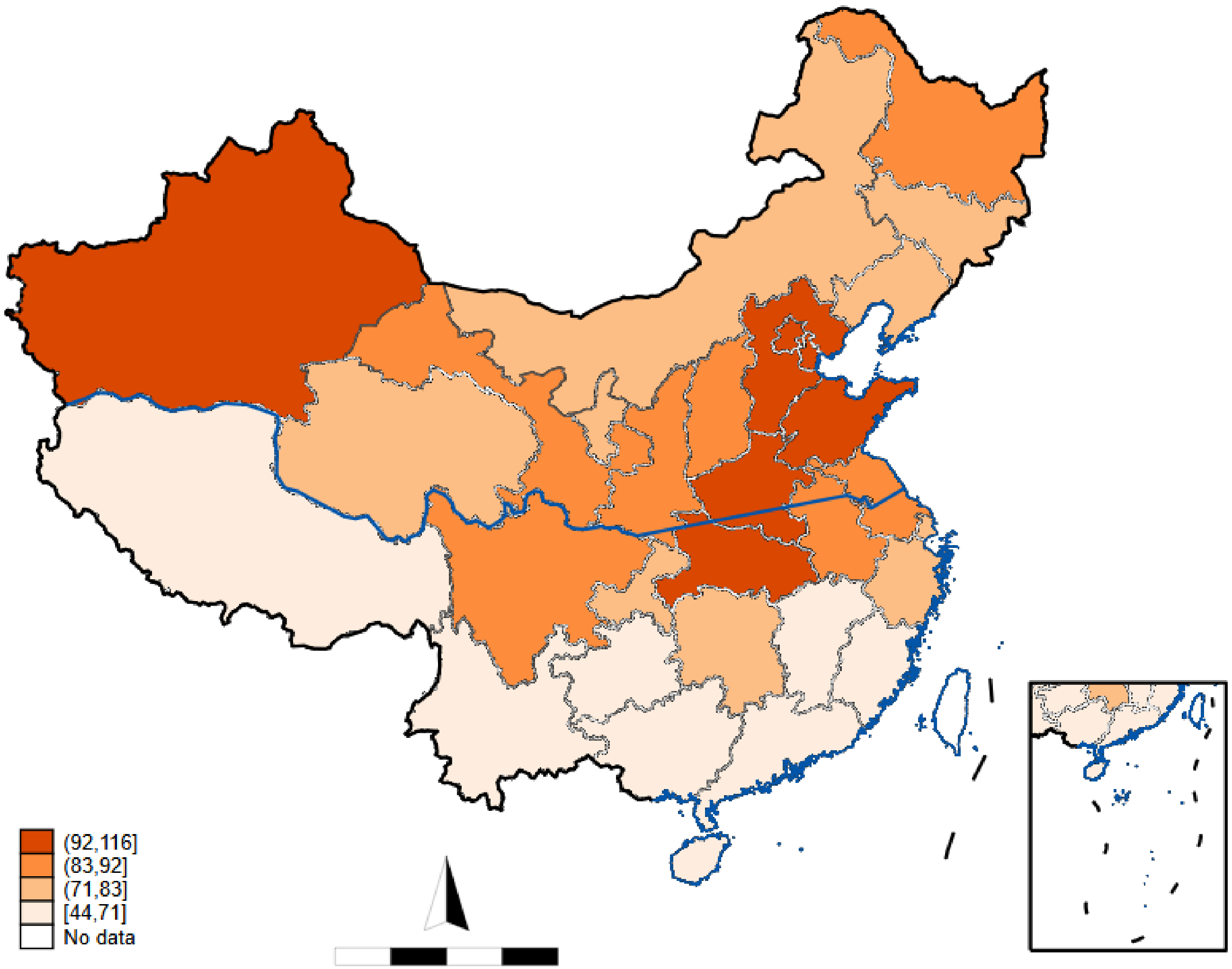

Table 2.1. Summary statistics

This table presents the summary statistics for the sample: mean, median, minimum, maximum, standard deviation, 25%,75%, and skewness of variables. In panel A, the M&A dummy is an indicator variable that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t* and 0 otherwise. Air pollution is the yearly average Air Quality Index (AQI) in which a firm is headquartered. AAQI is each acquiring firm city's annual average Air Quality Index (AQI). In Panel B, TAQI is the yearly average Air Quality Index (AQI) of each target. We divide AAQI (TAQI) by 1000 for the ease of interpretation of the regression coefficients. The definitions of the variables are provided in Appendix A.1. We winsorize the data at the 1% and 99% levels.

Panel A: Full Sample

Variable	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
M&A	22,327	0.120	0.000	0.000	1.000	0.325	0.000	0.000	2.338
Air pollution	22,327	0.082	0.079	1.25e-4	0.251	0.027	0.066	0.091	1.900
Size	22,327	22.142	21.947	19.673	26.161	1.323	21.187	22.889	0.754
Lev	22,327	0.423	0.414	0.053	0.922	0.211	0.252	0.580	0.241
ROA	22,327	0.038	0.039	-0.278	0.192	0.062	0.015	0.068	-1.793
Growth	22,327	0.177	0.096	-0.570	2.923	0.448	-0.013	0.262	3.422
BM	22,327	0.612	0.611	0.102	1.143	0.249	0.423	0.800	0.012
CH/at	22,327	0.017	0.004	-0.229	0.472	0.098	-0.022	0.039	1.784
List age	22,327	2.031	2.197	0.000	3.296	0.910	1.386	2.833	-0.629
Capex/at	22,327	0.048	0.034	2.1e-4	0.222	0.046	0.014	0.067	1.560
INST	22,327	0.063	0.064	3.2e-4	0.147	0.040	0.027	0.095	-0.105
Top 5	22,327	0.545	0.547	0.197	0.892	0.152	0.431	0.658	-0.056
BoardSize	22,327	2.128	2.197	1.609	2.708	0.200	1.946	2.197	-0.284
IndepR	22,327	0.376	0.364	0.125	0.571	0.053	0.333	0.429	1.306
Dual	22,327	0.281	0.000	0.000	1.000	0.449	0.000	1.000	0.974
SOE	22,327	0.353	0.000	0.000	1.000	0.478	0.000	1.000	0.616
Polluter	22,327	0.264	0.000	0.000	1.000	0.441	0.000	1.000	1.069

Panel B: M&A Subsample of acquisitions

Variable	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
AAQI	3,541	0.083	0.081	0.045	0.177	0.025	0.065	0.096	1.067
TAQI	3,541	0.085	0.082	0.045	0.179	0.025	0.069	0.098	1.070
Deal ratio	3,541	0.285	0.068	1e-4	5.767	0.764	0.016	0.219	5.415
Cash dummy	3,541	0.603	1.000	0.000	1.000	0.489	0.000	1.000	-0.420
Stock dummy	3,541	0.129	0.000	0.000	1.000	0.335	0.000	0.000	2.213
Size	3,541	21.985	21.881	19.658	23.309	1.086	21.250	22.667	0.529
Lev	3,541	0.412	0.400	0.057	0.884	0.192	0.261	0.552	0.279
ROA	3,541	0.035	0.037	-0.216	0.173	0.053	0.015	0.062	-1.509
Growth	3,541	0.317	0.192	-0.631	4.330	0.645	0.025	0.411	3.654
BM	3,541	0.521	0.517	0.000	1.060	0.254	0.339	0.712	0.020
CH/at	3,541	0.011	0.002	-0.243	0.414	0.094	-0.028	0.038	1.245
List age	3,541	2.038	1.946	0.693	3.296	0.737	1.386	2.708	0.049
Capex/at	3,541	0.043	0.030	2.4e-4	0.209	0.042	0.012	0.058	1.701

Continue

INST	3,541	0.060	0.059	8.2e-5	0.140	0.037	0.028	0.089	0.144
Top 5	3,541	0.525	0.529	0.200	0.832	0.141	0.423	0.628	-0.070
BoardSize	3,541	2.102	2.197	1.609	2.565	0.188	1.946	2.197	-0.529
IndepR	3,541	0.376	0.333	0.215	0.571	0.052	0.312	0.429	1.171
Dual	3,541	0.329	0.000	0.000	1.000	0.470	0.000	1.000	0.728
SOE	3,541	0.198	0.000	0.000	1.000	0.399	0.000	0.000	1.514
Polluter	3,541	0.246	0.000	0.000	1.000	0.431	0.000	0.000	1.176

Table 2.2. Univariate results

The table reports the results of univariate analysis on the quartile and bisection differences of M&A decisions between low and high air quality index regions. The value for differences is based on a *t*-test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Four quartiles						
	Bottom Quartile		Top Quartile		Diff	*t*-value
	N	Mean	N	Mean		
M&A decisions	5,689	14.80%	5,381	11.02%	3.78%**	5.92

Panel B: Median						
	Below Median		Above Median		Diff	*t*-value
	N	Mean	N	Mean		
M&A decisions	11,364	12.68%	10,963	11.30%	1.38%***	3.17

Table 2.3. Baseline regression

This table reports the results of baseline regressions. It shows the impact of air quality in the acquirers' city on the M&A deals' decisions. The dependent variable is the M&A dummy that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t* and 0 otherwise. The main independent variable is air pollution, measured by the air quality index level of the city where the firm *i*'s headquarter is located. Definitions of variables are presented in Appendix A.1. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	M&A	M&A	M&A
	(1)	(2)	(3)
Air pollution	-6.009***	-4.323***	-4.249***
	(-5.82)	(-4.00)	(-3.87)
Size		0.025	0.025
		(0.82)	(0.81)
Lev		0.285**	0.284**
		(2.07)	(2.06)
ROA		-0.939	-0.943
		(-1.27)	(-1.28)
Growth		0.387***	0.387***
		(9.15)	(9.16)
BM		-0.808***	-0.805***
		(-5.19)	(-5.15)
CH/at		0.166	0.171
		(0.69)	(0.71)
Capex/at		-1.900***	-1.904***
		(-3.49)	(-3.50)
INST		-0.123	-0.120
		(-0.16)	(-0.15)
Top 5		0.017	0.018
		(0.09)	(0.10)
ListAge		0.205***	0.207***
		(5.28)	(5.28)
BoardSize		-0.554***	-0.554***
		(-4.03)	(-4.03)
IndepR		-0.981**	-0.983*
		(-1.96)	(-1.96)
Dual		0.047	0.048
		(0.97)	(0.98)
SOE		-0.889***	-0.890***
		(-13.84)	(-13.86)
Polluter		-0.074	-0.075
		(-1.29)	(-1.30)
GDP growth			0.183

Continue

			(0.12)
GDP per capita			0.795
			(0.62)
Constant	-3.628***	-2.485***	-2.650***
	(-12.00)	(-3.47)	(-3.60)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	22,327	22,327	22,327
Pseudo/Adj R-squared	0.061	0.095	0.095

Table 2.4. Instrumental variable tests

Table 2.4. reports the results of 2SLS instrumental variable analysis, consisting of 22,327 firm-year observations. The dependent variable is the M&A dummy, which takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t*, and 0 otherwise. The main independent variable is air pollution, which is measured by the level of air quality index of the city where firm *i*'s headquarters located. The instrumental variable is thermal inversion in each city. Definitions of variables are presented in Appendix A.1. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	First Stage	Second Stage
Dependent Variable	Air pollution	M&A
	(1)	(3)
Thermal_Inversion_Dummy	0.004***	
	(13.57)	
Air pollution_Fitted		-4.495*
		(-1.74)
Size	0.003	0.003
	(0.12)	(1.22)
Lev	0.042***	0.019
	(3.27)	(1.35)
ROA	-0.001	-0.186
	(-0.31)	(-4.63)
Growth	0.004	0.057***
	(1.27)	(11.34)
BM	0.003***	-0.076***
	(4.11)	(-5.60)
CH/at	0.002	0.005
	(0.24)	(0.27)
Capex/at	-0.019***	-0.213***
	(-5.94)	(-4.04)
INST	0.015***	-0.039
	(3.24)	(-0.51)
Top 5	-0.004***	0.002
	(-3.87)	(0.12)
ListAge	-0.001***	0.020***
	(-4.55)	(5.38)
BoardSize	-0.003	-0.050***
	(-0.32)	(-3.52)
IndepR	-0.013***	-0.072*
	(-4.40)	(-1.45)
Dual	-0.002***	0.005
	(-5.08)	(0.93)
SOE	0.004***	-0.080***
	(10.98)	(-12.43)

Continue

Polluter	0.001***	-0.009
	(2.88)	(-1.55)
Industry	Yes	Yes
Year	Yes	Yes
S.E. Clustering	Firm	Firm
Adj R-squared		0.061
First Stage F statistic	32.02	
	(0.00)	
LM statistic	40.57	
	(0.00)	
Sargan-Hansen statistics	0.002	
	(0.96)	
Observations	21,603	21,603

Table 2.5. Propensity scores matching analysis

Table 2.5. presents the results of a propensity score matching analysis. We generate Free heating (FH) city as a dummy variable that equals 1 if the city is provided with free heating during the winter by the government under the Qinling-Huai River (QH) heating policy, and 0 otherwise. Panel A reports the parameter estimates from the logit model used to estimate propensity scores. Panels B and C present the differences in characteristics between with free heating cities and without free heating cities and the corresponding *t*-values in both pre- and post-match samples. Panel D reports the results of re-estimating the regression in Table 2.3. using the propensity score-matched sample. The dependent variable is the M&A dummy that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t*, and 0 otherwise. Definitions of variables are in Appendix A.1. *z*-statistics (*t*-statistics) are calculated based on robust standard errors and are reported in parentheses. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Pre-matched propensity score regression and post-matched regression		
	Dependent Variable: *Dummy variable (Free heating (FH) =1)*	
	Pre-match	Post-match
	(1)	(2)
Size	0.163^{***}	-0.022
	(9.34)	(-1.00)
Lev	-0.082^{***}	0.113
	(-0.92)	(1.01)
ROA	-1.318^{***}	0.318
	(-4.78)	(0.90)
Growth	0.084^{**}	-0.013
	(2.53)	(-0.31)
BM	-0.260^{***}	0.072
	(-3.33)	(0.73)
CH/at	0.117	0.053
	(1.25)	(0.18)
Capex/at	-1.937^{***}	0.149
	(-5.26)	(0.34)
INST	0.064	0.421
	(0.12)	(0.64)
Top 5	-0.569^{***}	0.053
	(-4.63)	(0.34)
ListAge	-0.120	-0.023
	(-0.497)	(-0.75)
BoardSize	0.395^{***}	-0.059
	(4.23)	(-0.51)
IndepR	0.520	0.182
	(1.59)	(0.44)
Dual	-0.161^{***}	0.035
	(-4.51)	(0.74)
SOE	0.612^{***}	0.088^{*}
	(16.67)	(1.93)

Continue

Polluter	0.217***	0.008
	(6.56)	(0.20)
Constant	-4.697***	0.254
	(-11.96)	(0.51)
Industry	Yes	Yes
Year	Yes	Yes
S.E. Clustering	Firm	Firm
Observations	22,327	11,958
Pseudo R^2	0.033	0.001

Panel B. Pre-matched differences in characteristics between with free heating cities and without free heating cities

Variables	No. of observations if *FH cities*= 1	Mean if *FH cities* =1	No. of observations if *FH cities* = 0	Mean if *FH cities* = 0	Mean Difference	*t*-value
Size	7,465	22.233	14,862	22.037	0.196***	10.17
Lev	7,465	0.438	14,862	0.418	0.020***	6.59
ROA	7,465	0.036	14,862	0.040	-0.004***	-5.06
Growth	7,465	0.186	14,862	0.194	0.003	-1.10
BM	7,465	0.630	14,862	0.596	0.034***	9.19
CHTA	7,465	0.015	14,862	0.018	-0.003	-1.61
Capex/at	7,465	0.047	14,862	0.050	-0.003***	-4.08
INST	7,465	0.065	14,862	0.062	0.003***	4.52
Top 5	7,465	0.544	14,862	0.543	0.001	0.86
ListAge	7,465	2.045	14,862	2.026	0.019	1.47
BoardSize	7,465	2.139	14,862	2.128	0.011***	3.78
IndepR	7,465	0.374	14,862	0.376	-0.002	-1.45
Dual	7,465	0.246	14,862	0.292	-0.046***	-7.11
SOE	7,465	0.412	14,862	0.332	0.080***	11.42
Polluter	7,465	0.292	14,862	0.246	0.046***	7.10

Panel C. Post-matched differences in characteristics between with free heating cities and without free heating cities

Variables	No. of observations if *FH cities* =1	Mean if *FH cities* =1	No. of observations if *FH cities* =0	Mean if *FH cities* =0	Mean Difference	*t*-value
Size	5,979	22.313	5,979	22.307	0.006	0.23
Lev	5,979	0.447	5,979	0.446	0.001	0.13
ROA	5,979	0.035	5,979	0.035	0.000	0.15
Growth	5,979	0.177	5,979	0.176	0.001	0.07
BM	5,979	0.632	5,979	0.633	-0.001	-0.19
CHTA	5,979	0.015	5,979	0.017	-0.002	-1.11
Capex/at	5,979	0.045	5,979	0.045	0.000	0.16
INST	5,979	0.068	5,979	0.067	0.001	0.44

Continue

Top 5	5,979	0.540	5,979	0.539	-0.001	-0.35
ListAge	5,979	2.156	5,979	2.157	-0.001	-0.06
BoardSize	5,979	2.145	5,979	2.143	0.002	0.69
IndepR	5,979	0.375	5,979	0.374	0.001	0.01
Dual	5,979	0.226	5,979	0.231	-0.005	-0.54
SOE	5,979	0.480	5,979	0.472	0.008	0.85
Polluter	5,979	0.287	5,979	0.289	-0.002	-0.25

Panel D. Matched sample regression analysis

Variables	M&A
Air pollution	-4.582***
	(-3.17)
Size	0.021
	(0.52)
Lev	0.137
	(0.73)
ROA	-0.951
	(-0.77)
Growth	0.435***
	(8.07)
BM	-0.841***
	(-4.41)
CH/at	-0.028
	(-0.90)
Capex/at	-1.967**
	(-2.43)
INST	-0.565*
	(-0.52)
Top 5	-0.067
	(-0.26)
ListAge	0.170***
	(3.23)
BoardSize	-0.518**
	(-2.57)
IndepR	-1.173*
	(-1.65)
Dual	0.067
	(0.93)
SOE	-0.794***
	(-9.90)

Continue

Polluter	-0.090
	(-1.16)
Constant	-2.097**
	(-2.13)
Industry	Yes
Year	Yes
S.E. Clustering	Firm
Observations	11,958
Pseudo R^2	0.089

Table 2.6. Channel tests: Firm's operating conditions and environmental investment

This table presents transmission channels results for the impact of air pollution on corporate M&A activities. The results show that the impact of air pollution on the firm's operating conditions and environmental investment. Detailed definitions of variables are given in Appendix A.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	CF	M&A	En-Investment	M&A
	(1)	(2)	(3)	(4)
Air pollution	-0.739**		1.966**	
	(-2.39)		(2.02)	
Fit_ CF		-0.049*		
		(-1.81)		
Fit_ En-Investment				-0.015***
				(-2.92)
Constant	3.834***	-2.916**	0.175	-2.929***
	(16.75)	(-3.30)	(0.24)	(-3.46)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	22,306	22,306	22,306	22,306
Adj/ Pseudo R-squared	0.324	0.096	0.000	0.094

Table 2.7. Cross-sectional test: External resource accessibility

This table reports the results of the cross-sectional test of external financing. External financing is measured by: (a) bank loans; (b) trade credit. The sample is divided into two groups—low and high—based on the median values of these two variables. Detailed definitions of variables are given in Appendix A.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	M&A	M&A	M&A	M&A
	Bank loans		Trade credit	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Air pollution	-5.199***	-3.734**	-4.985***	-3.764**
	(-2.98)	(-2.46)	(-2.91)	(-2.40)
GDP growth	0.166	0.109	-2.325	2.587
	(0.07)	(0.05)	(-0.99)	(1.16)
GDP per capita	2.666	-0.279	1.673	-0.232
	(1.35)	(-0.16)	(0.90)	(-0.13)
Constant	-3.667***	-1.615*	-2.765***	-2.502
	(-2.78)	(-1.67)	(-2.65)	(-2.06)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	8,024	14,280	10,835	11,459
Pseudo R-squared	0.107	0.093	0.095	0.101
Chow-test	0.045**		0.039**	

Table 2.8. Cross-sectional test: Environmental awareness

This table presents the results of the cross-sectional test of environmental awareness. We evaluate regions' environmental awarenesses based on the location of the firm's headquarters, using two proxies: (a) the economic development level of the province, as measured by the Fan-Gang index, which classifies provinces as well-developed or less-developed; and (b) the acquirer's air pollution level, categorizing provinces as more or less polluted based on whether the acquirer's AQI exceeds the sample median. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	M&A	M&A	M&A	M&A
	Well-developed provinces	Less-developed provinces	Less polluted provinces	More polluted provinces
	(1)	(2)	(3)	(4)
Air pollution	-5.377***	-3.367	-8.340***	-1.976
	(-3.94)	(-1.52)	(-3.59)	(-1.05)
GDP growth	2.347	1.272	-2.057	3.393
	(1.02)	(0.41)	(-1.09)	(0.88)
GDP per capita	0.355	-1.353	1.121	-1.174
	(0.21)	(-0.46)	(0.76)	(-0.33)
Constant	-4.459***	-0.834	-1.390	-3.642**
	(-5.47)	(-0.63)	(-1.52)	(-2.45)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	16,538	5,789	15,681	6,646
Pseudo R-squared	0.092	0.119	0.104	0.085

Table 2.9. Moderating effects

This table reports the results of moderating effects of the government support, firm's own financial health, and growth opportunities. The dependent variable is the M&A dummy that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t* and 0 otherwise. The main independent variable is air pollution, measured by the air quality index level of the city where the firm *i*'s headquarter is located. The moderating variables include government subsidy (*Subsidy*), firm's distance to default risk (*DD_KMV*), and firm's potential profitability and future growth (*Tobin's Q*). Detailed definitions of variables are given in Appendix A.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	M&A	M&A	M&A
	(1)	(2)	(3)
Air pollution	-3.958***	-4.955***	-8.319***
	(-3.34)	(-3.97)	(-4.86)
Air pollution × Subsidy	1.486*		
	(1.70)		
Air pollution × DD_kMV		0.701**	
		(2.51)	
Air pollution × Tobin's Q			1.742***
			(3.03)
Subsidy	-0.200		
	(-1.57)		
DD_KMV		-0.085***	
		(-3.46)	
Tobin's Q			-0.323
			(-1.34)
Constant	-2.417***	-2.023**	-1.018
	(-3.07)	(-2.50)	(-1.42)
Controls	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	19,418	21,710	22,309
Pseudo/Adj R-squared	0.094	0.093	0.098

Table 2.10. Robustness checks

This table reports the results of further robustness checks on the baseline results. In panel A, we add the province fixed effect in *Eq. (2.1)*. In panel B, we run the baseline results using an alternative model with the firm, industry, province, and year fixed effects. In panel C, we use the monthly average AQI during the winter (November to January) and other seasons (February to October) of the city where the firm headquarter is located. The *t*-statistics are reported in parentheses. The symbol *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Multiple fixed effect

Variables	M&A	M&A	M&A
	(1)	(2)	(3)
Air pollution	-2.836*	-2.227*	-2.201*
	(-1.79)	(-1.89)	(-1.86)
GDP growth			-1.763
			(-0.92)
GDP per capita			2.061
			(1.48)
Constant	-4.165***	-2.327***	-2.316***
	(-12.76)	(-2.71)	(-2.60)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Province	Yes	Yes	Yes
N	22,327	22,327	22,327
Adj R-squared	0.067	0.098	0.099

Panel B: Lead-lag model with High-density fixed effects

Variables	$M\&A_{t+1}$	$M\&A_{t+1}$	$M\&A_{t+1}$	$M\&A_{t+1}$	$M\&A_{t+1}$	$M\&A_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Air pollution	-0.391*	-0.390*	-0.443**	-0.442**	-0.444**	-0.443**
	(-1.92)	(-1.92)	(-2.16)	(-2.16)	(-2.16)	(-2.16)
GDP growth		-0.018		-0.002		-0.007
		(-0.05)		(-0.01)		(-0.02)
GDP per capita		-0.076		-0.079		-0.073
		(-0.25)		(-0.26)		(-0.24)
Constant	0.981***	0.988***	1.006***	1.013***	1.039***	1.045***
	(5.53)	(5.56)	(5.64)	(5.67)	(5.79)	(5.82)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	No	Yes	Yes

Continue

Province	No	No	Yes	Yes	Yes	Yes
N	18,062	18,062	18,062	18,062	18,062	18,062
Adj R-squared	0.107	0.107	0.107	0.107	0.107	0.106

Panel C: Seasonal influence

Variables	M&A	M&A	M&A	M&A	M&A	M&A
	(1)	(2)	(3)	(4)	(5)	(6)
$Air\ pollution_{Nov-Mar}$	-4.601***	-3.080***	-2.955***			
	(-4.84)	(-3.07)	(-2.87)			
$Air\ pollution_{Apr-Oct}$				-6.367***	-3.849***	-3.692**
				(-4.70)	(-2.67)	(-2.51)
GDP growth			0.075			0.291
			(0.05)			(0.18)
GDP per capita			1.231			1.185
			(0.94)			(0.92)
Constant	-2.720***	-0.297***	-0.518	-2.696***	-0.361	-0.608
	(-6.52)	(-0.37)	(-0.62)	(-6.45)	(-0.45)	(-0.74)
Controls	No	Yes	Yes	No	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	16,638	16,638	16,638	16,638	16,638	16,638
Pseudo R-squared	0.044	0.086	0.086	0.044	0.086	0.086

Table 2.11. Further robustness checks

This table reports the results of robustness checks on the baseline results. In panel A, we use the expense value of the M&A deals to replace the M&A dummy as the proxy for M&A. In panels B and C, we use $PM_{2.5}$ which is the logarithm value of the average yearly level of $PM_{2.5}$ in each acquirer's city and the natural logarithm of yearly average Air Quality Index (AQI), as the proxy for air pollution. In panel D, we use the sample period from 2013 to 2020 which includes the main independent variable AQI. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Alternative M&A metrics			
Variables	M&A expense value	M&A expense value	M&A expense value
	(1)	(2)	(3)
AQI	-12.794***	-9.387***	-4.249***
	(-6.06)	(-4.11)	(-3.87)
GDP growth			0.287
			(0.13)
GDP per capita			2.139
			(1.49)
Constant	0.888**	1.505	1.077
	(1.99)	(1.26)	(0.86)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	22,327	22,327	22,327
Adj R-squared	0.044	0.071	0.071

Panel B: Alternative air pollution metrics			
Variables	M&A	M&A	M&A
	(1)	(2)	(3)
PM 2.5	-0.503***	-0.489***	
	(-3.70)	(-3.55)	
Δ AQI			-1.423**
			(-2.37)
GDP growth		0.331	0.247
		(0.21)	(0.31)
GDP per capita		1.472	1.458
		(1.15)	(1.26)
Constant	0.062	-0.109	0.989***
	(0.09)	(-0.15)	(5.53)
Controls	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	18,046	18,046	22,016

Pseudo R-squared	0.084	0.085	0.093

Panel C: Alternative air pollution measurement

Continue

Variables	M&A	M&A	M&A
	(1)	(2)	(3)
Log AQI	-0.487***	-0.347***	-0.345***
	(-5.95)	(-4.17)	(-4.07)
GDP growth			-0.039
			(-0.03)
GDP per capita			0.980
			(0.77)
Constant	-1.993***	-1.172	-1.332
	(-4.43)	(-1.44)	(-1.58)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	22,327	22,327	22,327
Adj R-squared	0.098	0.095	0.095

Panel D: Alternative sample period (2013-2020)

Variables	M&A	M&A	M&A
	(1)	(2)	(3)
AQI	-5.900***	-4.201***	-4.057***
	(-5.64)	(-3.81)	(-3.61)
GDP growth			0.179
			(0.11)
GDP per capita			1.474
			(1.16)
Constant	-1.584***	0.113	-0.051
	(-5.97)	(0.15)	(-0.07)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	18,046	18,046	18,046
Pseudo R-squared	0.044	0.084	0.085

Table 2.12. Air pollution and M&A payments

This Table reports the results of the payment consideration linear logit models. The dependent variable in columns (1) and (2) is cash dummy that equals 1 if the payment for an M&A deal is fully in cash, and 0 otherwise, which in columns (3) and (4) is stock dummy that equals 1 if the payment for an M&A deal is fully in stock, and 0 otherwise. AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	Cash dummy	Cash dummy	Stock dummy	Stock dummy
	(1)	(2)	(3)	(4)
AAQI	-4.004**	-4.345**	7.212***	7.093***
	(-2.19)	(-2.36)	(2.85)	(2.78)
TAQI	2.158	2.081	2.924	2.919
	(1.19)	(1.14)	(1.16)	(1.15)
Deal ratio		-1.343***		0.157***
		(-9.54)		(4.04)
Diversifying dummy		-0.383***		0.105
		(-3.01)		(0.59)
Cross-city dummy		0.002		-0.304**
		(0.02)		(-2.37)
Intellectual Property dummy		-1.128		0.771
		(-0.90)		(0.78)
Constant	2.589	3.532**	-0.196	-0.167
	(1.59)	(2.13)	(-0.09)	(-0.08)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	3,541	3,541	3,541	3,541
Pseudo R-squared	0.186	0.190	0.120	0.123

Table 2.13. Air pollution and completion days

This table reports the relationship between AAQI, TAQI and completion days for M&A deals. The dependent variable is completion days, which is measured as the natural log of finish declare date minus first declare date, log (finish declare date - first declare date). AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A.1. *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	Completion days	Completion days	Completion days
	(1)	(2)	(3)
AAQI	2.437**	2.516**	1.734**
	(2.42)	(2.50)	(1.96)
TAQI	0.537	0.593	0.814
	(0.53)	(0.59)	(0.91)
Deal ratio		0.006**	0.214***
		(2.10)	(4.79)
Diversifying dummy		0.110	0.034
		(1.79)	(0.66)
Cross-city dummy		-0.045	-0.079*
		(-0.88)	(-1.82)
Intellectual Property dummy		0.619	-0.041
		(1.39)	(-0.11)
Cash dummy			-1.192***
			(-24.96)
Stock dummy			0.077
			(1.13)
Constant	5.129***	4.939***	4.799***
	(6.44)	(6.14)	(7.32)
Controls	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	2,736	2,736	2,736
Adj R-squared	0.010	0.100	0.356

Table 2.14. Air pollution and shareholder value

This table reports results of the acquirer CAR cross-sectional regressions. Panels A and B show the summary statistics of Average Abnormal Return (AAR) and Cumulative Average Abnormal Return (CAAR) of Acquire Firms. In panel C, the dependent variable CAR [-1, 0] is acquirer two-day CARs centred on the M&A announcement days. AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Average Abnormal Return (AAR) of Acquire Firms									
Event Day	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
-5	3,273	0.001**	-0.001	-0.061	0.086	0.024	-0.013	0.011	0.774
-4	3,273	0.001***	-0.001	-0.060	0.083	0.025	-0.012	0.012	0.665
-3	3,273	0.001***	-0.001	-0.067	0.096	0.026	-0.013	0.013	0.786
-2	3,273	0.002***	-0.001	-0.073	0.087	0.026	-0.012	0.013	0.520
-1	3,273	0.005***	0.001	-0.081	0.099	0.031	-0.012	0.018	0.626
0	3,273	0.017***	0.011	-0.128	0.153	0.065	-0.016	0.080	0.193
1	3,273	0.010***	-0.000	-0.119	0.136	0.057	-0.022	0.047	0.170
2	3,273	0.006***	-0.003	-0.106	0.129	0.050	-0.020	0.024	0.503
3	3,273	0.003***	-0.003	-0.105	0.132	0.045	-0.021	0.018	0.634
4	3,273	0.002***	-0.002	-0.099	0.115	0.040	-0.019	0.016	0.674
5	3,273	0.000**	-0.004	-0.095	0.116	0.037	-0.018	0.011	0.797
Panel B: Cumulative Average Abnormal Return (CAAR) of Acquire Firms									
Event Window	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
CAAR [-5, 0]	3,273	0.005***	0.004	-0.034	0.048	0.015	-0.004	0.014	0.221
CAAR [-3, 0]	3,273	0.007***	0.005	-0.047	0.065	0.021	-0.006	0.020	0.173
CAAR [-1, 0]	3,273	0.012***	0.008	-0.081	0.098	0.036	-0.008	0.040	0.067
CAAR [0, +1]	3,273	0.014***	0.005	-0.114	0.131	0.055	-0.013	0.051	0.005
CAAR [0, +3]	3,273	0.009***	0.002	-0.097	0.112	0.042	-0.010	0.025	0.403
CAAR [0, +5]	3,273	0.007***	0.001	-0.081	0.102	0.034	-0.008	0.016	0.735
CAAR [-1, +1]	3,273	0.012***	0.005	-0.079	0.097	0.038	-0.009	0.037	0.091
CAAR [-3, +3]	3,273	0.007***	0.002	-0.057	0.071	0.025	-0.006	0.016	0.483
CAAR [-5, +5]	3,273	0.005***	0.001	-0.043	0.062	0.019	-0.005	0.011	0.787

Panel C: Air pollution and acquirer's CAAR		
Variables	CAAR [-1, 0]	CAAR [-1, 0]
	(1)	(2)
AAQI	-0.063**	-0.062**
	(-2.09)	(-2.06)
TAQI	0.045	0.042
	(1.47)	(1.39)
Deal ratio		-0.000
		(-0.71)

Continue

Diversifying dummy		0.004**
		(2.03)
Cross-city dummy		0.003*
		(1.84)
Intellectual Property dummy		0.021
		(1.31)
Constant	0.118***	0.111***
	(5.23)	(4.92)
Controls	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
S.E. Clustering	Firm	Firm
N	3,273	3,273
Adj R-squared	0.075	0.077

Table 2.15. Air pollution and long-term benefits

This table reports the results of the acquirer's ROA and Growth in one year after M&A deals happened. AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	ROA_{t+1}	ROA_{t+1}	$Growth_{t+1}$	$Growth_{t+1}$
	(1)	(2)	(3)	(4)
AAQI	-0.142**	-0.141**	-1.837**	-1.754*
	(-2.55)	(-2.55)	(-1.82)	(-1.74)
TAQI	0.068	0.065	0.391	0.414
	(1.22)	(1.16)	(0.39)	(0.41)
Deal ratio		-0.000		0.035
		(-1.11)		(12.02)
Diversifying dummy		0.000		-0.002
		(0.08)		(-0.03)
Cross-city dummy		-0.004		0.014
		(-1.16)		(0.26)
Intellectual Property dummy		0.026		1.326**
		(0.89)		(2.54)
Constant	0.015***	0.022	6.393***	6.244***
	(0.31)	(0.43)	(7.13)	(6.93)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	2,092	2,092	2,092	2,092
Adj R-squared	0.265	0.268	0.116	0.118

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CHAPTER THREE ESSAY TWO

Adjusted air pollution exposure and corporate innovation investment: Evidence from China

Abstract

Using a novel measure of air pollution exposure adjusted for heterogeneity of exposures and the extent of local air pollution, we find a significant negative relationship between adjusted air pollution exposure and corporate innovation investment. This finding still holds after controlling for endogeneity and conducting a series of robustness tests. While the relationship is mediated through net operating cash flows and debt financing costs, we also find that firms with high adjusted air pollution exposure might have deteriorated productivity of R&D personnel, which ultimately hinders innovation input and output. However, state ownership appears to mitigate this adverse effect of adjusted air pollution exposure. Furthermore, the adverse effects of air pollution exposure on innovation investment are more pronounced among firms that disclose environmental information, exhibit low managerial risk tolerance, operate in non-polluting industries, or are located in developed and less polluted regions. Additionally, the negative impact is particularly evident in the subsample of firms after the signing of the 2015 Paris Agreement. This study sheds light on the importance of adjusted air pollution exposure and its influence on corporate investment in China.

Keywords: Adjusted air pollution exposure, corporate innovation investment, net operating cash flow, debt financing cost

JEL code: G38, O31, Q53, Q56

3.1. Introduction

Air pollution is known to harm human physical and mental health[19], and financial economists recognize that financial market performance is not immune to poor air quality. A strand of the literature suggests that air pollution affects the resources and performance of individual firms, such as worsened cost of debt financing (Tan et al., 2022), increased discounts on equity offerings (Han et al., 2022), decreased stock returns (Levy & Yagil, 2011), and decreased availability of bank loans (Tan, Tan, et al., 2021). Furthermore, some papers study the influence of air pollution on decision-making for firms' policies and activities, such as decreased corporate innovation (Tan & Yan, 2021), reduced the firm's investment efficiency (He & Lin, 2022), more conservative accounting policies (Wu et al., 2022), among others.

Previous studies have primarily relied on country- or city-level air quality index to examine the impact of air pollution on individual firms' behaviours and activities. Applying the air quality index implicitly assumes that all firms in the same regions have the same exposure to air pollution shocks. However, although air pollution does not differ in a region, the exposure of firms to air pollution does. Despite this variation, there is a lack of research systematically measuring how different degrees of air pollution exposure affect specific firm's decision-making and investment activities. This paper addresses this gap by developing a novel metric --- adjusted air pollution exposure, which combines city-level air quality index with the firm-level exposure to air pollution. This measure captures both the firms' exposures to abnormal air pollution and the firms' headquarters' air pollution levels, confirming heterogeneity among firms' exposures to air pollution.

To construct our main independent variable --- adjusted air pollution exposure (*A_AQI*

[19] Numerous scholarly studies find that ambient air pollution may have adverse impacts on human health, such as raising mortality rates from cardiac and respiratory diseases (Franklin et al., 2005) and raises healthcare cost (Zeng et al., 2019), raises suicidal tendencies (Bakian et al., 2015), reduces happiness (Zhang et al., 2017), and leads to anxiety and frustration (Evans et al., 1988), among other problems.

exposure), we consider both local air pollution and firm-specific sensitivity to abnormal air pollution. The first is the local air pollution. The important dimension is that air pollution is an economic 'bad' and is considered a negative externality. In other words, a zero or a very low AQI is always desirable. Second, each firm in different industry and location would have different exposure to the local air pollution. Following Bali, Brown, and Tang (2017) and Brogaard and Detzel (2015), we adopt the Fama-French three-factor model to estimate firm-level AQI sensitivity by regressing each firm's excess return on the market, size, value, and the air pollution anomaly risk[20]. This approach enables us to measure a firm's sensitivity to variations in abnormal air pollution levels and assumes that the possible effects of anomalous variations in air pollution on the firm value would be reflected, at least in part, in stock prices. Because firms may be more susceptible to significant increases or decreases in air pollution, we utilize the absolute value of the anomaly variable coefficient (*AQI sensitivity*) to quantify firm-level air pollution exposure (*AQI exposure*) (Nagar, Schoenfeld, & Wellman, 2019). However, this approach to air pollution exposure alone overlooks the intrinsic negative externalities associated with air pollution. More specifically, we find that firms in China's less-polluted southern provinces are generally more sensitive to abnormal air pollution than those in the high-polluted northern provinces[21]. This means that firms located in high air pollution areas do not necessarily incur high air pollution exposures, suggesting that neither pollution levels nor firm sensitivity alone fully capture the true exposure. To address this, we develop adjusted air pollution exposure by multiplying firm-level AQI exposure with city-level AQI[22], offering a more comprehensive measure of how air pollution affects corporate behaviours.

We focus on corporate innovation investment because it is crucial to a firm's competitiveness

[20] More details about the air pollution anomaly construction are described in Section 3.3.2.2.
[21] Please see Table 3.1 & Figure 3.4.
[22] Nagar, Schoenfeld, and Wellman (2019) also use the interaction term that multiplies the EPU index by EPU beta to see the interaction effect on investor information asymmetry and management disclosures.

and growth (Porter, 1985), it has the ability to drive sustained growth, competitive advantage, risk mitigation, and diversification in a rapidly changing business environment. And finding ways to improve the innovation ability of enterprises has been a hot topic. Scholars study the factors affecting innovation from various perspectives, including external and internal factors. External factors that can increase corporate innovation include government subsidies (Zhang & Guan, 2018), political connections (Su, Xiao, & Yu, 2019), and higher-educated immigrants (Fassio, Montobbio, & Venturini, 2019). Internal factors that can increase corporate innovation include cash holdings and profitability (Almeida, Campello, & Weisbach, 2004), executive team cognitive (Wang, Su, & Guo, 2019), foreign management experience (Yuan & Wen, 2018), mutual funds' holdings (Chi, Liao, & Yang, 2019) and exports (Chen, Chen, Wang, & Xiang, 2018), however, financing constraints (Silva & Carreira, 2012) hurts corporate innovation. However, little attention has been given to how heterogeneous air pollution exposure affects corporate innovation investment --- a gap this study aims to fill.

Our study is related to two theories. Strategic growth option theory suggests that firms may respond to uncertainty by investing in innovation activities to secure their market share and sustain competitive advantage (Kulatilaka & Perotti, 1998; Tajaddini & Gholipour, 2021). As a form of uncertainty, high adjusted air pollution exposure may prompt firms to accelerate innovation investment to seize opportunities, increase market shares, and achieve sustainable development. However, real options theory argues that uncertainty increases the value of the option to wait, and firms can avoid sunk costs by deferring risky investment projects. Empirical evidence shows that rising uncertainty tends to reduce firms' investment (Pastor & Veronesi, 2012; Kelly, Pástor, & Veronesi, 2016). In addition, some studies find that uncertainty increases financing costs and reduces future cash flow, thereby exacerbating financing constraints and decreasing corporate innovation investment (Lee & Wang, 2021; Xu, 2020).

To contribute to the ongoing debate, this chapter investigates the effect of adjusted air pollution exposure on innovation investment among Chinese listed firms. Furthermore, we also analyse its impact on patent applications as a robustness check. China provides a suitable setting for this analysis for three main reasons. First, air pollution is one of the most challenging environmental problems facing developing countries such as China and India (WHO, 2021). Since 2012, the Chinese government has prioritized environmental governance and sustainable development through structural reforms and regulatory policies (CBRC, 2014B)[23]. Second, China has a notable disparity in pollution levels across cities (Dong, Fisman, Wang, & Xu, 2021). This will also result in high variations in both air pollution and adjusted air pollution exposures. Third, China has experienced rapid economic development since the 1980s. It has strongly emphasized corporate innovation throughout the process, and its innovation activities and research and development investment are comparable to many developed markets (Hao, Guo, Guo, Wu, & Ren, 2020). Thus, using the Chinese stock market as a platform to study the impact of adjusted air pollution exposure on corporate innovation investment would be meaningful.

This chapter examines the impact of adjusted air pollution exposure of the firm on its innovation investment using a sample that includes 16,952 firm-year observations of 3,197 listed firms in mainland China from 2010 to 2022. We find that the adjusted air pollution exposure is negatively related to corporate innovation investment. The results are economically meaningful: a one standard deviation increase in adjusted air pollution exposure is associated with a 1.94% decline in corporate innovation investment. The findings remain robust after a series of robustness checks and endogeneity tests, including controls for multiple fixed effects and macroeconomic uncertainty, the use of propensity score matching (PSM) and a staggered difference-in-difference (DID) approach. Mediation analysis reveals that reduced net operating

[23] China Banking Regulatory Commission (CBRC), 2014b, No. 40 Document General Office of the China Banking Regulatory Commission, Options on Green Credit Implementation. Available at: http://www.cbrc.gov.cn/EngdocView.do?docID= C5AE0DDAFB3E43DF85DC12DD6840244A

cash flows and increased financing costs are key channels through which adjusted air pollution exposure inhibits corporate innovation investment. We also find that firms with high adjusted air pollution exposure could face challenges such as increased absenteeism and reduced efficiency among R&D personnel, which ultimately hinders innovation input and output.

Additional analysis shows that firms with higher adjusted air pollution exposure tend to shift their focus from general technological innovation toward green innovation to address regulatory or reputational risks. Moreover, we find that firm-specific factors, such as environmental information disclosure, manager's risk tolerance, industry types (polluters or non-polluters); and external factors, such as the level of regional development and pollution levels, shape the relationship between adjusted air pollution exposure and innovation investment. Notably, the negative impact intensifies following the 2015 Paris Agreement.

This chapter differs from some similar existing studies in the following ways[24]. For example, Liu, Xu, and Lu (2024) utilize country-level annual $PM_{2.5}$ and CO_2 emissions as measures of air pollution and identify its negative impact on corporate R&D in emerging markets. In contrast, we develop a firm-level adjusted air pollution exposure metric by combining city-level Air Quality Index (AQI) which captures six major pollutants[25] with firm-specific exposure to air pollution estimated using Fama-French three factor model, thereby providing a more holistic measure. Sautner, Van Lent, Vilkov, and Zhang (2023) develop a firm-level climate change exposure based on earning call transcripts, covering data from over 10,000 firms across 34 countries between 2002 and 2020. Their findings reveal that firms with higher climate change exposure are more likely to create green jobs and file green patents but also face heightened financial risks. Our study shares a common focus with Sautner et al. (2023) in

[24] We sincerely thank the anonymous reviewer for their valuable suggestions, which have strengthened the contribution of our proposed metric.

[25] These six pollutants include sulfur dioxide (SO_2), nitrogen dioxide (NO_2), particulate matter smaller than 10 μm (PM_{10}), particulate matter smaller than 2.5 μm ($PM_{2.5}$), carbon monoxide (CO), and ozone (O_3).

emphasizing the importance of granular, firm-level data to better understand the impact of environmental factors—whether climate change or air pollution—on businesses. However, the key distinction lies in the scope and nature of the exposures studied. First, climate change exposure reflects long-term, systemic risks, whereas air pollution exposure is more immediate and localized, affecting health, productivity, and operational dynamics. Moreover, their firm-level exposure is constructed using earning calls data, which tends to be more subjective[26]. In comparison, we use the Fama-French three-factors model to capture firms' exposures to abnormal air pollution (AQI exposure) and construct a more objective metric --- adjusted air pollution exposure --- by multiplying firm-level AQI exposure with the local AQI index. This adjusted measure provides a comprehensive and objective perspective on the impact of air pollution on firm behaviour.

We make the following contributions to the literature. First, we propose a novel firm-level measure of adjusted air pollution exposure by combining city-level Air Quality Index (AQI) with firm-specific exposure estimated using trading data and the Fama-French three-factor model. This measure captures both the intensity of local pollution and firms' sensitivity to it, offering a more comprehensive view of environmental uncertainty. Second, our paper provides evidence that adjusted air pollution exposure negatively affects corporate innovation investment. To our knowledge, this is among the first studies to investigate the effect of firm specific air pollution exposure on innovation investment. Third, we identify channels through which firms with higher adjusted air pollution exposure reduce innovation investment, primarily by decreasing corporate net operating cash flows and increased financing costs,

[26] Recent literature introduces a new measure for firm-level climate change exposure based on transcripts of quarterly earnings conference calls (Sautner et al., 2023). However, these measures may be limited by salience bias, where managers overweight the probability of events based on their proximity or ease of recall (Alok et al., 2020). This bias has been observed in managerial overreactions to local disasters, such as increased cash holdings following hurricanes (Dessaint & Matray, 2017) and professional money managers underweighting nearby firms' stocks (Alok et al., 2020). However, we believe our measure does not suffer from this shortcoming.

supporting the real options theory. Furthermore, we also provide the evidence that firms with high adjusted air pollution exposure may shift their focus toward environmentally adaptive technologies (green innovation) to manage regulatory or reputational risks.

The chapter is structured as follows: In Section 3.2, we review the theoretical background and propose the hypotheses. In Section 3.3, we describe the data and methodology. In Section 3.4, we present and discuss our empirical results, and in Section 3.5, we conclude the chapter.

3.2. Literature review and hypothesis development

3.2.1. The impact of air pollution

Environmental issues have become the focus of the government and scholars due to the global warming caused by economic development and the aggravation of pollution emissions. Air pollution is one of the heaviest types of environmental pollution worldwide, killing an estimated seven million people worldwide every year (WHO, 2022). The early studies pay more attention to the air pollution and individuals, such as the individual health and sentiments/moods (Bakian et al., 2015; Chen et al., 2013; Graff Zivin & Neidell, 2013; Lavy, Ebenstein, & Roth, 2014; Lim et al., 2012; Power et al., 2015; Tanaka, 2015). An increasing number of papers has begun to link air pollution to a wide range of macroeconomic activities (Chay & Greenstone, 2005; Chen et al., 2013; Ebenstein et al., 2015; Ebenstein et al., 2017). Recently, financial economists have extended this line of research to examine the impacts of air pollution on firms' accounting and other financial policies, investment policies, and activities.

Several studies focus on the effects of air pollution on the firm's accounting policies, financial report quality, and internal control quality. For example, Wu et al. (2022) find that increased air pollution induces firms to follow more conservative accounting practices and utilize more conservative estimates in their reporting. Jiang, Li, Shen, and Yu (2022) find that higher air pollution promotes earnings management by lowering labour productivity and strengthening executives' negative sentiments. Further analysis finds that air pollution transfers firms' real earnings management to accrual earnings management. Liu et al. (2019) and Hu et al. (2022) find that firms' internal control quality and financial reporting quality are significantly and negatively associated with the severity of air pollution in their home cities because the mood of managers becomes more negative as levels of air pollution increase and result in a management that is less motivated, less effective, less decision quality which leads to worse internal control quality and financial reporting quality.

Research exploring the influence of air pollution on firms' decision-making has generated momentum in recent years. Zhang et al. (2021) find that initial public offerings (IPOs) are under-priced for firms located in areas with severe air pollution compared to those with less air pollution. Liu et al. (2021) show that firms respond to increased air pollution by using more capital and less labour to remain competitive. Tan, Tan, et al. (2021) find that air pollution drives a pessimistic mood and/or weakens the cognitive ability of management, leading to poor operations and an increase in precautionary needs for more cash due to pollution abatement or decreased availability of bank loans. He and Lin (2022) also find a similar adverse impact on managers' moods that reduces firms' investment efficiency. Furthermore, Yao and Liu (2020) demonstrate that greater uncertainty in air quality increases firms' propensity to engage in earnings management, particularly downward adjustments.

In addition, a few papers examine the impacts of air pollution on corporate innovation. Tan and Yan (2021) find that air pollution reduces corporate innovation, as measured by patents because it drains financial resources, constraints firms even more, and increases environmental governance costs. Tan and Yan (2021) and Wang et al. (2021) find that air pollution adversely affects the psychology of executives, negatively affecting their decision-making regarding innovation, which ultimately reduces corporate innovation.

Existing research relies on city-level air quality indicators to investigate how air pollution influences firms' activities and behaviours. When applying the air quality index, it is implicitly assumed that all firms in the same areas are equally exposed to air pollution shocks. Although air pollution does not differ by location, businesses' susceptibility to it does. This is one of the limitations of the current literature on air pollution.

3.2.2. Corporate innovation

Innovation is a key component of economic expansion. Technology accumulation stimulates long-term economic development, supported by innovation (Change, 1990; Lucas, 1988). According to Fritsch (2017), firms are the primary forces behind innovation. Through innovation, they gain a competitive advantage and momentary monopolistic power, which generates abnormal profit.

Many other papers study the factors affecting corporate innovation from various perspectives, including external and internal factors. Zhang and Guan (2018) find that direct government subsidies benefit corporate innovation in the short term but hinder long-term innovation performance. Su et al. (2019) and Tsai, Zhang, and Zhao (2019) show that political connections have positive effects on corporate innovation. However, some argue that political connections can inhibit enterprise innovation (Yuan, Hou, & Cheng, 2015). Wu (2011) shows an inverted ‘U’ association between corporate innovation and political connections. Fassio et al. (2019) find that higher-educated immigrants have a positive effect on innovation. However, the effect varies by industry. By examining the impact of internal factors on corporate innovation, Almeida et al. (2004) discover that cash holdings and profitability are positively correlated with innovation. Silva and Carreira (2012) and Gorodnichenko and Schnitzer (2013) find that financing constraints can significantly inhibit corporate innovation. Wang et al. (2019) find that executive team cognitive conflict has a positive impact on exploratory innovation, but emotional conflict has a negative impact. In addition, Yuan and Wen (2018) find that foreign management experience has a positive impact on corporate innovation. Chi et al. (2019) show that mutual funds' holdings significantly increase corporate innovation, but grey institutional holdings (such as insurance companies and pension funds) and qualified foreign institutional investors' holdings have little or no significant impact on innovation. Chen et al. (2018) find that exports have a positive impact on corporate innovation.

The existing literature on the factors influencing corporate innovation has predominantly focused on the entity level, such as enterprises, governments, and markets. While some studies have examined the role of natural environmental factors, including city-level air quality index, city-level $PM_{2.5}$ levels, or climate change exposure (Liu et al., 2024; Sautner et al., 2023). These measurements often lack comprehensiveness or objectivity. Therefore, a deeper understanding of how adjusted air pollution exposure impacts corporate innovation investment is necessary.

In addition, innovation investment stands out for its potential to drive sustained growth, competitive advantage, risk mitigation, and diversification in a rapidly changing business environment. Patent applications are considered as the output of innovation. Fang, Tian, and Tice (2014) suggest that compared with R&D investment—which measures observable innovation input—patenting activity is a good proxy for corporate innovation because it captures both innovation output and the efficiency of corporate innovation. Thus, our paper also investigates the effects of the adjusted air pollution exposure on the output of innovation as a robustness test

3.2.3. Hypothesis development

Our study is motivated by two opposing theories on the relationship between uncertainty and innovation investment.

According to strategic growth option theory, uncertainty might encourage investment in a growth option under imperfect competition. The reasoning behind this theory is that uncertainty can generate a growth option. While delaying investments could leave the investment opportunity to other competitors, "immediate action may discourage entrants and enhance market share and profits" (Kulatilaka & Perotti, 1998), thus increasing competitive advantage in the future. Similarly, Weeds (2002) shows that waiting loses value when firms face competition or when investments can lead to worthwhile expansion prospects.

Moreover, Jiang, Xu, and Yao (2009) report a positive correlation between the uncertainty measured by idiosyncratic return volatility and R&D investment. Similarly, Van Vo and Le (2017) find that firms that face higher uncertainty measured by idiosyncratic return volatility invest more in R&D, and the effect is more pronounced for firms in more competitive industries. Stein and Stone (2012) find that R&D investment is increased by the uncertainty represented by implied volatility from equity options. Atanassov, Julio, and Leng (2015) document that R&D investment dramatically increases in gubernatorial election years.

In conclusion, we have reason to suspect that firms with high adjusted air pollution exposure may increase their investment in innovation to capture market share and realize sustainable development. Accordingly, we propose the following hypothesis:

Hypothesis 1a *(H1a)*: Adjusted air pollution exposure positively impacts corporate innovation investment.

In contrast to strategic growth option theory, the real option theory suggests that if an investment is irreversible, the investment opportunity can be regarded as an option held by the enterprise, and the uncertainty increases the value of the option to wait (Cui, Wang, Liao, Fang, & Cheng, 2021; Narayan, Narayan, Tran, & Thuraisamy, 2021; Pindyck, 1990). Therefore, enterprises tend to reduce or postpone investments in response to high uncertainty risks. From the risk aversion perspective, the enterprise would reduce operational risk by reducing investment in a business environment with vague and poor expectations in the presence of high-uncertainty risks (Bloom, 2007). Moreover, the existing literature indicates that the real option channel is one of the channels through which uncertainty shocks affect real economic activities. The real option channel proposed by (Myers, 1977), which is further examined by Bachmann and Bayer (2013) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) in general equilibrium models, showing that the "wait-and-see" attitude causes the delay of investment when the economy suffers from uncertainty shocks. In short, by deferring investment and keeping the option alive, firms can avoid costly mistakes and wait for additional information about an uncertain future (Atanassov et al., 2015).

Unlike traditional investments, innovation plays an important role in a firm's competitiveness but requires a longer time horizon and carries higher tail risk. The option to wait is particularly significant for investments in research and development (R&D), given that innovation involves exploring unknown approaches and untested methods (Ferreira, Manso, & Silva, 2014), requiring substantial investment in intangible assets. Previous studies find that various types of uncertainties reduce R&D investment. For example, Goel and Ram (2001) show that inflation uncertainty has a stronger negative impact on R&D investment than non-R&D investments in nine OECD countries. Using German data, Czarnitzki and Toole (2011) find that market uncertainty reduces R&D investment. Wang, Wei, and Song (2017) document that political uncertainty negatively affects corporate R&D investment in China. In addition, using data from 43 countries, Bhattacharya, Hsu, Tian, and Xu (2017) find that policy uncertainty measured by national elections adversely affects a country's innovation. Xu (2020) examines the impact of economic policy uncertainty (EPU) on corporate innovation in the U.S. market and shows that EPU increases firms' cost of capital, reducing R&D investment. In addition, some studies suggest that uncertainty increases financing costs and reduces future cash flow, thereby increasing financing constraints and decreasing corporate innovation investment (Lee & Chen, 2020; Lee & Wang, 2021; Xu, 2020).

Based on the above analysis, we contend that firms with high adjusted air pollution exposure will suffer more from the adverse effects of this uncertainty. Therefore, managers may choose to reduce or postpone firms' innovation investment. We propose that firms with high adjusted air pollution exposure would exacerbate their operational risk and financial distress and be more likely to take a "wait-it-out" decision and provide the following hypothesis:

Hypothesis 1b *(H1b):* Adjusted air pollution exposure negatively impacts corporate innovation investment.

3.3. Data and methodology

3.3.1. Sample selection and data sources

We study all Chinese A-share firms listed on the Shanghai and Shenzhen stock exchanges from 2010 to 2022. Following Lin, Lin, Song, and Li (2011) and Lin, Liu, and Manso (2021), we drop firm-year observations with missing information on R&D expenditures. Following Cui et al. (2021), we exclude (1) financial services firms, (2) special treatment (ST) firms, and (3) firm-year observations without sufficient financial data to construct control variables for regression analysis. Data on R&D investment, patents, Fama-French factors, stock returns, and accounting information are all obtained from economic and financial databases and the China Stock Market and Accounting Research (CSMAR). The final sample includes 16,952 firm-year observations of 3,197 unique firms in mainland China from 2010 to 2022.

3.3.2. Variable construction

3.3.2.1. Air pollution data

The Air Quality Index (AQI) is the most widely used indicator of air pollution. The AQI is constructed based on the levels of six atmospheric pollutants: sulfur dioxide (SO_2), nitrogen dioxide (NO_2), suspended particulates smaller than 10 μm in aero- dynamic diameter (PM_{10}), suspended particulates smaller than 2.5 μm in aerodynamic diameter ($PM_{2.5}$), carbon monoxide (CO), and ozone (O_3). Before 2013, the Chinese government monitored only SO_2, NO_2, and PM_{10}, which were used to construct the air pollution index (API) and served as a summary measure of air quality. While the API and AQI are not directly comparable, they are highly correlated (Zheng et al., 2014). Similar to Dong et al. (2021), we use the API before 2013 and the AQI after 2013 in our sample and for notational simplicity, we refer to both as AQI in what follows and divide AQI by 1000 to eliminate the dimension influence.

Fig. 3.1 shows the trend of AQI from 2000 to 2022 in China. During our sample period (2010 to 2022), the minimum and maximum values of the index ranged widely: 75.13 in 2022 and 222.80 in 2013, respectively. AQI shows noticeable fluctuations, with sharp increases observed in 2012, followed by a significant improvement in air quality after 2013. This improvement in 2013 can be largely attributed to policy measures such as the Action Plan on Air Pollution Prevention and Control (commonly referred to as the "Ten Measures for Air Pollution") introduced by the central government in 2013. We attribute the sudden increase in AQI in 2012 to the following factors: first, during this period, China experiences intensified air pollution due to rapid industrialization, urbanization, and increased coal consumption in key regions. These activities result in heightened levels of particulate matter and other pollutants, contributing to the observed spike in AQI (Genc, Zadeoglulari, Fuss, & Genc, 2012). Second, in 2012, China began implementing more comprehensive air quality monitoring systems, including monitoring for $PM_{2.5}$ (fine particulate matter), which was previously not accounted for in the AQI calculations. This likely caused an apparent spike in AQI readings (Chen, Jin, Kumar, & Shi, 2013). Third, increased public and policy attention plays a pivotal role. The severe smog episodes, particularly the infamous "airpocalypse" in Beijing, draw significant concern from both the public and policymakers. This led to more transparent reporting of air quality data (He, Fan, & Zhou, 2016).

Fig. 3.2. shows the trend of average annual population-weighted $PM_{2.5}$ (μg/m^3), similar to AQI's. *Fig. 3.3.* presents the average air quality (AQI) for each province from 2010 to 2022. It is evident that the northern provinces experience higher levels of air pollution than the southern provinces. Appendix B provides summary statistics for the average annual AQI for each province during our sample period. We can see that the five heaviest polluted regions are Hebei, Henan, Shanxi, Tianjin, and Shanxi, and the five least polluted regions are Hainan, Tibet, Yunnan, Guizhou, and Fujian.

[Insert Figures 3.1. & 3.2. &3.3. here]

Data on AQI, API, and $PM_{2.5}$ are all city-level indexes obtained from economic and financial databases, the China Stock Market and Accounting Research (CSMAR).

3.3.2.2. Firm-level air pollution exposure

We measure a firm's exposure to abnormal air pollution changes by regressing a stock's excess return on the Fama-French three factors and the air pollution anomaly variable. Specifically, we estimate the following time-series regression for stock *i*:

$$R_{i,t} - r_{f,t} = \alpha + \beta_{i,t}^{mkt} MKT_t + \beta_{i,t}^{smb} SMB_t + \beta_{i,t}^{hml} HML_t + \beta_{i,t}^{aqi} AQI\ Anomaly_t + e_t \quad (3.1)$$

where, $R_{i,t}$ is the contemporaneous return on firm *i* in month *t*, $r_{f,t}$ is the risk-free rate in month *t*. MKT_t, SMB_t, and HML_t are three Fama-French factors: the excess market returns, the factors small-minus-big, and the factors high-minus-low in month *t*, respectively. AQI $Anomaly_t$ is the abnormal AQI for each listed firm's headquarter city in month *t*. We define the abnormal AQI of each firm as the difference between $AQI_{i,t}$ of a firm *i* on month *t* and the average of AQI for all cities in the same month over the sample period. As the levels of AQI in the same city over the sample period differed drastically due to policy changes, our measure ensures that the return exposures only capture the impacts of the abnormal AQI within the same year or the same month, which makes the abnormal AQI more accurate and stricter. Using a 60-month rolling window, we measure air pollution sensitivity, $\beta_{i,t}^{aqi}$ from *Eq. (3.1)*. Then we average monthly data to obtain annual air pollution sensitivity, $\beta_{i,y}^{aqi}$. Finally, we use the absolute value of $\beta_{i,y}^{aqi}$ ($|\beta_{i,y}^{aqi}|$) to measure the firm's air pollution exposure (*AQI exposure*) following Nagar et al. (2019), as we do not know whether positive or negative sensitivities are more important for investors or have any expectation about whether a given firm will be negatively or positively affected by abnormal AQI over time[27]. *Fig. 3.4.* presents the average air pollution exposure (*AQI exposure*) for each province from 2010 to 2022. It is evident that the southern provinces experience higher levels of air pollution exposure than the northern provinces on average. To avoid the influence of outliers, we winsorize *AQI exposure* ($|\beta_{i,y}^{aqi}|$) at the 1% level.

[Insert Figure 3.4. here]

3.3.2.3. Firm-level adjusted air pollution exposure

Table 3.1. shows the distribution of AQI exposure ($|\beta_{i,y}^{aqi}|$) by province. Since exposure captures a firm's sensitivity to air pollution changes perceived by investors, the underlying assumption of such exposure estimation is that stock prices would at least partially reflect the potential impact of abnormal air pollution changes on firm value. While high AQI (low AQI) is expected to result in high (low) exposures, we find that firms in southern provinces (or less-polluted provinces) are generally more sensitive to air pollution than those in northern

[27] We run the Fama-French three-factor model, *Eq. (3.1)* for all firms for the whole sample and the sample period to gauge the statistical significance of the overall AQI exposure. The regression results reported in Appendix B.3 show that the coefficient estimate of AQI anomaly is positive and statistically significant at the 1% level, implying that the investor perceives the AQI anomaly as a significant factor. The result is also economically significant: one standard deviation change in abnormal air pollution implies a change equal to 7.57% of excess return.

provinces (or more-polluted provinces) in Table 3.1. & Figure 3.4. Table 3.2. shows the distribution of AQI exposure by industry. Firms in education, scientific research, technical service, accommodation, and food industries are more sensitive to air pollution. All of these less-polluted industries are more sensitive to air pollution. Some industries related to steel mills and chemical plants, coal-fired power plants, mining, transportation, and construction contribute heavily to air pollution[28]. If some industries are highly polluting (and they are from high AQI regions), but the investors perceive that the firm value depends on the essentially unavoidable production process, the investors' response is more likely to be lower, resulting in low exposures. Table 3.3., Panel A shows that the mean (median) of AQI exposures for non-polluting and polluting firms are 1.667 (0.900) and 1.460 (0.802), respectively. In addition, the mean (median) of AQI exposures for firms located in less-polluted provinces and polluted provinces are 1.692 (0.941) and 1.530 (0.806), respectively, as reported in Panel B. The *t*-test (Wilcoxon test) shows a significant difference in mean (median) in both panels.

The other important dimension is that air pollution is an economic 'bad' and is considered a negative externality. In other words, a zero or a very low AQI is always desirable. However, the exposure calculation is based on the abnormal AQI, where the average AQI for all cities in the same month is used as a benchmark. While the exposure measure captures investors' perception, it bypasses the importance of the inherent negative externality associated with air pollution as an economic 'bad'. Because of this, grouping firms based solely on exposures may not accurately reflect the extent of the impact of air pollution. Firms with the same high (low) exposures, irrespective of provinces with high and low air quality, should not be treated in the same group. Thus, it is necessary and reasonable to consider both the region's air pollution level (as an economic 'bad') and the firm's abnormal air pollution exposure (as perceived by

[28] Following CSRC Listed Company Industry Classification Guidelines (2012), the mining industry (B06, B07, B08, B09, B10, B11, B12), manufacturing industry (C17, C18, C19, C22, C25, C26, C27, C28, C29, C31, C32) as well as the industry of electric power and heat production and supply are classified as polluted industries (D44).

the investors) simultaneously to capture the true effects on R&D investments. To address this, we create a new variable, adjusted air pollution exposure, by multiplying the firm's air pollution exposure, *AQI exposure*, with the city-level air quality index, AQI[29]. This captures both individual exposures and regional air quality, providing a more nuanced measure of the impact of air pollution on firms. Formally,

$$\text{Adjusted air pollution exposure (A\_AQI exposure)} = \left|\beta_{i,y}^{aqi}\right| \times AQI_{i,y}$$

Such a measure ensures that two firms with very high $\left|\beta_{i,y}^{aqi}\right|$, one from a high AQI city and the other from a low AQI city, are not in the same group. A firm from a high AQI city with a high $\left|\beta_{i,y}^{aqi}\right|$ is differentiated more accurately from a firm from a low AQI city with a high $\left|\beta_{i,y}^{aqi}\right|$. Similarly, a firm from a high AQI city with a low $\left|\beta_{i,y}^{aqi}\right|$is differentiated more accurately from a firm from a low AQI city with a low $\left|\beta_{i,y}^{aqi}\right|$. In other words, AQI-adjusted exposures capture exposure to abnormal air quality and AQI levels, confirming heterogeneity among firms' exposure to AQI.

[Insert Table 3.1. & 3.2. & 3.3. here]

3.3.2.4. Corporate innovation investment

Following Chemmanur, Kong, Krishnan, and Yu (2019) and Mukherjee, Singh, and Žaldokas (2017), we measure corporate innovation investment using R&D expenses scaled by total assets (*R&D_Assets*). To facilitate the interpretation of the regression coefficients, we multiply *R&D_Assets* by 100.

[29] Nagar et al. (2019) also use the interaction term that multiplying the EPU index by EPU beta to see the interaction effect on investor information asymmetry and management disclosures.

3.3.3. Baseline model

To test the impact of adjusted air pollution exposure on corporate innovation investment, we propose the following baseline regression model:

$$Innovation_{i,y} = \alpha_0 + \beta_1 \times adjusted\ air\ pollution\ exposure_{i,y} + \gamma \times Controls_{i,y} + Year + Industry + Province + \varepsilon_{i,y} \quad (3.2)$$

where i indexes firms, and y denotes years. $Innovation_{i,y}$ refers to the corporate innovation investment of firm *i* in year *y*, measured by *R&D_Assets*. $Adjusted\ air\ pollution\ exposure_{i,y}$ is measured by $|\beta_{i,y}^{aqi}| \times AQI_{i,y}$. Following Cui et al. (2021) and Xu (2020), we control for some firm characteristics that may affect innovation investment, including firm size (*Size*), return on assets (*ROA*), growth rate of sales (*Growth*), firm financial leverage (*Lev*), the ratio of market value to book value of assets (*Tobin's Q*), managerial ownership (*Mshare*), financial constraints index (*KZ*), the top one major shareholding (*Top1*), independent directors' ratio (*IndepR*), the ratio of fixed assets (*Fixed*), number of board members (*BoardSize*), *Dual*, *Big 4*, state-owned enterprise (*SOE*) and polluting industries (*Polluter)*. The definitions of the variables are provided in Appendix B.1. All continuous variables are winsorized at the top and bottom 1% to mitigate the concern of outliers.

3.4. Empirical results

3.4.1. Descriptive statistics

We present descriptive statistics, including the mean, median, minimum, maximum, standard deviation, first quartile (*Q1*), and third quartile (*Q3*) value of variables in Table 3.4. As shown in Table 3.4., the maximum and minimum values of *R&D_Assets* are 11.650 percent and 0.010 percent, and the average value of *R&D_Assets* is 2.610 percent. These align with previous studies, such as Cui et al. (2021). Notably, the mean of *AQI exposure* is 1.610, and the median is 0.870. The mean and median for *A_AQI exposure* are 0.120 and 0.070, respectively. Regarding the control variables, the average firm size is 22.08, the average return on assets is 5.00%, and the average leverage ratio is 38%. The average fixed assets investment is 19.7%. Approximately 35% of the CEOs in our sample are also chairmen, and the top major shareholders, on average, hold 33% of firm stocks. The average board size consists of approximately 8 (log=2.10) members, 38% of whom are independent directors, consistent with the China Securities Regulatory Commission (CSRC) requirements on board independence. The distributions of the control variables are generally similar to those reported in previous research (Cui et al., 2021; Wen, Lee, & Zhou, 2022).

[Insert Table 3.4. here]

3.4.2. Baseline results

Table 5 presents the baseline regression results using firm and year fixed effects, with robustness checks incorporating industry, province, and year fixed effects, and clustering standard errors at the firm level (column 5). In columns (1) and (2), the coefficients on *AQI* and *AQI exposure* are statistically insignificant, providing preliminary support for the notion that these variables alone do not exert a consistent or significant influence on corporate innovation investment. In column (3), the coefficient on adjusted AQI exposure (*A_AQI exposure)* is -0.109 and statistically significant at the 10% level, implying that adjusted AQI exposure negatively affects the corporate innovation investment. When controlling simultaneously for *AQI* and *AQI exposure* in column (4), the coefficient on *A_AQI exposure* becomes larger (–0.484) and significant at the 5% level, reinforcing the robustness of the finding. Furthermore, when estimating the model with industry, province, and year fixed effects as well as clustering standard errors at the firm level, the coefficient on *A_AQI exposure* remains statistically significant, underscoring the robustness of the finding across alternative specifications. In the following tests, we follow Lai et al. (2023) by including year, industry, and province fixed effects and clustering standard errors at the firm level to account for potential time-varying confounders across different dimensions. Based on column (3), a one standard deviation increase in adjusted AQI exposure (SD = 0.170) is associated with a 0.71% decline in R&D intensity (*R&D_Assets*), indicating both statistically and economically meaningful effects of adjusted air pollution exposure on corporate innovation investment. Our results support the real option theory that if the investment is irreversible, the uncertainty increases the value of the option to wait, and firms can avoid sunk costs by deferring risky investment projects (Bulan, 2005; Gulen & Ion, 2016). Furthermore, *Fig. 5.* shows a clear negative correlation between *A_AQI exposure*, *AQI exposure*, and *R&D_Assets*. The findings support our baseline results, indicating that adjusted air pollution exposure negatively impacts corporate innovation investment.

The coefficients on the control variables are generally consistent with those reported in relevant studies (Cui et al., 2021; Wen et al., 2022). For example, the coefficients on *Growth*, *Tobin's Q,* and *Mshare* are all positive and significant at the 1% level, suggesting that firms with higher growth rate and higher market value are more likely to invest in innovative projects. The positive effect of managerial ownership on innovation implies that managerial ownership promotes innovative expenditures because innovation can increase a firm's long-run value. Overall, the results in Table 5 support our Hypothesis *1b*, that adjusted air pollution exposure has a negative impact on corporate innovation investment.

[Insert Table 3.5. & Figure 5 here]

To get a deeper understanding of our adjusted exposure measure, *A_AQI measure*, we re-run the baseline regressions on the absolute value of AQI exposure by creating sub-samples based on AQI quantiles, where *AQI_1* stands for First quantile (low AQI index), and *AQI_5* stands for Last quantile (high AQI index). Results reported in Appendix B.3. (Panel A) show that none of the AQI exposure coefficient estimates are statistically significant, confirming our earlier findings that AQI exposure, by itself, does not show any significant impact on R&D. We further substantiate the findings in Panel B, where four sub-samples are created based on the median value of both AQI and the absolute value of exposures: High AQI-High exposure, High AQI-Low exposure, Low AQI-High exposure, and Low AQI-Low exposure. The coefficient estimates of *A_AQI exposure* are negative and statistically significant except for High AQI-High exposure.

3.4.3. Endogeneity tests

In this section, we conduct two methods to address potential endogeneity issues: (1) controlling for multiple fixed effects and macroeconomic uncertainty and (2) propensity score matching (PSM) method.

3.4.3.1. Multiple fixed effects and macroeconomic uncertainty

To mitigate potential problems due to firm-specific, time-invariant heterogeneity and headquarters change, we re-estimate the baseline regression while controlling for firm, industry, province, and year-fixed effects (Lai et al., 2023). In addition, we add the GDP growth and GDP per capita as additional controls in *Eq. (3.2)* and re-estimate the impact of adjusted air pollution exposure on corporate innovation investment. The results in Table 3.6. show that the estimated coefficients on *A_AQI exposure* are all significantly negative, at least at the 10% level. This indicates that our baseline results are robust after controlling for multiple fixed effects and macroeconomic uncertainty.

[Insert Table 3.6. here]

3.4.3.2. Propensity score matching approach

To substantiate the observed effects of adjusted air pollution exposure on corporate innovation investment, we generate an adjusted air pollution exposure dummy variable based on its median level, which equals 1 if the firm faces high adjusted air pollution exposure and 0 otherwise. We assume there may be observable differences between firms with different adjusted air pollution exposure levels. Thus, we use the propensity score matching approach to resolve this issue.

The results from the pre-matched logistic model are presented in column (1), Panel A of Table 3.7. Then, by applying the one-to-one nearest-neighbour propensity score approach, each firm with high adjusted air pollution exposure is matched with the most similar firm with low adjusted air pollution exposure. To improve the matching accuracy, we exclude the pairs with a propensity score difference larger than 1%. We conduct two diagnostic tests to ensure matching accuracy. First, we re-conduct the logistic analysis using the propensity score-matched sample. The results are reported in column (2), Panel A of Table 3.7. All the coefficients on independent variables in the post-matched logistic model become much smaller and insignificant, suggesting no observable difference between treatment and control after matching. Second, we compare the characteristics of firms with high and low adjusted air pollution exposure using *t*-tests. The pre-matched *t*-test results are reported in Panel A of Appendix B.5., which reveals that firms are significantly different in their characteristics depending on whether they face high or low-adjusted air pollution exposure. The post-matched *t*-test results are reported in Panel B, which show no significant difference between firms with high and low adjusted air pollution exposure in the propensity score-matched sample.

Using the propensity score-matched sample, we re-estimate the baseline regression controlling for industry, province, and year-fixed effects. The results reported in Panel B of Table 3.7. show that the coefficients on *A_AQI exposure* are -0.012 and -0.083 in Columns (1) and (2) and are statistically significant at 5% and 1%, respectively. In general, the propensity score matching results confirm that the results of Table 3.5. are robust.

[Insert Table 3.7. here]

3.4.3.3. Staggered difference-in-difference analysis

In the above analysis, we confirm that there is a significant negative relationship between adjusted air pollution exposure and the corporate innovation investment, addressing endogeneity concerns through the inclusion of control variables, fixed effects, and propensity score matching (PSM) approach. In this section, we further employ a staggered difference-in-differences (DID) approach to validate our baseline results by examining an exogenous event: the implementation of the Action Plan for Air Pollution Prevention and Control and the Action Plan for Continuous Improvement of Air Quality[30].

The Action Plan for Air Pollution Prevention and Control (2013-2017), launched in 2013, was China's first comprehensive national initiative to combat air pollution. The plan aimed to address severe air quality issues by reducing particulate matter concentrations and improving overall air quality, particularly in regions experiencing the highest levels of pollution. It prioritized the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Pearl River Delta, where industrial emissions, coal combustion, and vehicle exhaust significantly contributed to pollution levels. The plan introduced a range of measures, including promoting clean energy alternatives to coal, implementing stricter vehicle emissions standards, enhancing industrial emissions controls, and encouraging the adoption of public transportation and green technologies. This plan marked a shift toward environmental accountability, with specific reduction targets set for cities and provinces[31].

Building on the achievements of the 2013 plan, the Action Plan for Continuous Improvement of Air Quality (2018-Present) expanded the scope and scale of China's air quality initiatives.

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[30] We thank the anonymous reviewer for suggesting this test and shock.

[31] More details can be found at: https://www.gov.cn/zhengce/content/2018-07/03/content_5303158.htm.

This plan broadened its focus to encompass a larger number of cities and regions, including economically developing areas in the Central Plains, Northeast China, and emerging industrial hubs. In 2018, it emphasized inter-city collaboration within key regions such as the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei region, implementing regionally coordinated air quality control measures to achieve comprehensive improvements. Since 2021, the plan has shifted its focus to region-based pollution control and the adoption of smart monitoring technologies to address pollution on a broader scale. This phase extends its efforts beyond major cities to include lower-tier cities in rapidly growing economic regions, as well as emerging industrial hubs and tourism destinations facing heightened pollution risks[32].

We construct the staggered DID regression model as follows:

$$Innovation_{i,y} = \alpha_0 + \beta_1 \times Adjusted\ air\ pollution\ exposure_{i,y} + \beta_2 \times Post_{i,y} + \beta_3 \times Aadjusted\ air\ pollution\ exposure_{i,y} \times Post_{i,y} + \gamma \times Controls_{i,y} + \varepsilon_{i,y} \quad (3.3)$$

where *i* stands for firm, and *y* denotes year. $Innovation_{i,y}$ refers to the corporate innovation investment of firm *i* in year *y*, measured by the R&D expenditure to total assets of the firm. $Adjusted\ air\ pollution\ exposure_{i,y}$ is measured by $\left|\beta_{i,y}^{aqi}\right| \times AQI_{i,y}$. $Post_{i,y}$ is the dummy variable that takes the value of 1 if the firm's headquarters city is designated as a priority air quality monitoring city in a given year, and 0 otherwise. The effect of adjusted air pollution exposure on corporate innovation after the policy launch is represented by the coefficient estimate (β_3) on $Aadjusted\ air\ pollution\ exposure_{i,y} \times Post_{i,y}$.

The estimated results are shown in Table 3.8. The *Post* coefficient is significantly positive at the 1% level, indicating that cities designated for air pollution monitoring have promoted innovation within corporations. Our main focus is on the *A_AQI exposure* × *Post* coefficient,

[32] More details can be found at: https://www.gov.cn/zhengce/content/202312/content_6919000.htm.

which measures the impact of adjusted air pollution exposure on innovation inputs of the companies following the implementation of the policy. Columns (1) and (2) both show that the DID coefficients are significantly positive at the 1% level, indicating that the launch of the Action Plan has mitigated the negative impact of adjusted air pollution exposure on innovation investments.

[Insert Table 3.8. here]

3.4.4. Robustness checks

3.4.4.1. Alternative measures of AQI_adjusted exposure

In this section, as a robustness check, we reconstruct the adjusted air pollution exposure measure using a 36-month rolling window. We control for industry, province, and year fixed effects to estimate *Eq. (3.2)*. Panel A of Table 3.9. shows that the coefficients on *A_AQI exposure (36)* are all significantly negative, at least at the 5% level in Columns (1) and (2).

Second, we construct an alternative measure of industry *A_AQI exposure* by replacing adjusted air pollution exposure in two steps. Since $|\beta_{i,t}^{aqi}|$ varies across industries, we measure the industry-adjusted exposure by subtracting $|\beta_{i,j,t}^{aqi}|$ of firm i of industry j in month t from the median[33] of exposure of industry j over the sample period, $|\overline{\beta_{j,t}^{aqi}}|$. Formally,

$$\text{Monthly industry-adjusted exposure} = |\overline{\beta_{j,t}^{aqi}}| - |\beta_{i,j,t}^{aqi}|$$

Then, we average monthly data to obtain absolute annual industry-adjusted exposure, $|\beta_{i,j,y}^{aqi}|$. Now, by multiplying this exposure with annual city-level AQI, we have industry A_AQI exposure = $|\beta_{i,j,y}^{aqi}| \times AQI_{i,y}$. We then re-run our baseline regression. Panel B of Table 3.9.

[33] Here, we also use the mean of exposure of industry j over the sample period, $|\overline{\beta_{j,y}^{aqi}}|$ as alternative measure, the results are still existing.

shows that the coefficients on industry *A_AQI exposure* are significantly negative at least at the 10% level in Columns (1) and (2).

Third, we use $|\beta_{i,y}^{aqi}|\times\log(1 + AQI_{i,y})$ as alternative measure of adjusted air pollution exposure for a robustness check to mitigate any potential non-linearity between "exposure" and "pollution". Panel C of Table 3.9. shows that the coefficients on $|\beta_{i,y}^{aqi}|\times\log(1 + AQI_{i,y})$ are both significantly negative at the 5% level in Columns (1) and (2).

[Insert Table 3.9. here]

3.4.4.2. Alternative measures of corporate innovation

Regarding the corporate innovation investment measurement, firstly, we use $R\&D\_Assets_{t+1}$ and *R&D_Sales* to replace the *R&D_Assets* as our dependent variables. The coefficients in Panels A and B of Table 3.10. on *A_AQI exposure* are still negative and significant, at least at the 10% level across all columns. The findings support our baseline results.

Secondly, Fang et al. (2014) suggest that compared with R&D investment—which measures observable innovation input—patenting activity is a good proxy for corporate innovation because it captures both innovation output and the efficiency of corporate innovation. We, therefore, use the number of invention patent applications during a fiscal year, $PAT\_Inv\_APP_{t+1}$, as the alternative measure of corporate innovation. Most of the invention patent application data used in this chapter are obtained from the CSMAR and Chinese Research Data Services Platform (CNRDS) databases, and we manually collect missing patent application data from the patent query system of the State Intellectual Property Office. The maximum and minimum natural logarithm values of the patent are 6.974 and 0, with an average value of 0.660. These align with Jie et al. (2021). The results indicate that patent applications vary greatly across sample firms. As shown in Panel C of Table 3.10., *A_AQI exposure* is negatively associated with the number of patent applications in Columns (1) and (2), at least the 5% level. The above results indicate that the negative impacts of adjusted air pollution exposure on corporate innovation investment remain significant when using patenting activity as the proxy for corporate innovation.

[Insert Table 3.10. here]

3.4.4.3. Sub-samples with positive and negative AQI sensitivity (AQI beta)

To measure firm-specific sensitivity to air pollution shocks, we regress the Fama-French three-factor model by including an air pollution anomaly factor in Eq. (1). The coefficient $\beta_{i,t}^{aqi}$ captures a firm's sensitivity to abnormal air pollution fluctuations. The sign of this coefficient (positive or negative) indicates the direction of the relationship between a firm's stock returns and abnormal changes in air quality, thereby reflecting the economic nature of the firm's exposure to pollution risk. A positive $\beta_{i,t}^{aqi}$ suggests that the firm's stock returns tend to increase with higher levels of air pollution. This typically applies to pollution-intensive firms (e.g., coal, steel) that benefit from either lax regulations or stable demand in polluted areas. Conversely, a negative $\beta_{i,t}^{aqi}$ implies that the firm's returns tend to decline as pollution worsens. This pattern is more common among environmentally sensitive or ESG-oriented firms, such as green technology companies or service-sector businesses (e.g., tourism), which face reduced consumer demand or increased costs during pollution episodes. While the sign of the sensitivity provides valuable economic interpretation, our primary focus is on the magnitude (e.g., the absolute value) of the coefficient to measure the intensity of a firm's exposure to air quality fluctuations (AQI exposure). This approach captures the extent of exposure regardless of its direction and avoids the issue of opposing effects cancelling each other out in aggregate analyses (Nagar, Schoenfeld, & Wellman, 2019).

However, if there is an asymmetric effect of positive and negative sensitivities on the dependent variable, then such transformation in absolute value would not be captured in the regression.

Thus, we divide the sample firms into two groups based on the original sign of $\beta_{i,y}^{aqi}$ and re-run the baseline regression:

Firms with positive sensitivities: $\left|\beta_{i,y}^{aqi}\right|$ when $\beta_{i,y}^{aqi} > 0$.

Firms with negative sensitivities: $\left|\beta_{i,y}^{aqi}\right|$ when $\beta_{i,y}^{aqi} < 0$.

The results are reported in Panels A and B of Table 11, which indicate that adjusted air pollution exposure negatively impacts corporate innovation regardless of whether the AQI sensitivity is originally positive or negative. In summary, the results of our baseline study remain robust, supporting our Hypothesis *1b* that adjusted air pollution exposure has a negative impact on corporate innovation investment[34].

[Insert Table 3.11. here]

3.4.5. Further analysis

3.4.5.1. Mediation effects

To explain the relationship between adjusted air pollution exposure and corporate innovation investment, we propose that firms with high adjusted air pollution exposure would exacerbate their operational risk and financial distress and be more likely to take a "wait-it-out" decision. This could serve as a potential mechanism that supports the real options theory. This study uses the net operating cash flow (*CF*) and debt financing cost (*Fincost*) to measure firms' operational risk and financial distress. Following Baron and Kenny (1986), we perform a series

[34] The effect is more pronounced for firms with positive AQI sensitivity. We thank an anonymous reviewer for spotting this interesting and valuable result. We believe this asymmetry may stem from two primary factors. First, as previously discussed, firms with positive AQI sensitivity tend to be concentrated in pollution-intensive industries. These firms are more likely to encounter tighter liquidity constraints, reflected in reduced operating performance and more limited access to low-cost financing. Second, firms in these sectors may be more vulnerable to declines in human capital efficiency, as adverse environmental conditions can negatively affect the productivity and well-being of R&D personnel. These findings are also consistent with the results of our mediation analysis. Together, these financial and operational frictions offer a plausible explanation for why the adverse effects of air pollution exposure on innovation are more pronounced among firms with positive AQI sensitivity.

of mediation analyses. Prior literature (Chen, Huang, Li, & Shevlin, 2019; Lang, Lins, & Maffett, 2012; Tsang, Xie, & Xin, 2014) has adopted this methodology to provide direct evidence on underlying channels in other settings.

The mediation analysis requires the following three conditions to be met. First, the independent variable (*A_AQI exposure*) should significantly relate to the dependent variable (*R&D_Assets*). Second, the independent variable (*A_AQI exposure*) should significantly relate to the mediator variable (i.e., *CF* or *Fincost*). Finally, the dependent variable (*R&D_Assets*) is regressed on both the independent variable (*A_AQI exposure*) and the mediators (*CF* or *Fincost*). If the mediator variable mediates the association between adjusted air pollution exposure and corporate innovation investment, the mediator should be significant, and the significance of the independent variable (*A_AQI exposure*) will be reduced after the mediator variable is added to the regression. The indirect (mediating) effect is presented in column (1) and the direct effect is shown in column (3). Following Krull and MacKinnon (2001), we use a Sobel (1982) test to examine whether the mediation effect is statistically significant.

Frijns, Gilbert, Lehnert, and Tourani-Rad (2013) show that uncertainty leads to cash flow volatility, thereby increasing operational risk. Previous research has documented that R&D expenditure decreases with increasing operational risk (Cleary, 2006; Minton & Schrand, 1999). Operational risk can, therefore, influence a firm's decision to wait, which could be a significant economic channel supporting the real options theory in its explanation of the relationship between corporate innovation investment and adjusted air pollution exposure.

Panel A of Table 3.12. shows the test results for the mediation effect of net operating cash flow (*CF*). In Column (1), the coefficient of *A_AQI exposure* is -0.242, which is the total effect, significant at the 1% level, implying that the adjusted air pollution exposure has a significant negative impact on corporate innovation investment. In Column (2), the regression coefficient of *A_AQI exposure* is significantly negative (-0.006), indicating that adjusted air pollution exposure significantly impacts the mediating variable of corporate net operating cash flow. In Column (3), the regression coefficient of the independent variable *A_AQI exposure* is -0.228 (the direct effect), still significant at the 1% level, and that of the mediating variable, *CF,* is 2.109 and significant at the 1% level. The indirect or mediating effect is, then, -0.014 (-0.242+0.228 or -0.006×2.109)[35]. Using a Sobel test, we find this mediation effect is significant with $p < 0.01$. In other words, net operating cash flow mediates around 5.2% of the total effect[36], showing it as an important channel through which adjusted air pollution exposure affects corporate innovation investment.

Previous research indicates that uncertainty exacerbates firms' financial distress. For instance, firms with greater idiosyncratic political exposure face higher costs of bank loans because of the strong positive correlation between uncertainty and information asymmetry (Francis, Hasan, & Zhu, 2014; Nagar et al., 2019). Bordo, Duca, and Koch (2016) demonstrate that as uncertainty rises, bank lending drastically decreases, which could lead to a decrease in corporate innovation investment (Aghion, Bloom, Blundell, Griffith, & Howitt, 2005). We anticipate that financial distress also increases the value of waiting, which could potentially be a key economic channel through which the real options theory explains the connection between adjusted air pollution exposure and corporate innovation investment.

Panel B of Table 3.12. shows the test results for the mediating effect of debt financing cost ($Fincost$). Following Xiang and Li (2022), corporate debt financing cost is calculated as the interest expense for the year divided by its average short- and long-term debt during the year.

[35] Because decimal places for coefficients are preserved, the number gained by these two approaches should be equivalent or extremely similar.
[36] The number is produced by Sobel test or can be calculated by mediating effect/total effect. More details about Soble test, please see https://www.trentonmize.com/software/sgmediation2.

In Column (1), the total effect measured by the coefficient of *A_AQI exposure* is -0.442 with statistical significance at the 1% level, implying that adjusted air pollution exposure adversely affects corporate innovation investment. In Column (2), the regression coefficient of *A_AQI exposure* is positive (0.071) and significant at the 1% level, which means that adjusted air pollution exposure has a significantly positive impact on the mediating variable, $Fincost$. In Column (3), while *A_AQI exposure*, direct effect, is negative and still significant at the 1% level with a value of -0.425, the coefficient estimate of the mediating variable, $Fincost$, is -0241 and significant at the 1% level. The indirect or mediating effect is, then, -0.017 (-0.442+0.425 or 0.071×-0.241). Using a Sobel test, we find this mediation effect is significant with $p < 0.01$. In other words, 3.9% of the total effect is mediated by the debt financing cost, supporting that debt financing cost is an important channel through which adjusted air pollution exposure affects corporate innovation investment.

[Insert Table 3.12. here]

3.4.5.2. Human capital effect[37]

In this section, we examine the role of human capital in this relationship using firms' R&D personnel ratio as a proxy for their reliance on human capital in innovation activities. The productivity and proportion of R&D staff in R&D-intensive firms is a critical factor that draws significant attention of managers and investors. Deteriorating air quality could affect firm innovation as it leads to health issues among key talents, such as increased absenteeism, reduced focus, and even turnover (Bakian et al., 2015; Luo, Chen, & Lin, 2022), and this effect will be stronger in firms with more R&D personnel. This low efficiency and productivity of human capital could therefore decrease firm innovation inputs and outputs, especially for the R&D intensive firms.

[37] We thank the anonymous reviewer for suggesting this test.

We divide the full sample into two groups based on the firms' R&D personnel ratio, categorizing them as either above or below the median level. The sub-sample regression results are presented in Table 3.13, we find that the negative impact of adjusted air pollution exposure on R&D inputs and outputs is more pronounced for R&D intensive firms with a higher R&D personnel ratio. The findings support our conjecture that firms with high adjusted air pollution exposure face challenges such as increased absenteeism and reduced efficiency among R&D personnel, which ultimately hinders innovation input and output.

[Insert Table 3.13 here]

3.4.5.3. Moderating effects

To explore the factors that can mitigate the negative relationship between adjusted air pollution exposure and corporate innovation investment, we introduce the interaction term of corporate ownership type with adjusted air pollution exposure. We use the state-owned enterprises dummy (*SOE*) and interact it with adjusted air pollution exposure. Compared with non-state-owned enterprises, state-owned enterprises have easier access to loans (Dewenter & Malatesta, 2001) to support long-term and risky innovation investment, being in a better position in innovation than non-state-owned enterprises. The regression results are reported in Table 3.14. We find that the regression coefficients of the interaction term of SOE and adjusted air pollution exposure, *A_AQI exposure* × *SOE*, are 0.642 and 0.873 in Columns (1) and (2), respectively, with statistical significance at least at the 5% level, while the coefficients of *A_AQI exposure* are still statistically significant. This indicates that state ownership can mitigate the negative impact of adjusted air pollution exposure on firm innovation activity.

[Insert Table 3.14. here]

3.4.5.4. Heterogeneity tests

Our findings thus far support the hypothesis that adjusted air pollution exposure negatively impacts corporate innovation investment. However, different internal and external characteristics may generate different results of this impact. To this end, we explore three internal factors: (a) environmental disclosures, (b) manager's risk tolerance, and (c) firm characteristics, such as polluter vs. non-polluter.

First, according to Solikhah and Maulina (2021), environmental disclosures represent a form of corporate responsibility to society by informing people about any negative environmental impact resulting from firm operations. Lin, Huang, and Yao (2021) find that the enterprises have poorer environmental governance and are more indifferent to environmental issues in more polluting areas, resulting in lower-quality or no environmental information disclosures. We expect that our baseline result will be more prominent in firms with environmental information disclosure because these firms pay more attention to environmental issues and are thus more susceptible to the effects of air pollution. Second, the prevailing perception in academic research is that CEO personal risk preferences tend to affect firm risk and performance by implementing different policies (Lewellen, 2006; Schooley & Worden, 1996). Cen and Doukas (2017) find that risk-taking CEOs pursue risky financial and investment policies. Caliendo, Cobb-Clark, Pfeifer, Uhlendorff, and Wehner (2024) find that risk-aversion managers are sensitive to the investment risk associated with training, avoiding more costly training or targeting those with less occupational expertise or nearing retirement. In light of this, we expect managers with low-risk tolerance to be more easily impacted by the firm's uncertainty and make conservative investment decisions. Third, data in Table 2 shows that firms in less polluted industries have higher air pollution exposures. This means that non-polluters are more sensitive to air pollution levels. In light of the above discussion, we expect that the impact of adjusted air pollution exposure on corporate innovation investment is more salient for firms with environmental disclosures, low managers' risk tolerance, and firms belonging to a non-polluted industry.

To investigate these three internal factors, we divide the full sample into two groups by checking whether information on the environment is disclosed in the listed firms' annual reports. We also divide sample firms into two groups based on the manager's risk tolerance, measured above or below the median level of the firm's illiquid assets to total assets. Finally, following the Ministry of Environment and Ecology classifications, we divide the sample firms into polluters and non-polluters. The sub-sample regression results are reported in columns (1), (3), and (5) in Panel A of Table 15 showing that the estimated coefficients of *A_AQI exposure* are negatively and significantly at the 1% levels for firms with environmental information disclosures, low manager's risk tolerance, and non-polluter firms as expected[38]. Furthermore, the *Chow*-tests indicate that the coefficients differ significantly across different sub-samples.

We also consider three external factors: (a) well-developed vs. developing provinces, (b) less-polluted vs. more-polluted provinces, and (c) before and after the 2015 Paris Agreement. First, Bao and Liu (2022) find that environmental attention in developed provinces, such as southern regions, is higher than in the northern regions. The governments in southern regions pay more attention to environmental issues and deal with air pollution issues positively. Similarly, Huang, Ding, and Failler (2022) find that improving government environmental attention inhibits ambient pollution through green development and industrial upgrading. However, this phenomenon is generally more pronounced in developed provinces. Furthermore, due to the Qinling-Huai River policy[39], the average air quality in southern provinces is better than in northern provinces. Therefore, we expect a more pronounced negative effect for firms in well-developed and less polluted provinces. Second, the Paris Agreement is a climate change

[38] Each regression includes GDP growth and per capita GDP by provinces as additional controls and other firm-level characteristics.

[39] The Huai River (please see Figure 3.3) splits China into northern and southern parts, and China's central government provides free winter heating only in cities north of the Huai River. Because the centralized winter heating system rests on the use of inefficient coal-based hot water boilers, which leads to substantial energy loss and releases a significant amount of air pollutants. This policy has unintentionally worsened air quality in northern regions, creating a discontinuity in terms of AQI for cities across the two sides of the Huai River (Lepori, 2016; Li et al., 2021).

agreement signed by 196 countries worldwide and is a unified arrangement for global action to address climate change after 2020. The Paris Agreement was formally put into effect on November 4, 2016, after being approved at the Paris Climate Conference on December 12, 2015, and signed at the United Nations building in New York, USA, on April 22, 2016. On 3 September 2016, the Standing Committee of the National People's Congress (NPC) approved China's accession to the Paris Climate Change Agreement, becoming one of the parties that completed ratification of the agreement[40]. Since then, several carbon policies and pollution protection regulations have been created (Dai & Zhang, 2023; Su, Naqvi, Shao, Li, & Jiao, 2020). Concerns and awareness about air pollution are given higher priority by both the central government and municipal governments. Thus, a natural question arises whether our baseline results are more pronounced after the 2015 Paris Agreement was signed.

To investigate these three external factors, first, we divide sample firms into developed and developing provinces based on the Fan-Gang marketization index; second, we divide sample firms into more polluted and less polluted provinces based on the median level of the air quality index of the firms' headquarters' locations; third, we divide firms into two subsamples: "Before 2015 (including 2015)" and "After 2015". Results reported in columns (1) and (3) in Panel B of Table 3.15 show that the estimated coefficients of *A_AQI exposure* are negative and highly significant for the firms located in well-developed, less polluted provinces, as expected. For the "After 2015" subsample, column (5) in Panel B shows the coefficient estimate of *A_AQI exposure* is -0.914 with a statistical significance level of 1%. Furthermore, the *Chow*-tests also show that the coefficients differ significantly across different sub-samples. The finding is consistent with our conjectures.

[Insert Table 3.15. here]

[40] More details please see: https://unfccc.int/process-and-meetings/the-paris-agreement.

3.5. Conclusion

This chapter creates a novel measure of air pollution exposure by combining the city-level air quality index and the firm-level exposure to air pollution, and examines the impact of adjusted air pollution exposure on corporate innovation investment in China. This new measure captures the firms' exposures to abnormal air pollution as perceived by the investors but does not bypass the importance of the inherent negative externality associated with air pollution as an economic 'bad'. We focus on corporate innovation investment because it is unlike traditional investments in tangible assets like capital expenditures, and innovation represents long-term, intangible assets intended to generate future profits. Besides this, innovation requires a longer time horizon and carries higher tail risk. The option to wait is particularly significant for investments in research and development (R&D), given that innovation involves exploring unknown approaches and untested methods (Ferreira et al., 2014), requiring substantial investment in intangible assets.

We find that adjusted air pollution exposure has a negative impact on corporate innovation investment. The results still hold after addressing endogeneity issues and applying a series of robustness checks and endogeneity tests. More importantly, our mediation analysis results suggest that a firm's operational risk and financial distress are critical mediating factors of this impact. We find that adjusted air pollution exposure lowers firms' corporate innovation investment due to reduced corporate net operating cash flow and increased debt financing cost. Our results favour the real options theory which argues that if the investment is irreversible, the uncertainty increases the value of the option to wait, and firms can avoid sunk costs by deferring risky investment projects (Bulan, 2005; Gulen & Ion, 2016). Additionally, we also find that firms with high adjusted air pollution exposure face challenges such as increased absenteeism and reduced efficiency among R&D personnel, which ultimately hinders both innovation input and output. Our results also indicate that state ownership can mitigate the negative impact of adjusted air pollution exposure on innovation investment. Furthermore, the adverse effects of adjusted air pollution exposure are more pronounced for firms with environmental disclosure, low managerial risk tolerance, non-polluting firms, and those located in developed and less polluted provinces. We also observe a significant negative effect of air pollution on firm innovation investment following the 2015 Paris Climate Agreement. Finally, in additional tests examining the differential effects of adjusted air pollution exposure on general technological innovation versus green innovation, we find that firms with high exposure may shift their focus toward environmentally adaptive technologies, likely in response to regulatory or reputational risks.

3.6. Tables and figures

Figure 3.1. The time trend of China's average annual air quality index (AQI)
The figure presents the time-trend of China's average annual AQI from 2000 to 2022.

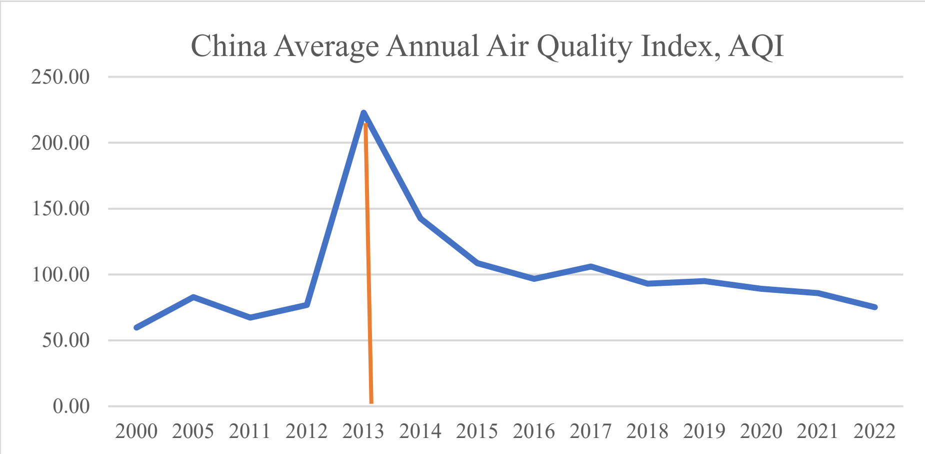

Figure 3.2. The time trend of China's average annual population weighted $PM_{2.5}$ (μg/m^3)
The figure presents the time-trend of China's average annual population weighted $PM_{2.5}$(μg/m^3) from 1990 to 2019.

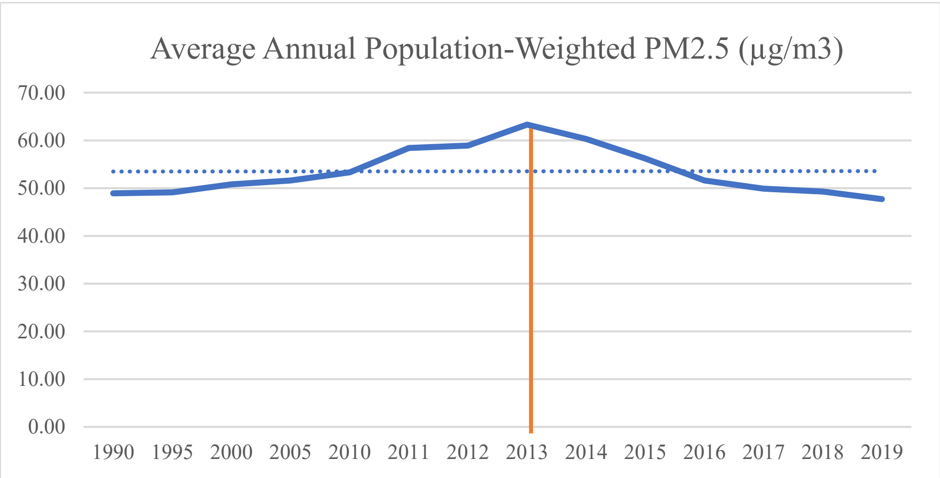

Figure 3.3. Average air quality index (AQI) among provinces between 2010 and 2022

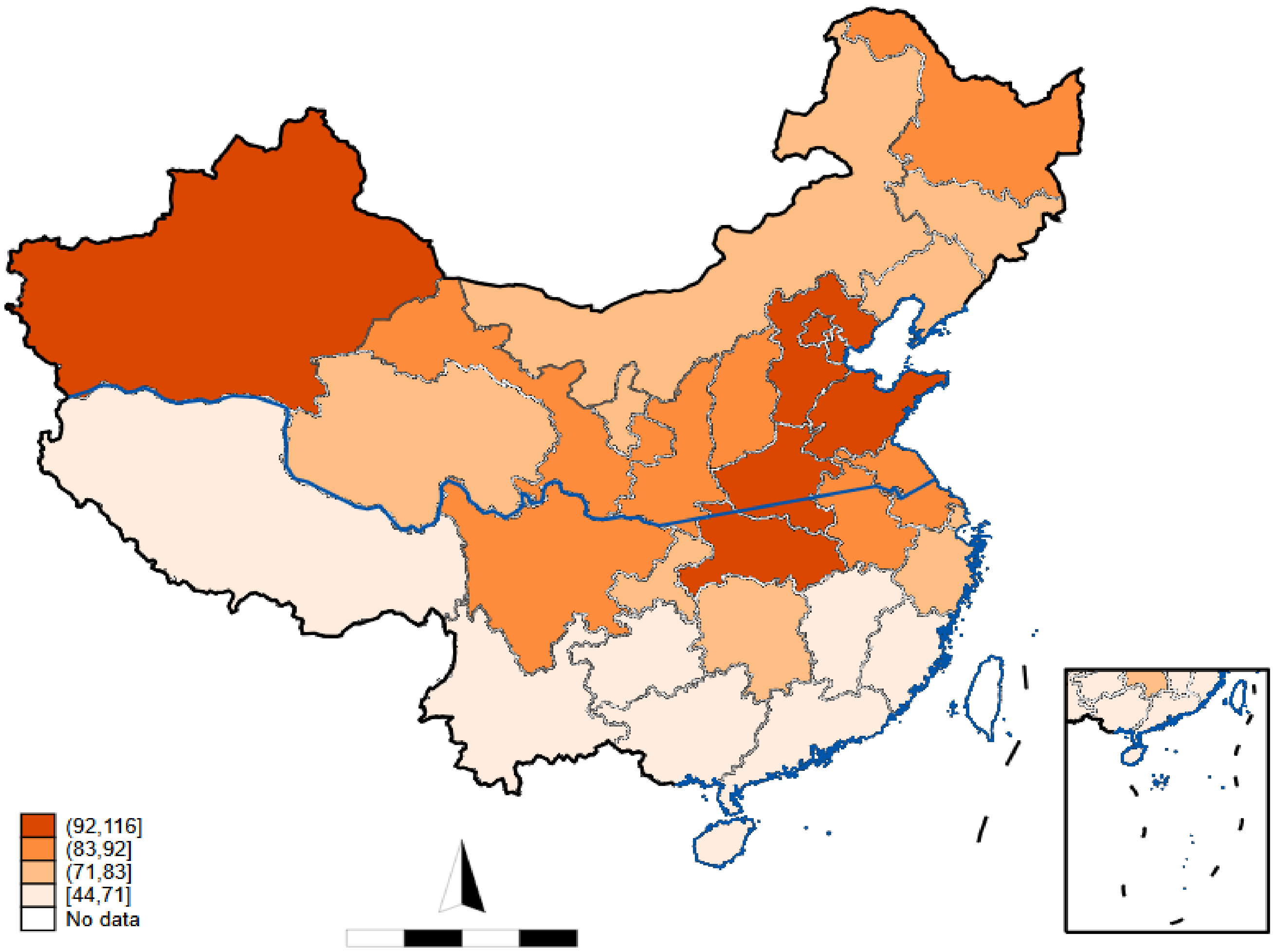

Figure 3.4. Average air pollution exposure (AQI exposure) among provinces between 2010 and 2022

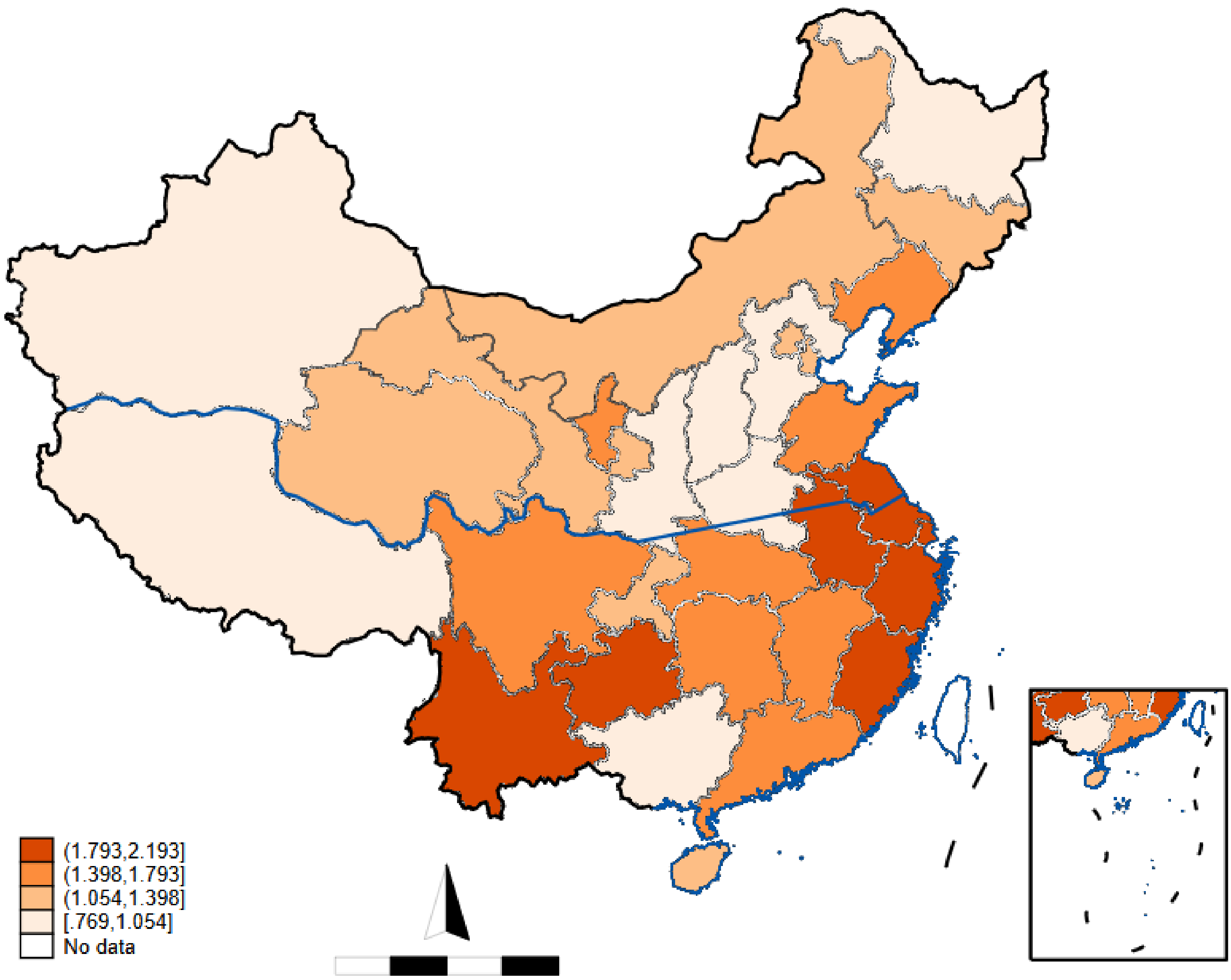

Figure 3.5. The time trend for AQI exposure, A_AQI exposure, and R&D_Assets

The figure presents the time-trend for China's AQI exposure, A_AQI exposure, and R&D_Assets from 2010 to 2022. The definitions of these three variables are provided in Appendix A.

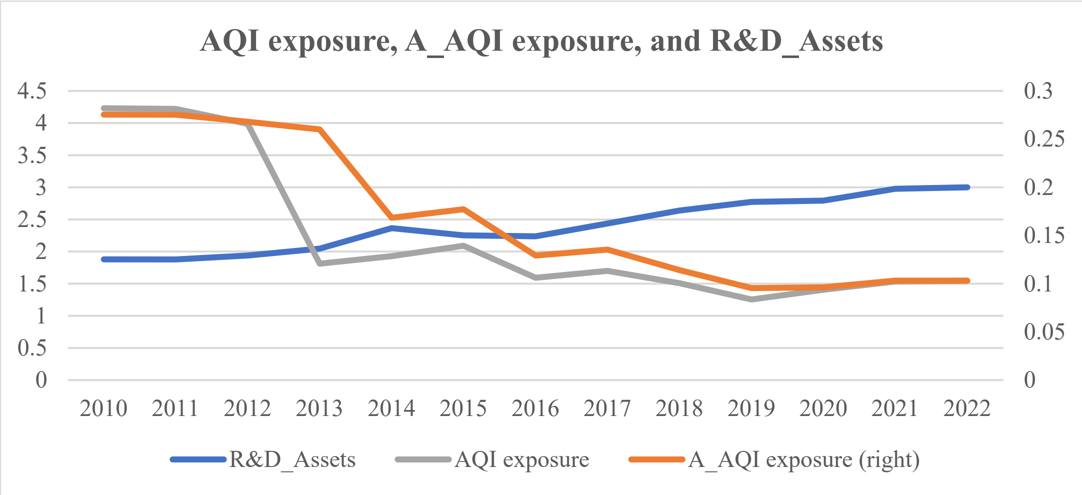

Table 3.1. Distribution of air pollution exposure (AQI exposure) by province

This table reports the distribution of AQI exposure by province in our sample period.[41]

Province_Chinese	Southern or Northern province	Province_English	N	Mean	Province_Chinese	Southern or Northern province	Province_English	N	Mean
贵州省	Southern	Guizhou Province	132	2.193	辽宁省	Northern	Liaoning Province	260	1.793
上海市	Southern	Shanghai	1,116	1.990	山东省	Northern	Shandong Province	971	1.636
江苏省	Southern	Jiangsu Province	2,243	1.947	宁夏回族自治区	Northern	Ningxia Hui	24	1.491
福建省	Southern	Fujian Province	605	1.884	天津市	Northern	Tianjin	243	1.360
安徽省	Southern	Anhui Province	532	1.879	青海省	Northern	Qinghai Province	33	1.341
浙江省	Southern	Zhejiang Province	2,338	1.840	内蒙古自治区	Northern	Inner Mongolia	107	1.281
云南省	Southern	Yunnan Province	113	1.827	甘肃省	Northern	Gansu Province	115	1.262
湖北省	Southern	Hubei Province	346	1.767	吉林省	Northern	Jilin Province	99	1.254
江西省	Southern	Jiangxi Province	204	1.737	北京市	Northern	Beijing	1,709	1.123
四川省	Southern	Sichuan Province	468	1.726	陕西省	Northern	Shaanxi Province	219	1.054
广东省	Southern	Guangdong Province	3,050	1.546	西藏自治区	Northern	Tibet	34	1.030
湖南省	Southern	Hunan Province	503	1.530	河南省	Northern	Henan Province	426	0.970
海南省	Southern	Hainan Province	68	1.398	河北省	Northern	Hebei Province	292	0.961
重庆市	Southern	Chongqing	190	1.098	山西省	Northern	Shanxi Province	114	0.911
广西壮族自治区	Southern	Guangxi	131	1.008	新疆维吾尔自治区	Northern	Xinjiang Uygur	154	0.888
					黑龙江省	Northern	Heilongjiang Province	114	0.769

[41] The southern and northern provinces are divided by the Qinling-Huai River (QH) heating policy. The Huai River splits China into northern and southern parts, and China's central government provides free winter heating only in cities north of the Huai River (Lepori, 2016; Li et al., 2021).

Table 3.2. Distribution of air pollution exposure (AQI exposure) by industry

This table reports the distribution of AQI exposure by industry in our sample period.

Industry	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
Education	13	2.240	0.878	0.006	11.544	3.938	0.506	1.187	1.881
Scientific research, technical service and geologic examination industry	268	2.142	1.116	0.001	11.544	2.666	0.483	2.464	2.060
Accommodation and food industry	1,586	1.876	1.078	0.001	11.544	2.357	0.477	2.152	2.410
Manufacturing industry	12,526	1.642	0.876	0.000	11.544	2.198	0.376	1.872	2.688
Leasehold and business service industry	159	1.578	1.075	0.023	11.544	1.776	0.581	1.995	3.123
Traffic, storage and mail business	303	1.421	0.802	0.000	11.544	1.851	0.424	1.648	3.268
Cultural, physical and entertainment industry	197	1.401	0.978	0.054	11.003	1.528	0.426	1.800	2.998
Water conservancy, environment and public institution management	223	1.394	0.753	0.003	11.544	1.898	0.288	1.603	2.791
Farming, forestry, animal husbandry and fishery	182	1.286	0.725	0.003	10.555	1.592	0.324	1.623	2.732
Information transfer, computer service and software industry	276	1.235	0.787	0.001	11.544	1.617	0.397	1.429	3.701
Production and supply of electric power, gas and water	234	1.226	0.623	0.004	11.544	2.124	0.247	1.141	3.684
Public administration and social organization	7	1.191	0.994	0.736	2.439	0.583	0.840	1.243	1.598
Construction industry	473	1.153	0.653	0.000	11.544	1.754	0.302	1.250	3.911
Sanitation, social security and social welfare industry	40	1.138	0.705	0.022	7.787	1.444	0.347	1.255	2.948
Neighborhood services and other service industry	4	1.085	1.123	0.578	1.515	0.401	0.782	1.387	-0.276
Wholesale and retail trade	20	0.968	0.465	0.007	10.555	2.275	0.246	0.754	4.022
Realty business	103	0.923	0.555	0.010	8.061	1.194	0.251	1.113	3.475
Total	16,952	1.610	0.871	0.000	11.544	2.163	0.374	1.830	2.746

Table 3.3. Mean and median difference of AQI exposure by industry and province

This table reports the mean and median difference of AQI exposure by industry and province. In Panel A, dummy variable that equals 1 if firm *i* belongs to the polluting industries, and 0 otherwise. Categorizations of these industries follow the CSRC Listed Company Industry Classification Guidelines (2012). In Panel B, dummy variable equals 1 if firm *i* is located in the heavily polluted provinces, and 0 otherwise. Categorizations of the heavily or not heavily polluted provinces follow the rules that are above and below the median level of the AQI index of all provinces in our sample.

Panel A: *t*-test and Wilcoxon test by heavy polluted industry						
	Non-polluters		Polluters		Diff	*t*-value
	N	Mean	N	Mean		
t-test	12,348	1.667	4,604	1.460	0.207***	5.54
	Non-polluters		Polluters		Diff	*p*-value
	N	Median	N	Median		
Wilcoxon test	12,348	0.900	4,604	0.802	0.098***	0.00
Panel B: *t*-test and Wilcoxon test by heavy polluted provinces						
	Less-polluted provinces		Polluted provinces		Diff	*t*-value
	N	Mean	N	Mean		
t-test	8,440	1.692	8,512	1.530	0.162***	0.00
	Less-polluted provinces		Polluted provinces		Diff	*p*-value
	N	Median	N	Median		
Wilcoxon test	8,440	0.941	8,512	0.806	0.135***	0.00

Table 3.4. Summary statistics

This table presents the summary statistics for the sample: mean, median, minimum, maximum, standard deviation, 25%,75%, and skewness of variables. *R&D_Assets* is the ratio of R&D expenditure to total assets of each firm and then multiplied by 100. *A_AQI exposure* is the interaction term that takes a value of AQI × AQI exposure. *AQI* is the yearly average Air Quality Index (AQI) in which a firm is headquartered. *AQI exposure* is the absolute value of AQI beta calculated based on the Fama-French three-factor model. The definitions of the variables are provided in Appendix B.1. We winsorize the data at the 1% and 99% levels.

Variable	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
R&D_Assets	16, 952	2.610	2.190	0.010	11.650	2.120	1.240	3.370	1.770
A_AQI exposure	16, 952	0.120	0.070	0.000	1.680	0.170	0.030	0.140	3.030
AQI	16, 952	0.080	0.080	0.020	0.250	0.020	0.060	0.090	1.190
AQI exposure	16, 952	1.610	0.870	0.000	11.540	2.160	0.370	1.830	2.750
Size	16, 952	22.080	21.890	19.520	26.430	1.220	21.220	22.700	1.000
ROA	16, 952	0.050	0.051	-0.400	0.250	0.070	0.020	0.080	-1.480
Lev	16, 952	0.380	0.370	0.030	0.920	0.190	0.230	0.520	0.330
Growth	16, 952	0.190	0.130	-0.660	4.330	0.370	0.000	0.290	3.410
Tobin's Q	16, 952	2.180	1.760	0.800	17.730	1.370	1.340	2.520	2.850
KZ	16, 952	0.776	1.059	-6.227	5.037	2.144	-0.377	2.239	-0.788
Top 1	16, 952	0.330	0.310	0.080	0.750	0.140	0.220	0.430	0.550
BoardSize	16, 952	2.100	2.200	1.610	2.710	0.190	1.950	2.200	-0.360
IndepR	16, 952	0.380	0.360	0.290	0.600	0.050	0.330	0.430	1.120
Dual	16, 952	0.350	0.000	0.000	1.000	0.480	0.000	1.000	0.640
Mshare	16, 952	0.190	0.110	0.000	0.710	0.210	0.000	0.360	0.750
Fixed	16, 952	0.197	0.171	0.002	0.714	0.139	0.089	0.274	0.951
Big 4	16, 952	0.050	0.000	0.000	1.000	0.220	0.000	0.000	4.000
Listage	16, 952	1.780	1.950	0.000	3.090	0.800	1.390	2.400	-0.600
SOE	16, 952	0.210	0.000	0.000	1.000	0.400	0.000	0.000	1.460
Polluter	16, 952	0.270	0.000	0.000	1.000	0.440	0.000	1.000	1.030
Inv_PAT_APP	13, 808	0.660	0.000	0.000	6.974	1.012	0.000	1.099	1.842

Table 3.5. Baseline regressions

This table reports the results of baseline regressions. It shows the impact of adjusted air pollution exposure on corporate innovation investment. The dependent variables are *R&D_Assets*, measured by R&D expenditure to total assets of each firm and then multiplied by 100 in $year_t$. The main independent variable is *A_AQI exposure*, measured by the *AQI* × *AQI exposure*. Definitions of variables are presented in Appendix A. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	(1)	(2)	(3)	(4)	(5)
A_AQI exposure			-0.109*	-0.484**	-0.478**
			(-1.79)	(-2.28)	(-2.20)
AQI	-0.664			0.212	-0.477
	(-0.68)			(0.20)	(-0.21)
AQI exposure		-0.005		0.032*	0.021
		(-1.10)		(1.86)	(1.42)
Size	0.010	0.010	0.012	0.013	0.001
	(0.10)	(0.12)	(0.10)	(0.11)	(0.03)
ROA	-0.077	-0.078	-0.076	-0.074	1.701**
	(-0.51)	(-0.52)	(-0.51)	(-0.50)	(2.66)
Lev	-0.142	-0.144	-0.141	-0.140	0.012
	(-1.47)	(-1.48)	(-1.46)	(-1.44)	(0.97)
Growth	0.046**	0.046**	0.046**	0.046**	0.032
	(2.24)	(2.26)	(2.27)	(2.26)	(0.29)
Tobin's Q	0.072***	0.072***	0.072***	0.072***	0.334***
	(8.79)	(8.83)	(8.86)	(8.82)	(8.13)
KZ	-0.042***	-0.042***	-0.042***	-0.041***	-0.022**
	(-6.48)	(-6.44)	(-6.42)	(-6.43)	(-1.98)
Top1	0.060	0.061	0.062	0.066	-0.947***
	(0.37)	(0.38)	(0.39)	(0.41)	(-3.14)
Board	0.444***	0.444***	0.445***	0.446***	0.158**
	(4.90)	(4.90)	(4.91)	(4.92)	(2.67)
IndepR	0.242	0.240	0.238	0.237	0.357
	(0.88)	(0.87)	(0.86)	(0.86)	(0.73)
Dual	0.024	0.024	0.023	0.023	0.098**
	(0.97)	(0.97)	(0.96)	(0.94)	(2.93)
Mshare	0.198**	0.196**	0.195*	0.196*	0.354***
	(1.97)	(1.96)	(1.95)	(1.95)	(3.93)
Fixed	0.612	0.612	0.612	0.617	-1.631***
	(1.47)	(1.49)	(1.48)	(1.48)	(-10.92)
Big4	0.230***	0.228***	0.229***	0.231***	0.451**
	(2.77)	(2.75)	(2.75)	(2.78)	(2.29)

List age	-0.087***	-0.103***	-0.113***	-0.109***	-0.207***
	(-2.59)	(-2.83)	(-3.09)	(-2.98)	(-6.68)
SOE	-0.094	-0.094	-0.094	-0.093	0.099
	(-1.64)	(-1.63)	(-1.63)	(-1.63)	(0.94)
Polluter	0.098	0.099	0.099	0.096	-0.315***
	(1.05)	(1.06)	(1.06)	(1.03)	(-14.31)
Constant	10.879***	10.869***	10.899***	10.877***	2.009**
	(18.85)	(18.99)	(19.04)	(18.81)	(2.57)
Firm	Yes	Yes	Yes	Yes	No
Year	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	No	Yes
Province	No	No	No	No	Yes
S.E. Cluster	No	No	No	No	Firm
N	16,393	16,393	16,393	16,393	16,952
Adj R-squared	0.864	0.864	0.863	0.864	0.275

Table 3.6. Endogeneity test: Multiple fixed effects and macroeconomic uncertainty
This table reports the results of endogeneity test on the baseline results. We control the firm, year, province, and industry fixed effects and also control the macroeconomic uncertainty based on the *Eq. (3.2)*. The *t*-statistics are reported in parentheses. The symbol *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	(1)	(2)	(3)
A_AQI exposure	-0.110*	-0.500**	-0.496**
	(-1.81)	(-2.36)	(-2.33)
AQI		-0.039	-0.027
		(-0.04)	(-0.03)
AQI exposure		0.034*	0.033
		(1.94)	(1.71)
GDP growth			-0.064
			(-0.12)
GDP per capita			0.127
			(0.41)
Constant	11.612***	11.609***	11.600***
	(20.08)	(19.88)	(19.81)
Controls	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Province	Yes	Yes	Yes
N	16,393	16,393	16,393
Adj R-squared	0.664	0.664	0.669

Table 3.7. Endogeneity test: Propensity scores matching analysis

Table 3.7. presents the results of a propensity score matching analysis. We generate an adjusted air pollution exposure dummy variable based on the median level of exposure. Panel A reports the parameter estimates from the logit model used to estimate propensity scores. The adjusted air pollution exposure dummy is the dependent variable, which equals 1 if the firm faces high adjusted air pollution exposure and 0 otherwise. Panel B reports the results of re-estimating the baseline regression using the propensity score-matched sample. The dependent variable is the *R&D_Assets*. Definitions of variables are in Appendix B.1. The *z*-statistics (*t*-statistics) are calculated based on robust standard errors and are reported in parentheses. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Propensity score regression (Logit model)			Panel B: Matched sample regression analysis	
	Pre-match	Post-match		
	(1)	(2)	(1)	(2)
Variables	Exposure dummy	Exposure dummy	*R&D_Assets*	*R&D_Assets*
A_AQI exposure			-0.122**	-0.083*
			(-2.51)	(-1.73)
AQI				-0.682
				(-0.46)
AQI exposure				-0.016
				(-1.51)
Size	-0.025***	-0.006	-0.050	-0.051
	(-5.31)	(-0.75)	(-1.36)	(-1.38)
ROA	0.117*	-0.140	1.684**	1.689**
	(1.83)	(-1.33)	(2.42)	(2.43)
Lev	0.115***	0.036	0.068	0.072
	(4.39)	(0.85)	(0.36)	(0.37)
Growth	0.039***	-0.007	0.040	0.042
	(3.68)	(-0.40)	(0.45)	(0.47)
Tobin's Q	0.018***	0.002	0.328***	0.328***
	(5.65)	(0.38)	(9.19)	(9.20)
KZ	0.181	0.079	-0.021**	-0.022**
	(1.72)	(1.03)	(-1.98)	(-2.01)
Top1	-0.078***	0.004	-1.466***	-1.466***
	(-2.78)	(0.08)	(-8.51)	(-8.53)
Board	-0.041	-0.033	-0.054	-0.052
	(-1.59)	(-0.79)	(-0.28)	(-0.27)
IndepR	-0.254	0.029	-0.412	-0.416
	(-1.23)	(0.20)	(-0.67)	(-0.68)
Dual	-0.013	-0.002	0.195***	0.195***
	(-1.63)	(-0.16)	(3.64)	(3.63)
Mshare	-0.026	0.021	0.482***	0.480***
	(-1.23)	(0.56)	(3.48)	(3.47)

Fixed	-0.012	-0.010	-1.631***	-1.631***
	(-0.34)	(-0.50)	(-13.09)	(-10.97)
Big4	-0.009	-0.001	0.429***	0.431***
	(-0.50)	(-0.03)	(3.30)	(3.31)
List age	-0.179***	0.004	-0.292***	-0.303***
	(-29.77)	(0.38)	(-5.99)	(-5.85)
SOE	-0.022*	-0.017	0.109	0.114*
	(-1.94)	(-0.96)	(1.62)	(1.67)
Polluter	-0.005	-0.018	-0.243***	-0.243***
	(-0.53)	(-1.22)	(-4.44)	(-4.44)
Constant	1.697***	0.917	1.809*	1.911*
	(13.16)	(0.34)	(1.81)	(1.91)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Observations	16,952	12,140	12,140	12,140
Pseudo R^2	0.133	0.028	0.295	0.296

Table 3.8. Endogeneity test: Staggered difference-in-difference approach

Table 8 presents the results of a staggered difference-indifference approach. We utilize the Action Plan for Air Pollution Prevention and Control, along with the Action Plan for Continuous Improvement of Air Quality, to examine whether air quality monitoring pilot cities could serve as a shock. The dependent variable is the *R&D_Assets*. $Post_{i,y}$ is the dummy variable that takes the value of 1 when the firm's headquarter city is designated as air quality monitoring city in a given year and 0 otherwise. The effect of adjusted air pollution exposure on corporate innovation after the policy launch is represented by the coefficient estimate on $Aadjusted\ air\ pollution\ exposure_{i,y} \times Post_{i,y}$. Definitions of variables are in Appendix A. The t-statistics are reported in parentheses. The superscripts *, **, and ***indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	*R&D_Assets*	*R&D_Assets*
Model	(1)	(2)
A_AQI exposure	-0.428***	-0.670*
	(-3.74)	(-1.75)
Post	0.087**	0.135***
	(2.30)	(3.27)
A_AQI exposure × Post	0.455**	0.456**
	(2.26)	(2.57)
AQI		-2.545**
		(-2.37)
AQI exposure		0.022
		(0.74)
Constant	2.233***	2.379***
	(4.96)	(5.22)
Controls	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,952	16,952
Adj R-squared	0.284	0.284

Table 3.9. Robustness check: Alternative measures of adjusted air pollution exposure

This table reports the results of robustness checks of the baseline results. In panel A, we reconstruct the adjusted air pollution exposure measure using the 36-month rolling window, *A_AQI exposure (36)*. In panel B, we run the baseline results using the industry *A_AQI exposure*, which takes the value of industry-adjusted exposure (median) × AQI. In panel C, we run the baseline results using the $|\beta_{i,t}^{aqi}|\times\log(1+AQI_{i,y})$ as alternative independent variable. The *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative adjusted air pollution exposure: A_AQI exposure (36)			Panel B: Alternative adjusted air pollution exposure: *Industry A_AQI exposure*		Panel C: Alternative adjusted air pollution exposure: $\lvert\beta_{i,t}^{aqi}\rvert\times\log(1+AQI_{i,y})$	
Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	(1)	(2)	(1)	(2)	(1)	(2)
A_AQI exposure (36)	-1.283***	-1.261**				
	(-5.16)	(-2.83)				
Industry A_AQI exposure			-0.218**	-0.413*		
			(-2.24)	(-1.85)		
$\lvert\beta_{i,y}^{aqi}\rvert\times\log(1+AQI_{i,y})$					-0.004**	-0.042**
					(-2.31)	(-2.51)
AQI		-0.705		-0.928		
		(-0.21)		(-0.42)		
$\log(1+AQI_{i,y})$						-0.134
						(-0.78)
AQI exposure (36)		-0.015				
		(-0.27)				
$\lvert\beta_{i,y}^{aqi}\rvert$ (AQI exposure)				0.016		0.175*
				(1.20)		(2.19)
Constant	1.578***	1.618	1.972***	2.014**	2.174***	3.385**
	(3.70)	(1.51)	(4.37)	(2.20)	(4.82)	(2.97)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	17,703	17,703	16,952	16,952	16,952	16,952
Adj R-squared	0.283	0.283	0.275	0.275	0.282	0.308

Table 3.10. Robustness check: Alternative measures of corporate innovation

This table reports the results of the robustness check based on the baseline results. In panel A, the dependent variable is $R\&D\_Assets_{t+1}$, measured by R&D expenditure to the total assets of each firm in $year_{t+1}$ (multiplied by 100). In panel B, the dependent variable is *R&D_Sales*, measured by R&D expenditure to the sales of each firm. Panel C shows the impact of adjusted air pollution exposure on invention patent applications in the following fiscal year, $Inv\_PAT\_APP_{t+1}$. The main independent variable is adjusted air pollution exposure, measured by the $AQI \times AQI\ exposure$. Definitions of variables are presented in Appendix B.1. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: $R\&D\_Assets_{t+1}$			Panel B: *R&D_Sales*		Panel C: $Inv\_PAT\_APP_{t+1}$	
Variables	$R\&D\_Assets_{t+1}$	$R\&D\_Assets_{t+1}$	*R&D_Sales*	*R&D_Sales*	$Inv\_PAT\_APP_{t+1}$	$Inv\_PAT\_APP_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
A_AQI exposure	-0.861***	-0.105*	-0.861***	-2.099*	-0.108***	-0.091**
	(-3.78)	(-1.73)	(-3.78)	(-1.90)	(-3.63)	(-2.49)
AQI		0.901		8.759		2.415*
		(0.44)		(1.60)		(1.89)
AQI exposure	0.062*	0.077	0.062*	0.151		-0.004
	(1.93)	(1.50)	(1.93)	(1.43)		(-0.59)
Constant	1.959**	1.904*	1.959**	-1.383	-4.068***	-4.192***
	(2.93)	(1.75)	(2.93)	(-0.66)	(-2.92)	(3.41)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	13,048	13,048	16,952	16,952	10,583	10,583
Adj R-squared	0.260	0.260	0.260	0.345	0.202	0.203

Table 3.11. Sub-samples with positive and negative AQI sensitivity (AQI beta)

This table reports the results of further robustness checks on the baseline results. In panel A, we run the baseline results using adjusted air pollution exposure under the positive AQI sensitivity (AQI beta) sample with industry, province, and year fixed effect. In panel B, we run the baseline results using adjusted air pollution exposure under the negative AQI sensitivity (AQI beta) sample with industry, province, and year fixed effect. The *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Positive AQI sensitivity (AQI beta) sample			Panel B: Negative AQI sensitivity (AQI beta) sample	
Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	(1)	(2)	(1)	(2)
A_AQI exposure	-0.876*	-0.879*	-0.188	-0.237*
	(-2.17)	(-2.19)	(-1.35)	(-1.82)
AQI		0.113		1.163
		(0.09)		(0.48)
AQI exposure	0.051	0.052	-0.003	0.002
	(1.41)	(1.45)	(-0.13)	(0.11)
Constant	2.519***	2.396***	1.552***	1.329***
	(4.73)	(4.49)	(4.59)	(3.69)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	8,295	8,295	8,657	8,657
Adj R-squared	0.264	0.265	0.285	0.287

Table 3.12. Mediating analysis of net operating cash flow and financing cost

This table reports the mediating effects of net operating cash flows (*CF*) and financing cost (*Fincost*) in Panel A and Panel B, respectively. Column (1) shows the regression results of *A_AQI exposure* on *R&D_Assets*. Column (2) of Panel A shows the effect of adjusted air pollution exposure (*A_AQI exposure*) on *CF* and *Fincost* in Panel A and B, respectively. Column (3) shows the effect of *A_AQI exposure* and *CF* and *Fincost* on *R&D_Assets* in Panel A and B, respectively. Panel C presents the indirect, direct, and total effects of *CF* and *Fincost*. Detailed definitions of variables are given in Appendix B.1. The *t*-statistics are reported in parentheses. The symbol *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Net operating cash flow (*CF*)				Panel B: Financing cost (*Fincost*)		
Variables	*R&D_Assets*	*CF*	*R&D_Assets*	*R&D_Assets*	*Fincost*	*R&D_Assets*
Model	(1)	(2)	(3)	(1)	(2)	(3)
A_AQI exposure	-0.242**	-0.006*	-0.228**	-0.442***	0.071***	-0.425***
	(-2.45)	(-1.98)	(-2.28)	(-3.71)	(4.50)	(-3.63)
CF			2.109***			
			(3.35)			
Fincost						-0.241***
						(-3.57)
Constant	2.193***	-0.124***	2.392***	4.488***	-0.149**	4.452***
	(2.71)	(-5.13)	(3.23)	(8.74)	(-2.20)	(8.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	16,952	16,952	16,952	13,037	13,037	13,037
Adj R-squared	0.283	0.286	0.286	0.134	0.252	0.135

Panel C: Indirect, Direct, and Total Effects of CF and Fincost

Panel D: Indirect, Direct, and Total Effects of Fincost

Type	Effect	Estimate	Estimate
Total	A_AQI exposure → R&D_Assets	-0.242	-0.442
Direct	A_AQI exposure → R&D_Assets	-0.228	-0.425
Indirect	A_AQI exposure → CF → R&D_Assets	-0.014	
Indirect	A_AQI exposure → Fincost → R&D_Assets		-0.017
Sobel test - *Z*- stat		-3.634*** (0.008)	-2.824*** (0.006)
	Proportion of total effect that is mediated:	0.052	0.039

Table 3.13. Human capital effect

This table reports the results of human capital effect on our baseline results. We divide the full sample into two groups based on the firms' R&D personnel ratio, categorizing them as either above or below the median level. The dependent variables are $R\&D\_Assets$ and $Inv\_PAT\_APP_{t+1}$, measured by R&D expenditure to total assets of each firm in $year_t$ and the natural logarithm of invention patent applications plus one in $year_{t+1}$.The main independent variable is adjusted air pollution exposure (*A_AQI exposure*). Detailed definitions of variables are given in Appendix A. The *t*-statistics are reported in parentheses. The symbol *, ** and ***indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	$R\&D\_Assets$	$R\&D\_Assets$	$Inv\_PAT\_APP_{t+1}$	$Inv\_PAT\_APP_{t+1}$
	(1)	(2)	(3)	(4)
	R&D Intensive Firms	R&D Light Firms	R&D Intensive Firms	R&D Light Firms
A_AQI exposure	-0.412***	-0.007	-0.161**	-0.024
	(-2.68)	(-0.07)	(-2.09)	(-0.35)
GDP growth	5.904***	3.676***	1.308*	1.999***
	(3.85)	(3.68)	(1.78)	(2.93)
GDP per capita	-2.865***	-2.407***	0.408	-0.154
	(-3.05)	(-3.63)	(0.88)	(-0.32)
Constant	-0.690	1.613***	-4.969***	-4.265***
	(-0.92)	(3.56)	(-12.51)	(-13.13)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	8,236	8,073	6,465	6,782
Adj R-squared	0.233	0.218	0.215	0.185

Table 3.14. Moderating effects: Firm's ownership control

This table reports the results of moderating effects of firm's ownership control. The dependent variables are $R\&D\_Assets$ and $R\&D\_Assets_{t+1}$, measured by R&D expenditure to total assets of each firm and then multiplied by 100 in $year_t$ and $year_{t+1}$. The main independent variable is adjusted air pollution exposure (*A_AQI exposure*). The interacted variable is SOE that takes value of 1 if the firm is state-owned-enterprise (*SOE*), and 0 otherwise. Detailed definitions of variables are given in Appendix B.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	$R\&D\_Assets$	$R\&D\_Assets_{t+1}$
Model	(1)	(2)
A_AQI exposure	-0.687*	-1.345**
	(-1.81)	(-2.25)
A_AQI exposure × SOE	0.642**	0.873***
	(2.70)	(2.93)
AQI	-0.224	1.260
	(-0.23)	(0.62)
AQI exposure	0.033	0.094*
	(1.10)	(1.92)
SOE	0.053	0.057
	(1.05)	(0.54)
Constant	1.905***	1.871***
	(4.25)	(3.62)
Controls	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,952	13,048
Adj R-squared	0.273	0.260

Table 3.15. Heterogeneity tests

This table reports the results of heterogeneity tests. To examine the impact of adjusted air pollution exposure and corporate innovation investment, we explore three internal factors: (a) environmental disclosure; (b) manager's risk tolerance, measured by the firm's illiquidity assets to total assets; (c) firms' characteristics: polluter or non-polluter; and two external factors: (d) well-developed provinces and others, we measure the development degree of the provinces using the Fan-Gang index; (e) the firms' headquarter air pollution level, we divide the sample into more polluted and less polluted provinces based on the firms' headquarters' AQI median level; (f) 2015 Paris Agreement. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Internal factors

Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	(1)	(2)	(3)	(4)	(5)	(6)
	Environmental disclosure	Non-Environmental disclosure	Low manager's risk tolerance	High manager's risk tolerance	Non-Polluter firms	polluter firms
A_AQI exposure	-0.286***	0.320	-0.231**	-0.096	-0.346***	0.323
	(-2.75)	(1.17)	(-2.17)	(-0.71)	(-3.65)	(1.58)
GDP growth	3.574***	7.435***	4.978	2.903**	5.005	2.257
	(3.63)	(3.93)	(1.35)	(2.55)	(1.68)	(1.21)
GDP per capita	-2.484***	-3.256***	-3.314***	-1.924***	-3.696***	-0.874
	(-4.08)	(-3.42)	(-6.92)	(-2.69)	(-7.27)	(-0.95)
Constant	0.955**	-3.128*	1.324	1.618***	0.746*	2.491***
	(2.08)	(1.74)	(1.63)	(3.05)	(1.77)	(3.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	14,805	1,506	8,476	8,476	11,913	5.039
Adj R-squared	0.089	0.143	0.245	0.289	0.284	0.206
Chow-test	0.018**		0.003***		0.026**	

Panel B: External factors

Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	(1)	(2)	(3)	(4)	(5)	(6)
	Well-developed provinces	Developing provinces	Less-polluted provinces	More-polluted provinces	After 2015	Before 2015 (including 2015)
A_AQI exposure	-0.199**	-0.286	-0.346**	-0.031	-0.914***	-0.005
	(-1.94)	(-1.20)	(-2.08)	(-0.27)	(-3.11)	(-0.01)
GDP growth	1.398	5.979***	1.168	4.795***	0.482	-6.065
	(1.14)	(3.28)	(0.76)	(3.45)	(0.82)	(-1.09)
GDP per capita	-2.345***	-2.609*	-3.697***	-1.915*	0.015	3.493
	(-3.25)	(-1.85)	(-4.53)	(-1.76)	(0.07)	(0.56)

Constant	1.294***	1.212	3.343***	0.218	13.269***	21.048***
	(2.69)	(1.44)	(5.40)	(0.38)	(5.38)	(4.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm	Firm	Firm
N	12,907	4,045	8,476	8,476	12,891	2,399
Adj R-squared	0.263	0.318	0.269	0.287	0.890	0.873
Chow-test	0.052*		0.026**		0.028**	

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CHAPTER FOUR ESSAY THREE

Climate policy uncertainty and corporate innovation investment: Evidence from China

Abstract

This chapter estimates how corporate innovation investment responds to climate policy uncertainty using panel data with 3,197 listed firms from 2010 to 2022 in China. The findings show that climate policy uncertainty positively contributes to corporate innovation investment, and this result continues to hold after controlling for endogeneity and conducting a series of robustness tests. Furthermore, we find that stringent government environmental regulation serves as a potential mechanism, compelling firms to adopt cleaner production and increase their investment in innovation. Additionally, this positive relationship for firms with higher government subsidies is stronger and for firms with higher allocation of fixed assets disappears. We also find that firms with fewer connections to the government are more sensitive to climate policy uncertainty and they tend to increase their investment in innovation to mitigate the uncertainty. Furthermore, when firms invest more in innovation during periods of high policy uncertainty, their long-term performance and firm value are likely to improve. This study sheds light on the importance and influence of climate policy uncertainty on corporate innovation investment in China.

Key words: Climate policy uncertainty, corporate innovation investment, stringent government environmental regulation, China

JEL code: G18, D80, O31, O32

4.1. Introduction

In recent decades, extreme weather changes and abnormal climate events, such as global warming, rising sea levels, cyclones, and forest fires, have become increasingly severe and posed unprecedented challenges to global sustainability, prompting governments worldwide to adopt diverse policy measures aimed at mitigating greenhouse gas emissions and promoting sustainable practices (IPCC, 2021)[42]. Particularly, since the signing of the 2015 Paris Agreement, an increasing number of countries have transformed their development strategies and implemented a series of climate policies, committed to reducing emissions voluntarily, and realizing the common vision of creating a "zero-carbon society" with "net zero emissions". However, these policies associated with climate change vary over time, and future government policies are largely unpredictable and change with political turnover and shifting policy preferences (Lee & Cho, 2023; Zhu et al., 2023). For example, Trump's decision to withdraw from the Paris Agreement, increasing the degree of uncertainty of climate policies.

With climate policy uncertainty now being quantified at the aggregate level, its impact is being increasingly examined in various studies (Bai et al., 2023; Lee & Cho, 2023; Xu, Huang, Lucey, & An, 2023). For corporations, navigating this uncertainty is crucial for their overall innovation investment decisions, as such investments are essential for advancing green economy development, meeting sustainable development conditions, and addressing climate policy uncertainties (Bai et al., 2023). In addition, it is also an important investment for the firm to advance technological solutions that drive economic growth, improve efficiency, and address various market demands (Kemp & Pontoglio, 2011). Thus, the purpose of this study is to examine how climate policy uncertainty affects innovation investment in Chinese listed firms.

[42] The Intergovernmental Panel on Climate Change (IPCC), 2021 report underscores the urgency of immediate, coordinated global action to reduce emissions and adapt to climate impacts. It forms a critical basis for international climate policy, including the Paris Agreement's goal of limiting global warming to 1.5°C or 2°C above pre-industrial levels.

Our study is motivated by two strands of research on the impact of uncertainty on corporate investment. Policy uncertainty hypothesis suggests that uncertainty in policies harms innovation. Models by Chen and Funke (2003), Bloom, Bond, and Van Reenen (2007), and Bloom, Draca, and Van Reenen (2016) show that when investments cannot be easily undone, companies delay investing during uncertain times, as waiting becomes more valuable. Recent research in finance and economics has demonstrated that policy uncertainty adversely affects firm-level investment and harms economic performance. Linking these findings to the nature of innovation, it is evident that, unlike traditional investments in tangible assets like capital expenditures, innovation represents long-term, intangible assets intended to generate future profits and requires a longer time horizon and carries higher tail risk. The option to wait is particularly significant for investments in research and development (R&D), given that innovation involves exploring unknown approaches and untested methods (Ferreira et al., 2014), requiring substantial investment in intangible assets.

However, strategic growth option theory suggests that enterprises may act immediately to invest in innovation activities to secure their market share when they face uncertainty (Kulatilaka & Perotti, 1998; Tajaddini & Gholipour, 2021). Bar-Ilan and Strange (1996) suggest that R&D investments tend to increase with uncertainty, as the step-by-step nature of R&D allows firms to make incremental decisions about further investments. This process enables firms to abandon unfavourable projects and continue with those showing promise. It is similar to Weeds (2002), who finds that uncertainty may promote investment in valuable growth opportunities to gain a competitive advantage. Additionally, uncertainty can stimulate innovation investment by encouraging firms to develop technologies that align with future regulatory requirements or emerging market opportunities, as highlighted by Kulatilaka and Perotti (1998), Perotti (1998), and Tajaddini and Gholipour (2021).

Recent studies indicate that firms may adjust their corporate innovation strategies in response to high levels of climate policy uncertainty (CPU). Niu, Zhang, Luo, and Feng (2023) find that the impact of climate policy uncertainty on technology innovation is negative. Huang (2023) also finds similar results, showing that firms reduce innovation activities in response to increased climate policy uncertainty. However, Bai et al. (2023) find that climate policy uncertainty can lead to stricter regional environmental regulations and higher levels of R&D investment by firms, ultimately boosting innovation. Similarly, Zhu et al. (2023) report a significant positive correlation between climate policy uncertainty and corporate innovation investment. Expanding on this, Liu et al. (2024) also confirm that climate policy uncertainty positively influences corporate innovation activities. Notably, most existing studies rely on the U.S. CPU rather than a Chinese-specific measure. An exception is Liu et al. (2024), who derive the Chinese CPU primarily from China News Network. However, as noted by Shao (2018) and Xu and Albert (2014), the strong media censorship in China may lead to an underrepresentation of uncertainty in such sources. Thus, the relationship between climate policy uncertainty and corporate innovation investment yields mixed results.

To contribute to the ongoing debate, this chapter examines how corporate innovation investment responds to climate policy uncertainty in Chinese listed firms. We use the Chinese climate policy uncertainty (CPU) index created by Lee and Cho (2023) and R&D expenditure as our measure of innovation. China is an ideal setting for this study for several reasons. First, as the world's largest emitter of carbon dioxide, accounting for 30.6% of global greenhouse gas emissions in 2020 (Friedlingstein et al., 2022). Thus, a Chinese climate policy uncertainty index would serve as a significant indicator of climate-related uncertainty within China[43].

[43] Recent literature introduces a new measure for firm-level climate change exposure based on transcripts of quarterly earnings conference calls (Huang, Kerstein, & Wang, 2018; Sautner, Van Lent, Vilkov, & Zhang, 2023). However, these measures may be limited by salience bias, where managers overweight the probability of events based on their proximity or ease of recall (Alok, Kumar, & Wermers, 2020; Cao, Chen, Dong, & Lee, 2024). This bias has been observed in managerial overreactions to local disasters, such as increased cash holdings following hurricanes (Dessaint & Matray, 2017) and professional money managers underweighting nearby firms' stocks (Alok et al., 2020). Given these limitations, we believe that the climate change index developed by Lee and Cho (2023) is more suitable for our study.

Understanding how this uncertainty impacts corporate innovation investment in China can provide valuable insights. Given the mixed results in previous studies, our research aims to add to the debate by providing new evidence on the relationship between Chinese climate policy uncertainty and corporate innovation investment.

Furthermore, as the second-largest economy in the world, China has consistently demonstrated a proactive stance towards reducing emissions and is committed to the strategic transformation and upgrading of its manufacturing sector. This commitment is evident from China's declaration in September 2020 to achieve carbon peaking by 2030 and carbon neutrality by 2060 (Hepburn et al., 2021; Razzaq, Sharif, Ozturk, & Yang, 2023; Xue, Razzaq, Afshan, & Yang, 2023). Following this announcement, the implementation of climate policies has accelerated significantly, particularly at the local level (Li, Xu, & Wang, 2023; Zhao, Cao, Feng, Guo, & Zhang, 2022). The Chinese government has introduced and enforced various significant measures, such as the National Program for Addressing Climate Change in China (Nuvvula et al., 2022). By analysing these dynamics, our study aims to shed light on the intricate relationship between climate policy uncertainty and corporate innovation in the context of China's evolving environmental landscape.

This chapter examines the impact of climate policy uncertainty on corporate innovation investment using a sample that includes 16,952 firm-year observations of 3,197 unique firms in mainland China from 2010 to 2022. We find that climate policy uncertainty positively contributes to corporate innovation investment. Our results are also economically meaningful, for example, when the level of climate policy uncertainty increases by one standard deviation, there will be an increase of 8.80 percent in corporate innovation investment. Our analysis further reveals that stringent government environmental regulation serves as a potential mechanism, compelling firms to adopt cleaner production practices and increasing their investment in innovation. Moreover, this positive relationship is amplified for firms receiving substantial government subsidies but weakens for those with higher fixed asset allocations. We further find that firms who have fewer connections with government such as non-SOEs and non-political connections are sensitive to the climate policy uncertainty and invest more in innovation to mitigate the climate policy uncertainty. Finally, we examine the impact of climate policy uncertainty on long-term firm performance and firm value. Analyzing the interaction between CPU and R&D investment with future Tobin's Q and ROA, we find that this positive relationship boosts long-term performance and firm value, which shows that innovation investment improved by the climate policy uncertainty will bring the positive market expectations for firms.

We also perform a battery of robustness analysis. We address potential endogeneity issues using multiple methods: applying the Generalized Method of Moments (GMM) approach and employing an instrumental variable (IV) approach. Using dynamic panel data GMM models and the Global Average Surface Temperature (GMST) index as an instrumental variable further validated our baseline results, demonstrating the robustness and validity of our findings. To ensure our findings are robust, we test three alternative measures of climate policy uncertainty. We use the Chinese Climate Policy Index by Lee and Cho (2023), the U.S. Climate Policy Uncertainty Index by Gavriilidis (2021), and the residual CPU, which is the error from the regression between the Chinese and U.S. indexes. All these measures show a positive and significant impact on corporate innovation investment.

Our findings align with Bai et al. (2023), Zhu et al. (2023), and Liu et al. (2024), who also report a significant positive relationship between climate policy uncertainty and corporate innovation investment. Our study differentiates itself from existing literature by using a climate policy uncertainty (CPU) index specifically tailored to the Chinese context, as developed by Lee and Cho (2023). This index offers several unique contributions. First, it captures climate policy uncertainty in China by leveraging information about China contained in tweets from users worldwide, not just in China. Tweets posted by global users could be a better source of measuring uncertainty than newspapers in China which are subject to strong media censorship (Shao, 2018; Xu & Albert, 2014) that could lead to the under-statement of uncertainty. Second, this method contrasts with prior research that predominantly relies on US data, thus providing a unique perspective that captures the specific context of the Chinese climate policy. Given that climate policies and their associated uncertainties vary significantly across countries, our approach offers a more accurate reflection of China's policy environment. Third, Lee and Cho (2023) also demonstrate that Chinese climate uncertainty indices are not predicted by the US climate-related indices, the US indices are well predicted by Chinese climate uncertainty indices. This evidence suggests that our used indices reflect China-specific information about climate uncertainty. Moreover, the fact that US climate-related indices are predicted by Chinese indices indirectly emphasizes the importance of China for climate uncertainty, which is reasonable given the fact that China is the world's largest emitter of carbon dioxide. Furthermore, compared to Liu et al. (2024), we focus on innovation inputs in our study rather than outputs (patents), as CPU comes from tweets, which is very current and short-lived information. Its impact on innovation outputs will be very indirect.

This chapter makes several contributions, first, to our best knowledge, we are the first work to use the Chinese Climate Policy Uncertainty (CPU) index to investigate the relationship between climate policy uncertainty and corporate innovation investment, thereby complementing the existing literature on climate policy uncertainty. While prior research has primarily relied on the US CPU, yielding mixed results, our study offers a new perspective by using the Chinese CPU and document additional information embedded in the Chinese CPU beyond the US context. Second, our empirical evidence demonstrates that climate policy uncertainty can prompt companies to adjust their development and innovation strategies. Investing in innovation during periods of uncertainty not only enables firms to adapt the policy uncertainty but also contributes to improve long-term performance and enhance firm value. Third, we provide empirical evidence that can inform policymakers in China about the mechanism of the impact of climate policy uncertainty on corporate innovation strategies -- stringent government environmental regulation . The research findings may help to create more flexible and effective climate policies that enhance corporate innovation.

The chapter is structured as follows. Section 4.2 is the literature review and hypothesis development. Section 4.3 describes the data, sample selection, and baseline model. Section 4.4 presents and discusses the main results, endogeneity tests, findings from the mechanism analysis. Section 4.5 discusses the moderating effect and further analysis. Section 4.6 concludes the chapter.

4.2. Literature review and hypothesis development

4.2.1. Literature review

The risks associated with climate change have been increasing in recent years due to the frequency of extreme weather and climate events worldwide, climate change has emerged as a significant threat to global governance (Ardia et al., 2023; Bai et al., 2021). The increasing recognition of climate change as a critical global issue has led to a series of government policies aimed at reducing carbon emissions, transitioning to clean energy, and achieving sustainability goals (Dai & Zhang, 2023). However, frequent shifts in climate policy, such as changes in carbon taxes, emissions trading systems, and renewable energy subsidies, create policy uncertainty, which significantly impacts stock and energy markets, corporate performance and risk management, and corporate decision makings especially the investment in innovation (Bai et al., 2023; Bouri, Iqbal, & Klein, 2022; Dai & Zhang, 2023; Shang, Han, Gozgor, Mahalik, & Sahoo, 2022).

Several studies have examined the impact of climate policy uncertainty (CPU) on the stock and energy markets, including stock market volatility, energy price volatility, and renewable energy demand. For example, Yan (2023) identifies that climate policy uncertainty have significant time-varying effects on the carbon price. The author further finds that CPU shocks generally show a positive and negative alternating impact on carbon driven by some important carbon-related policies or low-carbon events. Bouri et al. (2022) highlight that the climate policy uncertainty effect is positive and reveal that CPU is an essential factor driving the good performance of green energy stocks. Shang et al. (2022) confirm that CPU reduces the need for conventional energy sources while increasing the need for renewable sources.

Some studies have examined the influence of climate policy uncertainty on corporate financial performance and risk management, including corporate total factor productivity, excessive corporate debt, and bank risks. For example, Ren, Zhang, Yan, and Gozgor (2022) find that climate policy uncertainty significantly reduces firm-level total factor productivity mainly via its effects on the capital status of the companies, such as hinders research and development investment and reduces the amount of free cash flow. Ren, Qin, and Dong (2022) find that climate policy uncertainty not only directly curbs excessive debt, but also indirectly reduces excessive debt by increasing financing constraints. Moreover, the financing constraints channel is more effective in state-owned enterprises, high-tech enterprises, and high-carbon enterprises. Dai and Zhang (2023) find that climate policy uncertainty significantly reduces bank loan and investment risks while simultaneously increasing insolvency risks faced by banks.

In addition to the mentioned above, one of the most critical areas affected by climate policy uncertainty is innovation investment. Corporate innovation distinguishes itself from general corporate investment activities in the sustainable and technology innovation orientation (Afeltra, Alerasoul, & Strozzi, 2023; Hao, Huang, & Wu, 2019; Varadarajan, 2017). Corporate innovation investment fosters a greater focus on the effective combination of environmentally sustainable innovation and sustainable technology orientation. This generates positive environmental outcomes, such as reduced resource consumption, improved efficiency in resource allocation, the creation of positive knowledge externalities and spillovers, and the mitigation of environmental pollution through more responsible emissions management. (Amore & Bennedsen, 2016; Zheng, Feng, Jiang, & Chang, 2023). The various outcomes under innovation investment hold significant potential in addressing climate change and achieving climate policy requirements.

However, the existing literature on the factors influencing corporate innovation has predominantly focused on the entity level, such as enterprises, governments, and markets. While some studies have examined the role of natural environmental factors, including climate change and climate policy (Ren et al., 2022), recent research on the relationship between climate policy uncertainty and corporate innovation investment has mainly used US CPU index and yielded mixed results (Bai et al., 2023; Huang, 2023; Niu et al., 2023). Consequently, further investigation is needed to understand how uncertainty in climate policy impacts corporate innovation investments.

4.2.2. Hypothesis development

There are different perspectives on the impact of the uncertainty on corporate innovation investment (Cui et al., 2021; Guan, Xu, Huo, Hua, & Wang, 2021). Policy uncertainty hypothesis suggests that uncertainty in policies harms innovation. Models by Chen and Funke (2003), Bloom et al. (2007), and Bloom et al. (2016) show that when investments cannot be easily undone, companies delay investing during uncertain times, as waiting becomes more valuable. The option to wait is particularly significant for investments in research and development (R&D), given that innovation involves exploring unknown approaches, untested methods (Ferreira et al., 2014), and requiring substantial investment in intangible assets. Sendstad and Chronopoulos (2020) also argue that when entrepreneurs face policy uncertainty and do not know whether future policies are aggressive or conservative, the best they can do is to wait and see, shrink their long-term investments, and thus reduce the scope for innovation.

However, some scholars do not subscribe to the above mentioned perspective, and they argue that policy uncertainty creates risks and opportunities that can positively incentivize corporate R&D innovation and production investment (Atanassov et al., 2015; Bloom, 2007). Increased policy uncertainty can significantly influence corporate behaviours, encouraging firms to seize development opportunities and increase R&D investment to gain excess profits through technological innovation (Du, Wei, Zhang, & Pan, 2023; He, Ma, & Zhang, 2020).

This is consistent with the strategic growth option theory which suggests that uncertainty might encourage investment in a growth option under imperfect competition. The reasoning behind this theory is that uncertainty can generate a growth option. While delaying investments could leave the investment opportunity to other competitors, "immediate action may discourage entrants and enhance market share and profits" (Kulatilaka & Perotti, 1998), thus increasing competitive advantage in the future. Similarly, Weeds (2002) shows that waiting loses value when firms face competition or when investments can lead to worthwhile expansion prospects. Besides this, Jiang et al. (2009) report a positive correlation between the uncertainty measured by idiosyncratic return volatility and R&D investment. Similarly, Van Vo and Le (2017) find that firms that face higher uncertainty measured by idiosyncratic return volatility invest more in R&D, and the effect is more pronounced for firms in more competitive industries. Stein and Stone (2012) find that R&D investment is increased by the uncertainty represented by implied volatility from equity options. Atanassov et al. (2015) document that R&D investment dramatically increases in gubernatorial election years.

In conclusion, we have reason to suspect that climate policy uncertainty may promote firms invest more in innovation to capture market share and realize sustainable development. Accordingly, we propose the following hypothesis:

Hypothesis 1 *(H1)*: Climate policy uncertainty positively contributes to corporate innovation investment.

With climate risk rising, governments tend to implement policies to combat climate change, such as carbon taxes, emission caps, or renewable energy incentives (Dolge & Blumberga, 2021; Gkonis, Arsenopoulos, Stamatiou, & Doukas, 2020). However, these policies are full of uncertainties regarding the scope, timing, and stringency. For example, a change of government leadership always leads to different decisions under different climate backgrounds, such as Trump's decision to withdraw from the Paris Agreement, increasing the degree of uncertainty of climate policies. Climate policy uncertainty creates an unpredictable regulatory environment, compelling firms to proactively respond to potential risks and opportunities.

One way firms navigate this uncertainty is by anticipating stringent government environmental regulations that may emerge as part of climate policy adjustments (Liu, McKibbin, Morris, & Wilcoxen, 2020; Ren, Hao, & Wu, 2022). These regulations often mandate compliance with stricter environmental standards, requiring firms to adopt cleaner production methods and improve resource efficiency (Liu et al., 2020; Ren et al., 2022). This is also consistent with Porter's hypothesis, which posits that well-designed environmental regulations can drive innovation, improve resource efficiency, and enhance competitiveness, leading to both economic and environmental benefits (Porter, 1991). According to Kulatilaka and Perotti (1998) and Tajaddini and Gholipour (2021), uncertainty can stimulate innovation investment by encouraging firms to develop technologies that meet future regulatory requirements or emerging market opportunities. Zhu et al. (2023) also find that as climate risk rises, the government will strengthen environmental regulation of enterprises with high energy consumption and pollution, forcing them to use clean energy and improve production technology through environmental taxes and penalties.

Based on the above analysis, the following hypothesis is proposed:

Hypothesis 2 (*H2):* In the presence of climate policy uncertainty, stringent government environmental regulations enhance firms to adopt cleaner production methods and increase their investment in innovation.

Resource dependence theory proposes that firms are not self-sufficient entities; their activities depend on their access to external resources. Given the finite nature of resources, they must strategically allocate their limited resources to achieve their goals (Pfeffer & Salancik, 1978). Government subsidies are intended to reduce the financial burden and encourage growth or sustainability, so firms with more government subsidies have more financial resources on supporting long-term and risky innovation investment (Dewenter & Malatesta, 2001). The similar results have been found by Su, Song, Shang, and Fahad (2022), who suggest that government subsidies directly provide financial support for enterprises, which helps enterprises to alleviate the pressure of funds in innovation investment and enhance the financial strength of the enterprise, to enable it to better grasp the opportunities for innovation investment. Furthermore, in addition to the external resources such as government subsidies, corporations must strategically allocate internal resources in order to carry out their investment activities. However, higher fixed asset allocation constrains resource availability and flexibility, limiting the capacity for additional investments in research and development (R&D) or technological advancements (Tan, Tan, et al., 2021; Tan & Yan, 2021). Thus, we believe that if firms allocate more resources to one area, such as fixed assets, they will have fewer resources to spend in innovation activities.

Based on the above analysis, the following hypotheses are proposed:

Hypothesis 3a (*H3a):* Government subsidies boost the positive influence of climate policy uncertainty on corporate innovation investment.

Hypothesis 3b (*H3b*): Higher fixed asset allocation dampens the positive influence of climate policy uncertainty on corporate innovation investment.

4.3. Data and methodology

4.3.1. Sample selection and data sources

Our initial sample consists of all Chinese A-share firms listed on the Shanghai and Shenzhen stock exchanges in the CSMAR database from 2010 to 2022. Following Cui et al. (2021), we exclude (1) financial services firms, (2) special treatment (ST) firms, and (3) firm-year observations without sufficient financial data to construct control variables for regression analysis. The final sample includes 16,952 firm-year observations of 3,197 unique firms in mainland China from 2010 to 2022.

Climate policy uncertainty index (CPU) is obtained from Lee and Cho (2023) which measures Chinese climate policy uncertainty[44]. While the index is reported on a monthly basis beginning in 2010, we create an annual index for each firm-year observation by averaging the values over the 12 months[45]. Following Chemmanur et al. (2019) and Mukherjee et al. (2017), we measure corporate innovation investment using R&D expenses scaled by total assets (*R&D_Assets*). We multiply *R&D_Assets* by 100 for the ease of interpretation of the regression coefficients.

4.3.2. Baseline model

We examine the impact of climate policy uncertainty (CPU) on corporate innovation investment using the following regression model[46]:

[44] The authors count the number of tweets that are related to climate policy uncertainty. They search for tweets that contain at least one keyword in each of the following categories of terms: (1) "China", (2) "Climate", and (3) "Uncertainty", and (4) "Policy". More details for constructing this index, please see: https://www.sciencedirect.com/science/article/pii/S1059056023002149.

[45] We also provide the figure to show the Chinese Climate (Policy) Uncertainty major events from March 2010 to December 2022 (Figure 4.1.).

[46] We also use the lead-lag model, the results still remain and are reported in Appendix C.3.

$$Innovation_{i,t} = \alpha_0 + \beta_1 \times CPU\ Index_{i,t} + \gamma \times Controls_{i,t} + Industry + Year + Province + \varepsilon_{i,t}$$

(4.1)

where subscripts i and t relate to firm and year respectively. $Innovation_{i,t}$ refers to the corporate innovation investment of firm *i* in year *t*, measured by *R&D_Assets*. $CPU\ Index_{i,t}$ is the climate policy uncertainty index of firm *i* in year *t*. Following Cui et al. (2021) and Xu (2020), we include several control variables to account for firm-level characteristics and operations, such as firm size (*Size*), firm age (*Age*), leverage ratio (*Leverage*), return on assets (*ROA*), growth rate of sales (*Growth*), *Tobin's Q*, and financial constraints index (*KZ*). Furthermore, we also control for other firm characteristics that may affect innovation investment, including managerial ownership (*Mshare*), the top one major shareholding (*Top1*), independent directors' ratio (*IndepR*), the ratio of fixed assets (*Fixed*), number of board members (*BoardSize*), *Dual*, *Big 4*, state-owned enterprise (*SOE*) and polluting industries (*Polluter)*. Detailed definitions of these variables are provided in Appendix C.1. All continuous variables are winsorized at the top and bottom 1% to mitigate the concern of outliers.

4.4. Empirical results

4.4.1. Descriptive statistics

Table 4.1. shows the descriptive statistics, including the mean, median, minimum, maximum, standard deviation, first quartile (*Q1*), and third quartile (*Q3*) value of variables. We can see that the mean of *R&D_Assets* is 2.610 percent, the minimum and maximum values of *R&D_Assets* are 0.010 percent and 11.650 percent. These align with previous studies, such as Cui et al. (2021). The mean and median of climate policy uncertainty *(CPU)* are 0.157 and 0.079, and the mean and median for climate uncertainty index (*CU)* are 0.149 and 0.096 respectively. In terms of the control variables, the average firm size is 22.08, the average return on assets is 5.00%, and the average leverage ratio is 38%. The average fixed assets investment

is 19.7%. Approximately 35% of the CEOs in our sample are also chairmen, and the top one major shareholders on average hold 33% of firm stocks. The average board size consists of approximately 8 (log=2.10) members, 38% of whom are independent directors, which is consistent with the China Securities Regulatory Commission (CSRC) requirements on board independence. The distributions of the control variables are generally similar to those reported in previous research (Cui et al., 2021; Wen et al., 2022). We report the correlation coefficients among variables in Appendix C.2. The correlation coefficients among variables are smaller than 0.6, indicating that the multi-collinearity issue is not a severe concern.

[Insert Table 4.1. here]

4.4.2. Baseline results

To study the effect of climate policy uncertainty on corporate innovation investment, we conduct the OLS regression, controlling for industry, year and province fixed effects as well as clustering the standard errors at the firm level. Table 4.2. presents the baseline regression results. From columns (1) and (2), we can see that the coefficients on *CPU* are positive (1.800 and 1.306) and statistically significant at the 1% level, implying that climate policy uncertainty positively contributes to the corporate innovation investment. We further control for the natural logarithm of the province GDP per capita and province GDP growth rate in Column (3). The coefficient of *CPU* remains positive (1.166) and statistically significant at the 1% level. Using the coefficient estimates of *CPU* in Column (3), we calculate the economic significance of the effect of climate policy uncertainty on corporate innovation investment, holding other variables constant at their sample means: a 1-standard-deviation increase in climate policy uncertainty is associated with 8.80 percent increase in corporate innovation investment[47]. These estimates

[47] We calculate the economic significance of climate policy uncertainty through $E_{\bar{y}}^{s} = \left|\frac{bs_x}{\bar{y}}\right|$, where b is the estimated regression coefficient for the explanatory variable (1.166), s_x is the sample standard deviation of the explanatory variable (0.197), and $\bar{y}$ is the sample mean of the dependent variable (2.610). After the calculation,

indicate a statistically and economically significant impact of climate policy uncertainty on corporate innovation investment.

The coefficients on the control variables are generally consistent with those reported in relevant studies (Aghion, Van Reenen, & Zingales, 2013; Almor, Bazel-Shoham, & Lee, 2022; Becker-Blease, 2011). For example, the coefficients on *ROA* and *Tobin's Q* are both positive and significant at the 1% level, suggesting that firms with higher profitability and higher market value are more likely to invest in innovative projects. In addition, the coefficient on *Fixed* is significantly negative, indicating that investment in fixed assets reduces corporate innovation investment. Overall, the results in Table 4.2. confirm that climate policy uncertainty positively contributes to corporate innovation investment, providing support for *H1*.

[Insert Table 4.2. here]

4.4.3. Robustness checks

4.4.3.1. Alternative measures of corporate innovation

Regarding the corporate innovation investment measurement, we use $R\&D\_Assets_{t+1}$ to replace the $R\&D\_Assets_t$ as dependent variable to check the lead-lag effect; *R&D_Sales* and $R\&D\_Sales_{t+1}$ to replace the $R\&D\_Assets_t$ as our alternative dependent variables. The coefficients in Panels A and B of Table 4.3. on *CPU* are still positive and significant at least at the 5% level across all columns. The findings support our baseline results.

[Insert Table 4.3. here]

4.4.3.2. Alternative measures of climate policy uncertainty

In this section, we use three alternative measures to replace the climate policy uncertainty and re-run the baseline regression in *Eq. (4.1)*. First, we use Chinese climate policy index (*CU*)

a 1-standard-deviation increase in climate policy uncertainty is associated with 9.74% increase in corporate innovation investment (1.166 × 0.197 ÷ 2.610 = 0.0880).

created by Lee and Cho (2023) as an alternative climate policy uncertainty to do a robustness check. Second, we use the U.S. climate policy uncertainty index (*US_CPU*) construct by Gavriilidis (2021) as an alternative climate policy uncertainty to do a robustness check. Third, we construct the residual CPU ($Residual\_CPU$), which is the standard error that runs the regression between the Chinese CPU and the U.S. CPU in *Eq. (4.2)*.

$$Chinese\ CPU\ Index_{i,t} = \alpha_0 + \beta_1 \times US\_CPU\ Index_{i,t} + \varepsilon_{i,t} \tag{4.2}$$

The results have been showed in Table 4.4., and the coefficients on the alternative measures of climate policy uncertainty are all significantly positive at the 1% level across the columns.

The above results indicate that the positive impacts of climate policy uncertainty on corporate innovation investment remain significant when using alternative dependent and independent variables to do robustness checks.

In addition, observations from the year 2020 are excluded to account for potential impacts of COVID-19. The results, reported in Appendix C.6, continue to show positive and statistically significant effects, providing further support for our baseline findings.

[Insert Table 4.4. here]

4.4.4. Endogeneity tests

We conduct two methods to address potential endogeneity issues: (1) Generalized Method of Moments (GMM) approach; and (2) Instrumental variable (IV) approach.

4.4.4.1. Generalized method of moments (GMM) approach

Considering that using fixed-effect (FE) is a time-invariant process and loses a certain amount of information, the results of inferring the variance at higher levels are potentially biased (Bell & Jones, 2015). The dynamic panel data GMM model further extends the fixed-effects model, in addition to the internal transformation process, the lagged values of the dependent variable are also included as instruments to control for dynamic endogeneity.

Therefore, drawing on the treatment of Arellano and Bond (1991), a first difference GMM (FD-GMM) and systematic GMM (SYS-GMM) estimations are used for re-estimation. Table 4.5. shows the estimation results. Specifically, after controlling for the innovation investment lag term, the coefficient of *CPU* is 0.751 (0.691) and significant at the 1% level for the FD-GMM (SYS-GMM). The final results are consistent with the conclusions presented in the baseline regressions, which verifies the robustness of the baseline results. Furthermore, we can find that the *p*-values of AR(2) and Hansen test are both greater than 0.1 across columns (1) and (2) of Table 4.5., which indicates that there are no serial correlations for the standard errors and the instrument variable is valid.

$$CPU_{i,t} = \alpha_0 + \alpha_1 \times GMST_{i,t} + \alpha_2 \times Controls_{i,t} + Year + Industry + Province + \varepsilon_{i,t} \quad (4.3)$$

$$R\&D\_Assets_{i,t} = \beta_0 + \beta_1 \times \widehat{CPU}_{i,t} + \beta_2 \times Controls_{i,t} + Year + Industry + Province + \varepsilon_{i,t} \quad (4.4)$$

[Insert Table 4.5. here]

4.4.4.2. Instrumental variable (IV) approach

In this section, we use Global Average Surface Temperature (GMST)[48] as an instrumental variable for the CPU to reduce endogenous bias, following the approach of Niu et al. (2023). A valid instrumental variable needs to satisfy both correlation and exogenous conditions. On the one hand, GMST is one of the key indicators for in-depth understanding of the impact of human activities on global climate change, which can directly reflect climate fluctuations and is also one of the reference factors for climate policy formulation, so GMST is highly correlated with CPU. On the other hand, GMST depends on global natural conditions, which influence

[48] We collect the Global Average Surface Temperature (GMST) data from NASA official website. https://climate.nasa.gov/vital-signs/global-temperature/?intent=121

climate policy formulation and generally do not directly affect the output of technologies or innovation, and therefore the instrumental variable is exclusive.

Table 4.6. reports the results of the estimation using instrumental variables. In the first stage, we regress the CPU on the instrumental variables, column (1) shows that *CPU* increases with increasing *GMST* and statistical significance at the 1% level. Moreover, the first-stage F statistic is high (*F*-statistic = 363.29), and LM-statistic is statistically significant, showing that the instrumental variable is not weak. Column (2) reports the results of the second-stage regression. The explanatory variable is the fitted value of the CPU (*CPU_Fitted*). *CPU_Fitted* is positively correlated with the corporate innovation investment, with statistical significance at the 1% level, with no change in the significance or sign of the core variables compared to the baseline regression results. Robustness analysis shows that our benchmark regression results are valid and reliable.

[Insert Table 4.6. here]

4.4.5. Mechanism analysis

The baseline results reveal that climate policy uncertainty positively contributes to corporate innovation investment. To explore the potential mechanism of CPU on corporate innovation investment, we conduct the subsample regressions based on our *H2* and consider the environmental regulations.

To examine the effect of CPU on corporate innovation investment according to environmental regulations (policies), we divide the sample based on two key environmental regulations (policies): the low-carbon pilot city policy and the 2015 Paris Agreement. The low-carbon pilot city policies[49] were implemented by the Chinese central government to promote sustainable

[49] This policy is launched in 2010 by the National Development and Reform Commission (NDRC), and it includes three phases: Phase 1 (2010): Pilots started in 5 provinces (Guangdong, Liaoning, Hubei, Shaanxi, and Yunnan) and 8 cities, including Shenzhen, Tianjin, and Chongqing. Phase 2 (2012): Expanded to an additional 28 cities,

urban development and reduce greenhouse gas emissions. These policies designate specific cities as "low-carbon pilots," encouraging them to adopt innovative practices and technologies aimed at lowering carbon emissions and improving energy efficiency (Ren, Liu, Klein, & Sheenan, 2024; Zeng, Jin, Tan, & Liu, 2023). The Paris Agreement is a climate change agreement signed by 196 countries worldwide and is a unified arrangement for global action to address climate change after 2020. The Paris Agreement was formally put into effect on November 4, 2016, after being approved at the Paris Climate Conference on December 12, 2015, and signed at the United Nations building in New York, USA, on April 22, 2016. On 3 September 2016, the Standing Committee of the National People's Congress (NPC) approved China's accession to the Paris Climate Change Agreement, becoming one of the parties that completed ratification of the agreement[50]. Since then, several carbon policies and pollution protection regulations have been created (Dai & Zhang, 2023; Su et al., 2020).

In the analysis, low-carbon pilot is the dummy variable, with a value of 1 when the firm's headquarter city is designated as low-carbon pilot city and 0 otherwise. Firstly, we divide sample firms into low-carbon pilot cities and other cities based on the low-carbon pilots dummy variable. Secondly, we divide firms into two subsamples: "Before 2015 (including 2015)" and "After 2015". The regression results are shown in Table 4.7. Columns (1) and (2) show that the coefficients of CPU are both significantly positive. However, the sample for low-carbon pilot cities has higher influence of CPU on corporate innovation investment, compared to the sample for other cities; and *Chow*-test indicates that there is a significant difference between these two coefficients. Columns (3) and (4) show that the positive impact of CPU on corporate innovation investment is stronger after the signing 2015 Paris Agreement. The results demonstrate that stringent government environmental regulations serve as a potential

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such as Beijing and Shanghai. Phase 3 (2017): Focus shifted to integrating low-carbon policies into urban planning and industrial restructuring.

[50] More details please see: https://unfccc.int/process-and-meetings/the-paris-agreement.

mechanism, compelling firms to adopt cleaner production and increasing their investment in innovation, providing support for *H2*.

[Insert Table 4.7. here]

4.5. Moderating effect and further analysis

4.5.1. Moderating effect

Our findings thus far support the hypothesis that climate policy uncertainty positively contributes to corporate innovation investment. To further explore the factors that may amplify or diminish this relationship, we introduce additional variables related to corporate innovation investment, such as government subsidies and corporate asset allocation.

Government subsidies, as a key financial tool, not only impact corporate financing but also influence corporate innovation decisions, which in turn will act on the CPU and corporate innovation activities (Li et al., 2021). Government support through subsidies has provided firms with sufficient R&D funds, reduced the financing pressure faced by firms, and thus enhanced the enthusiasm of companies to carry out innovation activities (Dewenter & Malatesta, 2001). Furthermore, beyond external resources like government subsidies, firms must also efficiently allocate internal resources to sustain their investment activities. Given that corporate resources are scarce and limited, firms with higher allocations to fixed assets are likely to have fewer resources available for investment in other areas (Tan, Tan, et al., 2021; Tan & Yan, 2021). Therefore, we posit that when firms allocate more resources to specific areas, such as fixed assets, their capacity to allocate resources toward innovation activities diminishes.

This section discusses how government subsidies (*Subsidy*) and fixed asset allocation (*Fixed*) act as moderating variables on CPU and corporate innovation investment. The regression results are reported in Table 4.8. We find that the regression coefficient of the interaction term

(*CPU*×*Subsidy*) is significantly positive at the 5% level, suggesting that firms receiving greater government subsidies experience a stronger positive effect of climate policy uncertainty on corporate innovation investment. Conversely, the regression coefficient for the interaction term (*CPU*×*Fixed*) is significantly negative at the 1% level, indicating that firms with higher allocations in fixed assets tend to weaken the positive impact of climate policy uncertainty on innovation investment.

[Insert Table 4.8. here]

4.5.2. Further analysis

4.5.2.1. Enterprise-government relationship

Based on prior studies, some scholars conclude that the effect of policy uncertainty on the corporate innovation depends on the government connections of corporations (Banerjee & Siebert, 2017). For example, state-owned enterprises (SOEs) are characterized by their large scale, state credit guarantee, and advantages in taxation, financing, technology, and human resources, as well as sufficient resources, compared to non-state-owned enterprises (non-SOEs), which can help them reduce the degree of policy uncertainty (Bai et al., 2023). This is similar to firms with political connections[51], politically connected firms have more information about government officials' change and policy uncertainty due to their close relationship with the government, reducing the degree of policy uncertainty (Wang et al., 2017). Thus, compared to SOEs and politically connected firms, non-SOEs and non-politically connected firms may be more likely to be affected by climate policy uncertainty (Bai et al., 2023; Zhang, Deng, Ahmad, Draz, & Abid, 2023).

To examine the effect of CPU on corporate innovation investment according to enterprise-

[51] Following Fan et al. (2007), the political connection equals 1 if the CEO has prior work experience in the government, and 0 otherwise.

government relationship, we categorize the sample based on firms' ownership structures and political connections. Specifically, we divide firms into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs), as well as politically connected firms and non-politically connected firms. In the analysis, SOE is the dummy variable, with a value of 1 when the firm is state owned and 0 otherwise. Political connection is the dummy variable, with a value of 1 when the firm is politically connected and 0 otherwise. Table 4.9. shows that the coefficients of CPU are significantly positive for the non-SOEs and non-politically connected groups, as shown in columns (1) and (3), but insignificant for the SOEs and politically connected groups in column (2) and (4). Furthermore, Chow-tests indicate that the coefficients differ significantly between columns (1) and (2), as well as columns (3) and (4). These results suggest that CPU significantly contributes to corporate innovation investment in non-SOEs and non-politically connected firms, while it has no significant impact on SOEs or politically connected firms.

[Insert Table 4.9. here]

4.5.2.2. Long-term performance and firm value

Until now, the results have presented whether and how climate policy uncertainty affects corporate innovation investment. In this section, we further examine how firms' reaction of innovation investments towards climate policy uncertainty would impact the firm performance and their value.

We find that under climate policy uncertainty, firms would improve their spendings on innovation investment. Does this also generate the positive impact on firm's long-run performance after the innovation investment during this high uncertainty period? To check the long-run performance, we run regressions of the future *Tobin's Q* and *ROA* on the interaction term, $CPU \times R\&D\_Assets$. The results are reported in panels A and B of Table 4.10. We find that the coefficient estimates of interaction term ($CPU \times R\&D\_Assets$) are positive and significant at the 1% level, confirming our conjecture that the positive relationship between climate policy uncertainty and corporate innovation investment further enhances long-term firm performance and value.

[Insert Table 4.10. here]

4.6. Conclusion

With the climate policy uncertainty now being quantified at the aggregate level, its impact is being increasingly examined in various studies (Bai et al., 2023; Lee & Cho, 2023; Xu et al., 2023). For corporations, navigating this uncertainty is crucial for their overall innovation investment decisions since innovation plays a key role in coping with green economy development, meet sustainable development conditions, and counter climate policy uncertainties (Bai et al., 2023; Kemp & Pontoglio, 2011).

This chapter examines how corporate innovation investment responds to climate policy uncertainty in China. We find that climate policy uncertainty positively contributes to corporate innovation investment. The results are still reliable after addressing endogeneity issues and applying a series of robustness checks. Our analysis further indicates that stringent government environmental regulation serves as a potential mechanism, compelling firms to adopt cleaner production and increase their investment in innovation. Additionally, we find that government subsidies are conducive to promoting corporate innovation investment and higher fixed asset allocation dampens the positive influence of climate policy uncertainty on corporate innovation investment. We also find that firms with fewer connections to the government, such as non-state-owned enterprises and those without political connections, are more sensitive to climate policy uncertainty and they tend to increase their investment in innovation to mitigate the uncertainty. Furthermore, we discover that the positive relationship between climate policy uncertainty and corporate innovation investment will further foster the firm’s long-term performance and firm value, which shows that increased innovation investment driven by climate policy uncertainty generates favourable market expectations for firms.

4.7. Tables and figures

Table 4.1. Summary statistics

This table presents the summary statistics for the sample: mean, median, minimum, maximum, standard deviation, 25%,75%, and skewness of variables. *R&D_Assets* is the ratio of R&D expenditure to total assets of each firm and then multiplied by 100. *CPU* is the Twitter based_Climate policy Uncertainty Index divide 1000, as developed by Lee and Cho (2023). It is constructed by averaging the values over the preceding 12 months relative to the firm's fiscal year-end. The definitions of the variables are provided in Appendix C.1. We winsorize the data at the 1% and 99% levels.

Variable	N	Mean	STD	Min	Q1	Median	Q3	Max	Skew.
R&D_Assets	16, 952	2.610	2.120	0.010	1.240	2.190	3.370	11.650	1.770
CPU	16, 952	0.157	0.197	0.010	0.026	0.079	0.116	0.565	1.498
CU	16, 952	0.149	0.121	0.019	0.059	0.096	0.147	0.395	1.372
Size	16, 952	22.080	1.220	19.520	21.220	21.890	22.700	26.430	1.000
ROA	16, 952	0.050	0.070	-0.400	0.020	0.051	0.080	0.250	-1.480
Lev	16, 952	0.380	0.190	0.030	0.230	0.370	0.520	0.920	0.330
Growth	16, 952	0.190	0.370	-0.660	0.000	0.130	0.290	4.330	3.410
Tobin's Q	16, 952	2.180	1.370	0.800	1.340	1.760	2.520	17.730	2.850
KZ	16, 952	0.776	2.144	-6.227	-0.377	1.059	2.239	5.037	-0.788
Top 1	16, 952	0.330	0.140	0.080	0.220	0.310	0.430	0.750	0.550
BoardSize	16, 952	2.100	0.190	1.610	1.950	2.200	2.200	2.710	-0.360
IndepR	16, 952	0.380	0.050	0.290	0.330	0.360	0.430	0.600	1.120
Dual	16, 952	0.350	0.480	0.000	0.000	0.000	1.000	1.000	0.640
Mshare	16, 952	0.190	0.210	0.000	0.000	0.110	0.360	0.710	0.750
Fixed	16, 952	0.197	0.139	0.002	0.089	0.171	0.274	0.714	0.951
Big 4	16, 952	0.050	0.220	0.000	0.000	0.000	0.000	1.000	4.000
Listage	16, 952	1.780	0.800	0.000	1.390	1.950	2.400	3.090	-0.600
SOE	16, 952	0.210	0.400	0.000	0.000	0.000	0.000	1.000	1.460
Polluter	16, 952	0.270	0.440	0.000	0.000	0.000	1.000	1.000	1.030

Table 4.2. Baseline regressions

This table reports the results of baseline regressions. It shows the impact of climate policy uncertainty on corporate innovation investment. The dependent variable is *R&D_Assets*, measured by R&D expenditure to total assets of each firm and then multiplied by 100 in $year_t$. The main independent variable is Twitter-based Chinese climate policy uncertainty index (*CPU*) by Lee and Cho (2023). Definitions of variables are presented in Appendix C.1. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	(1)	(2)	(3)
CPU	1.800***	1.306***	1.166***
	(7.95)	(5.35)	(4.34)
Size		0.124***	0.124***
		(2.73)	(2.72)
ROA		1.036**	1.039**
		(2.26)	(2.27)
Lev		0.029	0.029
		(0.14)	(0.14)
Growth		-0.010	-0.010
		(-0.21)	(-0.20)
Tobin's Q		0.300***	0.300***
		(9.11)	(9.12)
KZ		-0.004	-0.004
		(-0.25)	(-0.27)
Top1		-0.805***	-0.805***
		(-3.66)	(-3.66)
Board		0.138	0.138
		(0.68)	(0.68)
IndepR		0.082	0.081
		(0.13)	(0.12)
Dual		0.055	0.055
		(0.92)	(0.92)
Mshare		0.190	0.190
		(1.15)	(1.15)
Fixed		-0.129***	-0.129***
		(-5.29)	(-5.28)
Big4		0.193	0.193
		(1.27)	(1.27)
List age		-0.186***	-0.186***
		(-4.36)	(-4.35)
SOE		0.109	0.109
		(1.17)	(1.17)
Polluter		-0.157**	-0.157**

		(-2.28)	(-2.29)
GDP growth			-0.658
			(-0.91)
GDP per capita			-0.314
			(-0.75)
Constant	0.904***	-1.972	-1.798
	(3.24)	(-1.81)	(-1.64)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Province	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	16,952	16,310	16,310
Adj R-squared	0.247	0.313	0.313

Table 4.3. Robustness check: Alternative measures of corporate innovation investment

This table reports the results of robustness check based on the baseline results. In panel A, the dependent variable is $R\&D\_Assets_{t+1}$, measured by R&D expenditure to total assets of each firm and then multiplied by 100 in $year_{t+1}$. In panel B, the dependent variable is $R\&D\_Sales$ and $R\&D\_Sales_{t+1}$, measured by R&D expenditure to the sales of each firm in $year_t$ and $year_{t+1}$. The main independent variable is *CPU* index. The *t*-statistics are reported in parentheses. The symbol *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative corporate innovation investment: $R\&D\_Assets_{t+1}$		
Variables	$R\&D\_Assets_{t+1}$	$R\&D\_Assets_{t+1}$
	(1)	(2)
CPU	7.201***	5.229**
	(3.98)	(2.53)
GDP growth		-0.770
		(-0.84)
GDP per capita		-0.285
		(-0.47)
Constant	-1.929	-1.691
	(-1.56)	(-1.36)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	13,048	13,048
Adj R-squared	0.301	0.302

Panel B: Alternative corporate innovation investment: $R\&D\_Sales$		
Variables	$R\&D\_Sales$	$R\&D\_Sales_{t+1}$
	(1)	(2)
CPU	5.029***	17.180***
	(9.14)	(3.99)
GDP growth	2.153	0.799
	(1.27)	(0.35)
GDP per capita	-1.963*	-3.019**
	(-1.88)	(-2.10)
Constant	-9.444***	-7.606***
	(-4.15)	(-3.05)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,310	13,048
Adj R-squared	0.373	0.357

Table 4.4. Robustness check: Alternative measures of climate policy uncertainty

This table reports the results of robustness checks of the baseline results. In panel A, the alternative independent variable is the climate uncertainty index (*CU*) construct by Lee and Cho (2023). In panel B, the alternative independent variable is the U.S. climate policy uncertainty index (*U.S. CPU*) construct by Gavriilidis (2021). In panel C, the alternative independent variable is the residual *CPU*, the standard error that runs the regression between the Chinese CPU and the U.S. CPU. The dependent variable is $R\&D\_Assets$, measured by R&D expenditure to total assets of each firm. The *t*-statistics are reported in parentheses. The symbol *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative climate policy uncertainty: Climate Uncertainty (CU)		
Variables	*R&D_Assets*	*R&D_Assets*
	(1)	(2)
CU	2.026***	1.808***
	(5.35)	(4.34)
GDP growth		-0.658
		(-0.91)
GDP per capita		-0.314
		(-0.75)
Constant	-2.034*	-1.853*
	(-1.86)	(-1.69)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,310	16,952
Adj R-squared	0.313	0.313
Panel B: Alternative climate policy uncertainty: US_CPU		
Variables	*R&D_Assets*	*R&D_Assets*
	(1)	(2)
US_CPU	39.185***	34.967***
	(5.35)	(4.34)
GDP growth		-0.658
		(-0.91)
GDP per capita		-0.314
		(-0.75)
Constant	-8.100***	-7.267***
	(-5.00)	(-4.18)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,310	16,310
Adj R-squared	0.313	0.313
Panel C: Alternative climate policy uncertainty: Residual_CPU		
Variables	*R&D_Assets*	*R&D_Assets*
	(1)	(2)
Residual_CPU	1.321***	1.179***

	(5.35)	(4.34)
GDP growth		-0.658
		(-0.91)
GDP per capita		-0.315
		(-0.75)
Constant	-1.775	-1.622
	(-1.63)	(-1.48)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,310	16,310
Adj R-squared	0.312	0.313

Table 4.5. Endogeneity test: Generalized method of moments

This table reports the results of Generalized Method of Moments (GMM) endogeneity test on the baseline results. Definitions of variables are presented in Appendix C.1. The *t*-statistics are reported in parentheses. The symbol *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*R&D_Assets*	*R&D_Assets*
	(1)	(2)
	FD-GMM	SYS-GMM
L. R&D_Assets	0.327***	0.864***
	(2.88)	(20.03)
CPU	0.751***	0.691***
	(5.43)	(4.41)
Size	0.121	0.198
	(0.51)	(1.13)
ROA	-1.820	-3.478*
	(-1.19)	(-1.79)
Lev	0.693	-2.886
	(0.26)	(-1.51)
Growth	-0.909**	0.074
	(-2.59)	(0.26)
Tobin's Q	-0.248**	-0.302***
	(-2.49)	(-3.76)
KZ	0.039	-0.012
	(0.56)	(-0.19)
Top1	6.089	-1.625
	(0.98)	(-0.56)
Board	-4.552	0.348
	(-1.59)	(0.20)
IndepR	-9.001	1.063
	(-1.16)	(0.18)
Dual	-0.539	-1.115**
	(-0.75)	(-2.07)
Mshare	2.861	5.224**
	(1.15)	(2.38)
Fixed	-1.436	3.444*
	(-0.51)	(1.78)
Big4	3.086	0.443
	(1.06)	(0.30)
List age	0.085	0.394
	(0.25)	(1.50)
SOE	1.006	0.545
	(0.60)	(0.50)

Polluter	0.900	-0.350
	(0.51)	(-0.39)
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Cluster	Firm	Firm
N	10,320	13,161
AR(2)	1.11	0.25
	(0.267)	(0.804)
Hansen test	58.25	76.05
	(0.911)	(0.350)

Table 4.6. Endogeneity test: Instrumental variable tests

This table reports the results of 2SLS instrumental variable analysis. Column (1) reports the results of the first-stage regression, we use the Global Average Surface Temperature (GMST) as the instrumental variable. Column (2) reports the results of the second stage regression. The explanatory variable is the fitted value of the CPU (*CPU_Fitted*). A set of control variables is included and definitions of variables are presented in Appendix C.1. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	First Stage	Second Stage
Dependent Variable	CPU	*R&D_Assets*
	(1)	(2)
GMST	1.971***	
	(59.32)	
CPU_Fitted		2.147***
		(14.99)
Size	0.007***	0.050
	(5.79)	(1.15)
Lev	-0.033***	0.077
	(-3.65)	(0.36)
ROA	0.005	1.498***
	(0.21)	(3.24)
Growth	0.028***	-0.093*
	(7.83)	(-1.81)
Tobin's Q	0.007***	0.253***
	(7.08)	(8.40)
KZ	0.008***	-0.010
	(8.60)	(-0.56)
Top1	-0.022***	-0.746***
	(-3.07)	(-3.39)
Board	-0.016**	0.212
	(-2.13)	(1.03)
IndepR	-0.018	0.247
	(-0.68)	(0.38)
Dual	0.005**	0.053
	(2.08)	(0.89)
Mshare	-0.013**	0.203
	(-2.10)	(1.22)
Fixed	-0.021**	-1.301***
	(-2.46)	(-5.29)
Big4	0.005	0.247
	(1.06)	(1.62)
List age	-0.016***	-0.135***
	(-8.95)	(-3.23)

SOE	0.018***	0.074
	(6.32)	(0.78)
Polluter	0.006***	-0.169**
	(2.83)	(-2.46)
Constant	-1.746***	-0.423
	(-35.57)	(-0.40)
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
Cluster S.E.	Firm	Firm
Adj R-squared		0.285
First Stage F statistic	363.29	
	(0.00)	
LM statistic	237.28	
	(0.00)	
Observations	16,310	16,310

Table 4.7. Mechanism analysis: Environmental regulations

This table reports the results of the heterogeneity tests of government environmental regulations. Environmental regulations (policies) are measured by: (a) Low-carbon pilot cities and other cities, low-carbon pilot city is the dummy variable, with a value of 1 when the firm's headquarter city is designated as low-carbon pilot city and 0 otherwise. (b) 2015 Paris Agreement. We divide firms into two subsamples: "Before 2015 (including 2015)" and "After 2015". The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	Low-carbon pilot cities	Other cities	After 2015	Before 2015 (including 2015)
	(1)	(2)	(3)	(4)
CPU	2.474***	0.968***	1.471***	14.401
	(5.01)	(3.37)	(18.02)	(0.25)
Constant	-0.959	3.389**	-2.505**	1.973
	(-0.78)	(2.06)	(-2.20)	(0.81)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Provice	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	11,421	4,889	13,455	2,855
Adj R-squared	0.320	0.273	0.314	0.316
Chow-test	0.014**		0.000***	

Table 4.8. Moderating effect: Government subsidy supporting and corporate internal asset allocation

This table reports the results of moderating effect of government subsidy supporting and corporate internal asset allocation. The dependent variables are *R&D_Assets*, measured by R&D expenditure to total assets of each firm. The main independent variable is *CPU* index. Subsidy is measured by government subsidy received by each firm scaled by its total assets; Fixed is the ratio of fixed assets for the firm to total assets. Detailed definitions of variables are given in Appendix C.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	*R&D_Assets*	*R&D_Assets*
	(1)	(2)
CPU × Subsidy	11.531**	
	(2.33)	
CPU × Fixed		-1.854***
		(-4.09)
CPU	1.269***	1.809***
	(3.32)	(6.94)
Subsidy	0.042	0.796
	(0.04)	(0.84)
Fixed	-1.263***	-1.044***
	(-9.26)	(-4.02)
Constant	-1.758***	1.055
	(-2.95)	(1.05)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	13,216	16,310
Adj R-squared	0.309	0.312

Table 4.9. Climate policy uncertainty and enterprise-government relationship

This table reports the results of the heterogeneity tests of government-enterprise relationship. We use (a) enterprise's ownership structure (SOEs and Non-SOEs); (b) political connection (Politically connected firms and Non-politically connected firm) to represent the enterprise- government relationship. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

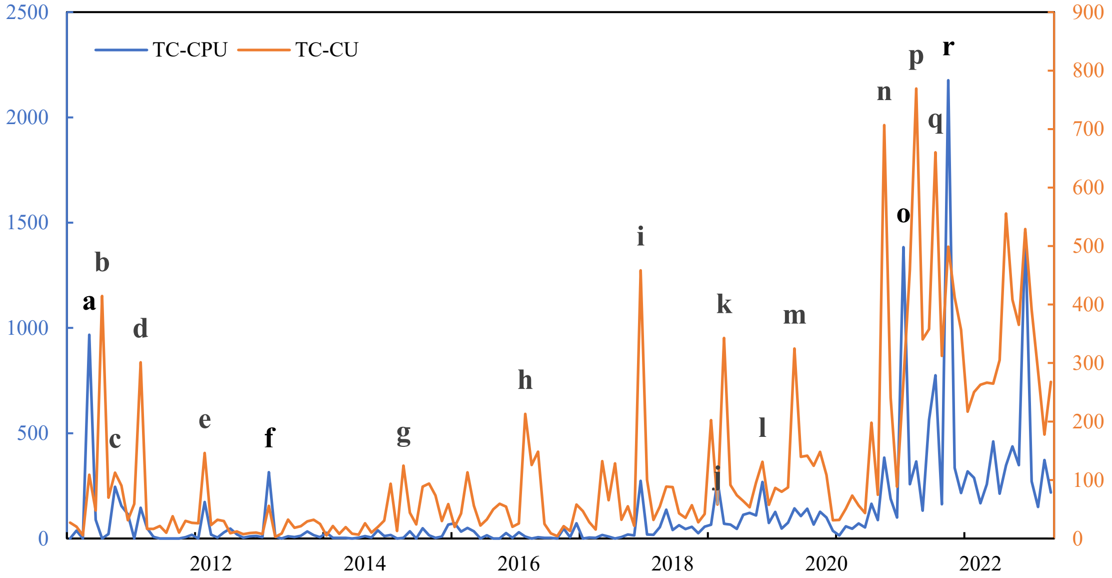
Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	Non-SOEs	SOEs	Non-political connection	Political connection
	(1)	(2)	(3)	(4)
CPU	1.536***	0.866	7.386***	2.537
	(5.86)	(1.54)	(4.22)	(0.64)
Constant	-2.257*	-3.153	-2.598**	1.388
	(-1.81)	(-1.49)	(-2.12)	(0.49)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	13,130	3,180	11,143	1,989
Adj R-squared	0.305	0.376	0.325	0.318
Chow-test	0.039**		0.043**	

Table 4.10. Climate policy uncertainty and firm performance predictability

This table reports the results between climate policy uncertainty and firm performance predictability. We use the *ROA* and *Tobin's Q* to present the firm performance and firm value. The interaction term is *CPU* multiplying the innovation investment. Detailed definitions of variables are given in Appendix C.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Climate policy uncertainty and Tobin's Q		
Variables	$Tobin's\ Q_{t+1}$	$Tobin's\ Q_{t+2}$
	(1)	(2)
CPU × R&D_Assets	0.444***	0.988***
	(4.42)	(6.45)
CPU	3.694***	2.969***
	(5.27)	(2.22)
R&D_Assets	0.019**	0.021**
	(2.13)	(2.11)
Constant	0.908***	5.272***
	(2.72)	(5.23)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	12,877	10,425
Adj R-squared	0.583	0.384
Panel B: Climate policy uncertainty and ROA		
Variables	ROA_{t+1}	ROA_{t+2}
	(1)	(2)
CPU × R&D_Assets	0.020***	0.018**
	(3.05)	(2.28)
CPU	0.043*	-0.094
	(1.66)	(-1.14)
R&D_Assets	0.001	0.003***
	(1.24)	(5.61)
Constant	0.618***	-0.144***
	(12.85)	(-5.63)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	12,784	10,516
Adj R-squared	0.428	0.244

Figure 4.1. Twitter-based Chinese climate policy (TC-CU) and twitter-based Chinese climate policy uncertainty (TC-CPU) with major events



This figure plots Twitter-based Chinese Climate (Policy) Uncertainty from March 2010 to December 2022, Twitter-based Chinese Climate Uncertainty (TC-CU) and Twitter-based Chinese Climate Policy Uncertainty (TC-CPU) Index are obtained from Lee and Cho (2023). The following denotes major events with year and months in "YYYY-MM" format (we will give some examples for the major events): a. 2010-07, a major investment by China Investment Corporation into the AES's wind power generation was dropped over; b. 2010-09, Warning on climate change risk for China's crops by a study in Nature; g. 2014-08, Warning on coal-to-gas plants in Inner Mongolia; i. 2017-09, President Xi Jinping warned risks associated with resisting climate change; j. 2018-09, President Xi Jinping emphasized Russia-China ties amid unpredictable geopolitical climate; l. 2019-04, President Xi Jinping highlighted building an infrastructure of sustainability under the Belt and Road Initiative; p. 2021-04, China drafted a plan to develop its hydrogen industry by the National Development and Reform Commission; r. 2021–09, UK-led Cop26 talks at risk of failure over Chinas refusal to cut emission, China warned US climate cooperation at risk over political tension (More details can be found from Lee and Cho (2023)).

CHAPTER FIVE CONCLUSION

5.1. Main findings and implications

Overall, this thesis provides comprehensive insights into how environmental factors influence firms' investment behaviours in China, specifically examining the impact of air pollution on mergers and acquisitions (M&As) activities, the effect of adjusted air quality on corporate innovation investments, and the role of climate policy uncertainty in shaping corporate innovation.

This first essay reveals that air pollution decreases local firms' M&A activities and this is achieved through its adverse effects on firms' operational conditions, as air pollution raises environmental awareness among external stakeholders, prompting their negative responses that constrain firms' cash flows and elevate environmental expenditures. Furthermore, this impact is more pronounced for firms with limited access to external resources and those located in regions with heightened environmental awareness. Firms receiving higher government subsidies or having strong financial health are more capable of alleviating this negative impact. This study also reveals that acquirers in heavy air pollution areas prefer to use stock-based payment, take longer to complete acquisitions, create less shareholder wealth and bring negative market reaction, as well as suffering from declining performance in the long-term. Overall, the first essay offers an in-depth perspective on how air pollution harms corporate M&A.

Essay two develops an adjusted measure of air pollution exposure that captures both firm exposure levels and the severity of local air pollution. Using this measure, the essay finds a significant negative relationship between adjusted air pollution exposure and corporate investment in innovation. Furthermore, the negative effect of air pollution exposure is found to be mediated through reduced net operating cash flows and increased debt financing costs. Nevertheless, firms with state ownership demonstrate a notable ability to counteract these adverse effects. The negative influence is more pronounced in firms that disclose environmental information, exhibit low managerial risk tolerance, operate in non-polluting industries, or are located in more developed and less polluted regions, as well as in periods following the 2015 Paris Agreement. This research highlights the critical role of adjusted air pollution exposure in shaping corporate innovation investment in China.

Essay three explores the effect of climate policy uncertainty on corporate innovation investment. The findings indicate that climate policy uncertainty positively contributes to corporate innovation investment. Our analysis reveals that stringent government environmental regulation drive firms to adopt cleaner production and boost innovation investments. Additionally, the positive association is amplified for firms receiving substantial government subsidies, while it weakens for those with higher proportions of fixed assets. We also find that firms with fewer connections to the government, such as non-state-owned enterprises and those without political connections, are more sensitive to climate policy uncertainty and they tend to increase their investment in innovation to mitigate the uncertainty. The study further reveals that firms increasing innovation investments during periods of heightened climate policy uncertainty experience improvements in their long-term performance and firm value. Overall, this essay highlights the critical role of climate policy uncertainty in shaping corporate innovation investment in China.

In conclusion, this thesis highlights complex connections between environmental factors and corporate investment decisions in China. These studies provide insights into how environmental and policy factors shape corporate decision-making and underscore the importance of regulatory frameworks and environmental awareness in driving sustainable corporate practices.

5.2. Future areas of research

The essays in this thesis highlight several promising areas for future research. For example, Chapter Two focuses on the relationship between air pollution and mergers and acquisitions (M&As) in China, and future studies could explore whether similar patterns hold across different regions with varied environmental regulations and pollution levels. A comparative analysis of developed and developing economies could reveal the impact of different regulatory frameworks on M&A activities. Building on Chapter Three's findings on adjusted air pollution exposure and corporate innovation investment, future research could examine how this relationship evolves over time as firms adapt to environmental pressures. This approach would provide insights into how companies' innovation strategies adjust to regulatory changes and increased environmental awareness. Chapter Four's findings on climate policy uncertainty and corporate innovation suggest that uncertain policy environments may drive firms to invest in innovation. Future research could investigate how these investments impact not only firm value and long-term performance but also broader industry standards and sector-wide shifts in innovation. Moreover, more granular data—such as the city-level climate policy uncertainty (*CPU*) index developed by Ma et al. (2024)—may be better suited to capture the localized impact of climate-related policy uncertainty on firms' innovation decisions. In addition, future research could examine whether different types of government subsidies play distinct roles in shaping these positive contributions.

Overall, these directions would add depth to understanding how environmental and policy contexts influence corporate strategy and could inform policymakers aiming to enhance sustainable corporate practices.

APPENDIX A FOR ESSAY ONE

Appendix A.1. Variables definition

This table presents definitions of all the variables.

	Variables	Definition
Dependent variable	M&A	Dummy variable that equals 1 if firm *i* makes at least one acquisition announcement in year t, and 0 otherwise.
Explanatory variable	Air pollution	Yearly average Air Quality Index (AQI) divide 1000 of the city where firm *i*'s headquarters located.
	AAQI	Yearly average Air Quality Index (AQI) divide 1000 of each acquirer's city.
	TAQI	Yearly average Air Quality Index (AQI) divide 1000 of each target's city.
Control variables	Size	Natural logarithm of total assets.
	Lev	The ratio of total debt to total assets.
	ROA	Returns on assets, calculated as net income over total assets.
	Growth	The growth rate of income.
	BM	The ratio of the book value to the market value of assets.
	CH/at	The ratio of net cash holding to the total assets.
	Capex/at	The funds used by a company to acquire, upgrade, and maintain physical assets such as property, plants, buildings, technology, or equipment divided by total assets.
	INST	Total shares held by institutional investors divided by outstanding share capital.
	Top 5	The sum of the shareholding ratio of the top 5 major shareholders.
	ListAge	The natural log of current year minus listed year and plus one, ln (current year-listed year+1).
	BoardSize	Take the natural log of the number of board members.
	IndepR	The proportion of independent directors.
	Dual	The dummy variable equals 1 if chairman of the board and CEO are the same individual, and 0 if otherwise.
	SOE	The dummy variable equals 1 if the firm is SOE, and 0 if otherwise.
	Deal ratio	The ratio of deal value to total assets.
	Polluter	Dummy variable that equals 1 if firm *i* belongs to the polluting industries, and 0 otherwise. Categorizations of these industries follow the CSRC Listed Company Industry Classification Guidelines (2012).
	Cash dummy	The dummy variable that equals 1 if an M&A deal is fully funded by cash, and 0 otherwise.
	Stock dummy	The dummy variable that equals 1 if an M&A deal is fully funded by stock, and 0 otherwise.
	Diversifying dummy	The dummy variable equals 1 if the deal is a diversified M&A, and 0 otherwise.
	Intellectual property dummy	The dummy variable that equals 1 if an M&A deal is related to the intellectual property transaction, and 0 otherwise.
	Cross-city dummy	The dummy variable that equals 1 if the acquirer and target firm in the different city, and 0 otherwise.
	CF	The ratio of net cash flow to the total assets.
	Environmental investment	The ratio of firm's environmental investment to the total assets.
	Government subsidy	The ratio is measured by government subsidy to total assets of each firm.
	Bank loans	The ratio is measured by long-term bank loans to total assets of each firm.
	Trade credit	Account payable ratio (AP Ratio); the ratio of accounts payable to the cost of goods sold.

Notes: All control variables are about acquirer's characteristics.

Appendix A.2. Distribution of M&As by year and industry

This table reports the annual and 2-digit code industry distribution of M&A subsample for the period 2010–2020.

Panel A: M&A Subsample Distribution by Year.

Year	Frequency	Percent
2010	27	0.76%
2011	100	2.82%
2012	199	5.62%
2013	178	5.03%
2014	452	12.76%
2015	653	18.44%
2016	553	15.62%
2017	467	13.19%
2018	382	10.79%
2019	329	9.29%
2020	201	5.68%
Total	3,541	100.00%

Panel B: M&A Distribution by Industries.

2-digit code industry	Industry Description	Frequency	Percent
C39	Computer, Communications, and other electronic equipment manufacturing	374	10.56%
I	Information transmission, software, and information technology service	330	9.32%
C26	Chemical material and products manufacturing	257	7.26%
C35	Special equipment manufacturing	220	6.21%
C27	Medicine manufacturing	193	5.45%
F	Wholesale and retail	168	4.74%
C34	Common machines manufacturing	152	4.29%
K	Real estate	109	3.08%
C36	Automobile manufacturing	94	2.65%
C30	Non-metal mineral products	88	2.49%
C38	Electric equipment and parts manufacturing	88	2.49%
E	Construction	86	2.43%
C18	Textile clothing, apparel manufacturing	81	2.29%
C33	Metal products industry	75	2.12%
C40	Instrument manufacturing	73	2.06%
G	Transportation	62	1.75%
C29	Rubber and plastic products manufacturing	61	1.72%
R	Culture, sports, and entertainment	60	1.69%
B	Mining	56	1.58%
D	Utilities	55	1.55%
	Industries with <1.5% representation		
	Total	3,541	100.00%

Appendix A.3. Distribution of air pollution by year and province

This table provides the summary statistics for air quality index from 2010 to 2020 in each province in China.

Province	Mean	Median	Min	Max	STD
Hebei	0.116	0.113	0.054	0.246	0.038
Henan	0.109	0.112	0.07	0.174	0.022
Shanxi	0.102	0.097	0.062	0.195	0.022
Xinjiang	0.101	0.099	0.048	0.251	0.021
Tianjin	0.099	0.098	0.073	0.156	0.021
Beijing	0.097	0.094	0.079	0.125	0.016
Hubei	0.095	0.088	0.065	0.225	0.033
Shandong	0.095	0.086	0.04	0.243	0.031
Shanxi	0.092	0.097	0.051	0.162	0.019
Gansu	0.091	0.094	0.053	0.117	0.013
Jiangsu	0.089	0.085	0.062	0.196	0.026
Sichuan	0.088	0.08	0.038	0.24	0.027
Anhui	0.087	0.085	0.042	0.222	0.029
Heilongjiang	0.085	0.076	0.042	0.197	0.033
Hunan	0.083	0.082	0.051	0.177	0.025
Qinghai	0.083	0.085	0.069	0.104	0.009
Ningxia	0.083	0.081	0.063	0.108	0.011
Nei Mongol	0.081	0.08	0.033	0.139	0.017
Liaoning	0.08	0.078	0.056	0.15	0.014
Chongqing	0.08	0.075	0.067	0.13	0.016
Zhejiang	0.08	0.072	0.001	0.198	0.026
Shanghai	0.08	0.074	0.058	0.158	0.023
Jilin	0.078	0.071	0.018	0.146	0.021
Jiangxi	0.071	0.069	0.048	0.135	0.016
Guangxi	0.066	0.059	0.047	0.199	0.024
Guizhou	0.062	0.061	0.039	0.178	0.019
Guangdong	0.061	0.057	0.041	0.132	0.015
Yunnan	0.057	0.055	0.041	0.112	0.01
Fujian	0.056	0.055	0.043	0.084	0.007
Tibet	0.056	0.053	0.038	0.078	0.011
Hainan	0.044	0.042	0.021	0.103	0.013

Appendix A.4. Correlation matrix

This table reports the correlation coefficients between key variables. Definitions of variables are in Appendix A.1. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables		1	2	3	4	5	6	7	8	9
1	M&A	1.000								
2	Air pollution	-0.007***	1.000							
3	Size	-0.051**	0.028***	1.000						
4	Lev	-0.021***	0.024***	0.485***	1.000					
5	ROA	-0.021***	-0.014***	-0.019***	-0.358***	1.000				
6	Growth	0.080***	0.006	0.034***	0.048***	0.189***	1.000			
7	BM	-0.117***	0.004	0.582***	0.340***	-0.154***	-0.047***	1.000		
8	CH/at	-0.021***	-0.065***	0.074***	-0.119***	0.119***	0.028	-0.022***	1.000	
9	Capex/at	-0.074***	-0.119***	-0.034***	-0.075***	0.135***	0.041***	-0.008	0.067***	1.000
10	INST	-0.038***	0.040***	0.468***	0.243***	0.040***	0.008	0.068***	-0.031***	-0.025***
11	Top 5	-0.041***	-0.005	0.156***	-0.088***	0.216***	0.015***	0.148***	0.078***	0.123***
12	ListAge	0.004	0.030***	0.389***	0.408***	-0.238***	0.004	0.129***	-0.017***	-0.239***
13	BoardSize	-0.065***	0.041***	0.279***	0.165***	0.005	-0.012	0.172***	-0.004***	0.035***
14	IndepR	0.014***	-0.029***	0.000	-0.008	-0.020***	-0.002	-0.023***	-0.004	-0.008
15	Dual	0.040***	-0.061***	-0.187***	-0.162***	0.058***	0.008	-0.123***	0.052	0.067***
16	SOE	-0.123***	0.077***	0.371***	0.317***	-0.100***	-0.053***	0.249***	-0.048***	-0.082***
17	Polluter	-0.017***	0.023***	0.050***	-0.018***	0.017***	-0.016***	0.039***	-0.023***	0.098***

(Continuous)

Variables		10	11	12	13	14	15	16	17
1	M&A								
2	Air pollution								
3	Size								
4	Lev								
5	ROA								
6	Growth								
7	BM								
8	CH/at								
9	Capex/at								
10	INST	1.000							
11	Top 5	0.284***	1.000						
12	ListAge	0.415***	-0.351***	1.000					
13	BoardSize	0.210***	0.009	0.138***	1.000				
14	IndepR	-0.041***	0.047***	-0.024***	-0.535***	1.000			
15	Dual	-0.207***	0.027***	-0.261***	-0.181***	0.101***	1.000		
16	SOE	0.412***	0.033***	0.438***	0.267***	-0.048***	-0.313***	1.000	
17	Polluter	0.042***	0.012	0.063***	0.087***	-0.050***	-0.023***	0.032***	1.000

Appendix A.5. Baseline regression between SOEs and Non-SOEs

This table reports the results of baseline regressions. It shows the impact of air quality on the M&A deals' decisions. Definitions of variables are presented in Appendix A.1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	SOE	Non-SOE	SOE	Non-SOE
	(1)	(2)	(3)	(4)
Air pollution	-8.002***	-3.001**	-6.876***	-3.302***
	(-3.21)	(-2.48)	(-2.79)	(-2.66)
Size	0.014	0.043	0.014	0.043
	(0.22)	(1.23)	(0.22)	(1.25)
Lev	-0.028	0.451***	-0.014	0.453***
	(-0.09)	(2.93)	(-0.05)	(2.95)
ROA	0.250	-1.269	0.244	-1.263
	(0.28)	(-1.52)	(0.27)	(-1.52)
Growth	0.321***	0.390***	0.321***	0.389***
	(3.83)	(7.76)	(3.80)	(7.74)
BM	-0.538*	-0.901***	-0.530*	-0.909***
	(-1.82)	(-4.89)	(-1.79)	(-4.93)
CH/at	1.516**	0.052	1.499**	0.052
	(2.17)	(0.19)	(2.15)	(0.19)
Capex/at	-1.547	-1.959***	-1.648	-1.942***
	(-1.23)	(-3.19)	(-1.30)	(-3.16)
INST	-1.771	0.120	-1.889*	0.095
	(-0.92)	(0.14)	(-0.98)	(0.11)
Top 5	-0.513	0.327	-0.504	0.330
	(-1.15)	(1.52)	(-1.13)	(0.75)
ListAge	-0.148	0.261***	-0.134	0.260***
	(-1.50)	(6.18)	(-1.35)	(6.16)
BoardSize	-0.739***	-0.483***	-0.734***	-0.482***
	(-2.62)	(-2.97)	(-2.60)	(-2.97)
IndepR	-1.553	-0.619	-1.530	-0.618
	(-1.55)	(-1.04)	(-1.53)	(-1.04)
Dual	0.194	0.039	0.196	0.039
	(1.28)	(0.76)	(1.29)	(0.75)
Polluter	0.064	-0.096	0.064	-0.098
	(0.50)	(-1.48)	(0.50)	(-1.52)
GDP growth			9.610***	-2.271
			(2.59)	(-1.28)
GDP per capita			-6.015*	1.718
			(-1.91)	(1.18)

Constant	-1.703	-4.039***	-2.610	-3.898***
	(-0.93)	(-3.82)	(-1.40)	(-3.62)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	7,876	14,451	7,876	14,451
Pseudo R-squared	0.049	0.094	0.051	0.094

Appendix A.6. Propensity score matching analysis: Industry-stratified design

This table reports the results of the propensity score matching analysis using a within-industry matching procedure, which restricts treated firms to be matched only with control firms operating in the same industry. The reported coefficients are based on the matched sample regressions. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	M&A
Air pollution	-3.462***
	(-4.57)
Size	0.023
	(0.42)
Lev	0.147
	(0.53)
ROA	-0.943
	(-0.57)
Growth	0.575***
	(6.27)
BM	-0.801***
	(-3.41)
CH/at	-0.029
	(-0.90)
Capex/at	-1.767**
	(-2.44)
INST	-0.365
	(-0.42)
Top 5	-0.054
	(-0.26)
ListAge	0.140***
	(3.23)
BoardSize	-0.538**
	(-2.47)
IndepR	-1.193*
	(-1.75)
Dual	0.065
	(0.83)
SOE	-0.594***
	(-5.90)
Polluter	-0.090
	(-1.16)
Constant	-2.097**
	(-2.13)

Year	Yes
Firm	Yes
Observations	7,958
Pseudo R^2	0.069

APPENDIX B FOR ESSAY TWO

Appendix B.1. Variables definition

This table presents definitions of all the variables.

	Variables	Definition
Dependent variable	R&D_Assets	The ratio of R&D expenditure to total assets multiply by 100.
	Inv_PAT_APP	Natural logarithm of total number of invention patents applications plus one.
Explanatory variable	A_AQI exposure	Adjusted air pollution exposure, measured by AQI × AQI exposure.
	AQI	Annual average Air Quality Index (AQI) divide 1000 of the city where firm *i*'s headquarter is located.
	AQI exposure	Air pollution exposure is the absolute air pollution beta, which is calculated through the Fama-French three-factor model.
Control variables	Size	Natural logarithm of total assets.
	Lev	The ratio of total debt to total assets.
	ROA	Returns on assets, calculated as net income over total assets.
	Growth	The growth rate of sales.
	Tobin's Q	The ratio of market value to book value of assets.
	KZ	KZ Index; higher KZ index, higher financial constraints.
	Top1	The shareholding ratio of the top one major shareholder.
	ListAge	The natural logarithm of current year minus listed year and plus one, ln (current year-listed year+1).
	BoardSize	The natural logarithm of the number of board members.
	IndepR	The proportion of independent directors.
	Dual	The dummy variable equals 1 if chairman of the board and CEO are the same individual, and 0 if otherwise.
	Mshare	Management's shareholding
	Fixed	The ratio of fixed assets to total assets.
	Big 4	Dummy variable that equals 1 if the firm employs a Big Four auditor, and 0 otherwise
	SOE	The dummy variable equals 1 if the firm is state - owned-enterprise (SOE), and 0 if otherwise.
	Polluter	Dummy variable that equals 1 if firm *i* belongs to the polluting industries, and 0 otherwise. Categorizations of these industries follow the CSRC Listed Company Industry Classification Guidelines (2012).
	CF	The ratio of net operating cash flow to the total assets.
	Fincost	Debt financing cost: Interest expense/Average short- and long-term debt (%).

Appendix B.2. Distribution of air pollution by province

This table provides the summary statistics for air quality index in our sample in each province.

Province	Mean	p50	Min	Max	SD
Hainan	0.043	0.042	0.019	0.103	0.008
Tibet	0.051	0.050	0.038	0.058	0.005
Yunnan	0.052	0.054	0.041	0.060	0.004
Guizhou	0.054	0.051	0.039	0.128	0.012
Fujian	0.054	0.053	0.043	0.082	0.005
Guangdong	0.060	0.057	0.045	0.147	0.011
Guangxi	0.060	0.057	0.047	0.093	0.009
Jiangxi	0.065	0.065	0.048	0.084	0.007
Zhejiang	0.073	0.071	0.047	0.181	0.013
Jilin	0.073	0.070	0.052	0.101	0.013
Chongqing	0.074	0.072	0.062	0.093	0.009
Shanghai	0.074	0.072	0.047	0.125	0.008
Heilongjiang	0.074	0.070	0.051	0.103	0.014
Qinghai	0.080	0.084	0.069	0.090	0.007
Liaoning	0.080	0.078	0.065	0.112	0.012
Hunan	0.080	0.080	0.053	0.172	0.014
Anhui	0.081	0.083	0.045	0.147	0.013
Nei Mongol	0.083	0.083	0.057	0.139	0.015
Sichuan	0.083	0.077	0.053	0.155	0.013
Jiangsu	0.083	0.083	0.046	0.239	0.015
Gansu	0.084	0.087	0.052	0.102	0.013
Ningxia	0.086	0.086	0.076	0.100	0.006
Hubei	0.087	0.086	0.059	0.138	0.013
Shandong	0.092	0.094	0.040	0.144	0.019
Xinjiang	0.094	0.094	0.056	0.124	0.015
Beijing	0.095	0.094	0.061	0.125	0.017
Shanxi	0.096	0.098	0.073	0.123	0.012
Tianjin	0.098	0.099	0.085	0.121	0.010
Shanxi	0.102	0.100	0.060	0.218	0.016
Henan	0.111	0.111	0.072	0.172	0.018
Hebei	0.114	0.109	0.066	0.246	0.029

Appendix B.3. Correlation Matrix

This table reports the correlation coefficients between key variables. Definitions of variables are in Appendix B.1. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Variables	1	2	3	4	5	6	7	8	9	10	11
1	R&D_Assets	1.000										
2	A_AQI exposure	-0.044	1.000									
3	AQI	-0.072	0.118	1.000								
4	AQI exposure	0.044	0.959	-0.053	1.000							
5	size	-0.189*	0.048***	0.057***	-0.245***	1.000						
6	roa	0.114***	0.001	0.001	0.140***	-0.020***	1.000					
7	lev	-0.176***	0.026***	0.014*	-0.141***	0.522***	-0.353***	1.000				
8	growth	0.049**	0.066***	-0.005	0.069***	0.041***	0.275***	0.024***	1.000			
9	tobinq	0.267***	0.014**	-0.025***	0.053***	-0.295***	0.205***	-0.281***	0.088***	1.000		
10	KZ	-0.095***	0.075***	-0.025***	-0.179***	0.205***	-0.575***	0.545***	-0.088***	-0.045***	1.000	
11	top1	-0.150***	-0.047***	0.043***	0.030***	0.174***	0.140***	0.038***	-0.025***	-0.083***	-0.121***	1.000
12	board	-0.087***	-0.061***	0.096***	-0.041***	0.261***	0.004	0.131***	-0.013***	-0.099***	0.042***	0.006***
13	indep	0.036***	0.019***	-0.051***	-0.015*	-0.018**	-0.011	-0.013*	-0.010	0.045***	-0.002***	0.055***
14	dual	0.097***	0.045***	-0.107***	0.082***	-0.170***	0.051***	-0.127***	0.035***	0.070***	-0.088***	-0.018***
15	mshare	0.126***	-0.023***	-0.040***	0.178***	-0.358***	0.175***	-0.268***	0.063***	0.016**	-0.245***	-0.069***
16	fixed	-0.223***	-0.068***	0.066***	-0.072***	0.149***	-0.071***	0.127***	-0.069***	-0.104***	0.095***	0.128***
17	big4	-0.009	0.025***	0.022***	-0.034***	0.359***	0.026***	0.120***	-0.006	-0.057***	0.009***	0.138***
18	listage	-0.124***	0.013*	0.034***	-0.475***	0.445***	-0.259***	0.310***	-0.076***	-0.018**	0.359***	-0.108***
19	soe	-0.145***	-0.014*	0.138***	-0.139***	0.383***	-0.083***	0.263***	-0.078***	-0.118***	0.165***	0.242***
20	polluter	-0.111***	-0.026***	0.039***	-0.043***	0.076***	0.053***	-0.040***	-0.020***	-0.053***	-0.048***	0.057***

(Continuous)

Variables		12	13	14	15	16	17	18	19	20
1	R&D_Assets									
2	A_AQI exposure									
3	AQI									
4	AQI exposure									
5	size									
6	roa									
7	lev									
8	growth									
9	tobinq									
10	KZ									
11	top1									
12	board	1.000								
13	indep	-0.602	1.000							
14	dual	-0.175***	0.116**	1.000						
15	mshare	-0.187***	0.072***	0.198***	1.000					
16	fixed	0.133***	-0.042***	-0.087***	-0.178***	1.000				
17	big4	0.069	0.043***	-0.055***	-0.134***	0.047***	1.000			
18	listage	0.134***	-0.010***	-0.190***	-0.430	0.159***	0.052***	1.000		
19	soe	0.270***	-0.058***	-0.266***	-0.415***	0.186***	0.157***	0.325***	1.000	
20	polluter	0.077***	-0.055***	-0.028***	-0.055***	0.308***	0.006	0.095***	0.051***	1.000

Appendix B.4. Fama-French three factors regression

This table reports the sensitivity of AQI anomaly using the Fama-French three-factor model for the whole sample period:

$$R_{i,t} - r_{f,t} = \alpha + \beta_{i,t}^{mkt} MKT_t + \beta_{i,t}^{smb} SMB_t + \beta_{i,t}^{hml} HML_t + \beta_{i,t}^{aqi} AQI\ Anomaly_t + e_t$$

where, $R_{i,t}$ is the contemporaneous return on firm *i* in month *t*, $r_{f,t}$ is the risk-free rate in month *t*. MKT_t, SMB_t, and HML_t are three Fama-French factors: the excess market returns, the factors small-minus-big, and the factors high-minus-low in month *t*, respectively. AQI $Anomaly_t$ is the abnormal AQI for each listed firm defined as the difference between $AQI_{i,t}$ of the firm *i*'s headquarter city on month *t* and the average of AQI for all cities in the same month. This table provides the result to show the statistical and economic significance of beta estimation using Fama-French three factors rolling regression.

Variables	*Excess Return (ER)*
MKT	0.931***
	(117.14)
SMB	1.022***
	(79.07)
HML	-0.305***
	(-20.09)
AQI Anomaly	0.054**
	(2.42)
Constant	0.005***
	(65.51)
Firm	Yes
Year	Yes
Province	Yes
S.E. Clustering	Firm
N	228,969
Adj R-squared	0.206

Appendix B.5. Baseline results under different sub-samples

This table provides the results to show the baseline results of sub-samples based on (1) quantiles of AQI (Panel A), where AQI_1 is the First quantile (low AQI index), and AQI_5 is the Last quantile (high AQI index); and (2) the median level of AQI and AQI exposures (Panel B). In Panels A and B, the main independent variable is AQI exposure and A_AQI exposure, respectively. The *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sub-samples based on quantiles of AQI (independent variable AQI exposure)

Variables	*R&D _Assets*	*R&D _Assets*	*R&D _Assets*	*R&D _Assets*	*R&D _Assets*
	(1)	(2)	(3)	(4)	(5)
	AQI_1	AQI_2	AQI_3	AQI_4	AQI_5
AQI exposure	-0.004	-0.004	-0.015	-0.016	-0.001
	(-0.12)	(-0.51)	(-1.22)	(-1.15)	(-0.04)
Constant	3.168	3.168***	2.876***	2.281**	2.121**
	(1.00)	(4.14)	(3.76)	(2.09)	(2.14)
Controls	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes
N	3,297	3,297	6,587	9,876	3,177
Adj R-squared	0.291	0.291	0.277	0.284	0.292

Panel B: Sub-samples based on the median level of AQI and AQI exposures

Variables	High AQI High exposure	High AQI Low exposure	Low AQI Low exposure	Low AQI High exposure
	(1)	(2)	(3)	(4)
A_AQI exposure	-0.071	-2.275**	-3.197*	-0.469**
	(-0.49)	(-2.04)	(-1.78)	(-2.29)
Constant	3.407***	0.082	2.892***	3.244***
	(3.30)	(0.10)	(3.10)	(3.35)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
N	3,831	4,268	3,890	4,317
Adj R-squared	0.302	0.294	0.270	0.287

Appendix B.6. Further analysis on green innovation

This table provides the results to show the differential effects of adjusted air pollution exposure on general technological innovation and green innovation. The main dependent variables are the natural logarithm of total number of invention patents application plus one in $year_{t+1}$ ($Inv\_PAT\_APP_{t+1}$) and the natural logarithm of total number of green invention plus one in $year_{t+1}$ ($Green\_Inv\_PAT\_APP_{t+1}$). The main independent variable is adjusted air pollution exposure (A_AQI *exposure*). The *t*-statistics are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	$Inv\_PAT\_APP_{t+1}$	$Inv\_PAT\_APP_{t+1}$	$Green\_Inv\_PAT\_APP_{t+1}$	$Green\_Inv\_PAT\_APP_{t+1}$
	(1)	(2)	(3)	(4)
A_AQI exposure	-0.108***	-0.091**	0.177*	-0.194
	(-3.63)	(-2.49)	(1.82)	(-0.70)
AQI		2.415*		2.909**
		(1.89)		(2.08)
AQI exposure		-0.004		0.032
		(-0.59)		(1.28)
Constant	-4.068***	-4.192***	10.717***	10.479***
	(-2.92)	(3.41)	(16.86)	(16.22)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm	Firm
N	10,583	10,583	2.512	2,512
Adj R-squared	0.202	0.203	0.125	0.127

Appendix B.7. Endogeneity test: Propensity scores matching analysis

This table presents pre-matching and post-matching differences in characteristics between high-adjusted air pollution exposure and low-adjusted air pollution exposure from the propensity score regression. The logit model is used to estimate propensity scores, where the dependent variable is the dummy variable, which equals 1 if the adjusted air pollution exposure for the firm is above the median and 0 otherwise. Definitions of variables are in Appendix B.1. The *t*-statistics are calculated based on robust standard errors. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Pre-matched differences in characteristics between high-adjusted air pollution exposure and low-adjusted air pollution exposure

Variables	*No. of observations if adjusted air pollution exposure dummy* = 1	*Mean if adjusted air pollution exposure dummy* =1	*No. of observations if adjusted air pollution exposure dummy* = 0	*Mean if adjusted air pollution exposure dummy* = 0	Mean Difference	*t*-value
Size	8,476	21.821	8,476	22.307	-0.486***	-26.32
ROA	8,476	0.053	8,476	0.040	0.013***	11.82
Lev	8,476	0.361	8,476	0.402	-0.041***	-13.99
Growth	8,476	0.209	8,476	0.163	0.046***	8.02
Tobin's Q	8,476	2.303	8,476	2.082	0.221***	10.34
KZ	8,476	0.764	8,476	1.047	0.283***	11.26
Top1	8,476	0.332	8,476	0.330	0.002	0.67
Board	8,476	2.090	8,476	2.105	-0.015***	-4.97
IndepR	8,476	0.377	8,476	0.379	-0.002**	-2.38
Dual	8,476	0.376	8,476	0.330	0.046***	6.08
Mshare	8,476	0.221	8,476	0.164	0.057***	17.67
Intangibility	8,476	0.045	8,476	0.044	0.001***	3.82
Fixed	8,476	0.197	8,476	0.195	0.002***	5.58
Big4	8,476	0.040	8,476	0.060	-0.020***	-5.82
Listage	8,476	1.528	8,476	2.023	-0.495***	-42.39
SOE	8,476	0.147	8,476	0.243	-0.096***	-15.48
Polluter	8,476	0.252	8,476	0.287	-0.035***	-5.05

Panel B. Post-matched differences in characteristics between high-adjusted air pollution exposure and low-adjusted air pollution exposure

Variables	*No. of observations if adjusted air pollution exposure dummy* =1	Mean if *adjusted air pollution exposure dummy =1*	No. of observations if *adjusted air pollution exposure dummy* =0	Mean if *adjusted air pollution exposure dummy =0*	Mean Difference	*t*-value
Size	6,070	21.821	6,070	21.872	-0.051*	-1.96
ROA	6,070	0.053	6,070	0.057	-0.003	-1.10
Lev	6,070	0.361	6,070	0.360	0.001	0.25
Growth	6,070	0.210	6,070	0.218	-0.008	-1.29
Tobin's Q	6,070	2.303	6,070	2.277	0.026	1.13
KZ	8,476	0.764	8,476	0.771	0.007	0.81

Top1	6,070	0.332	6,070	0.331	0.001	0.36
Board	6,070	2.090	6,070	2.092	-0.002	-0.78
IndepR	6,070	0.377	6,070	0.376	0.001	1.23
Dual	6,070	0.376	6,070	0.379	-0.003	-0.39
Mshare	6,070	0.221	6,070	0.217	0.004	1.32
Intangibility	6,070	0.045	6,070	0.044	0.001	1.08
Fixed	6,070	0.196	6,070	0.195	0.001	1.32
Big4	6,070	0.040	6,070	0.045	-0.004	-1.4
Listage	6,070	1.528	6,070	1.521	0.008	0.57
SOE	6,070	0.147	6,070	0.150	-0.002	-0.44
Polluter	6,070	0.252	6,070	0.265	-0.013*	-1.84

APPENDIX C FOR ESSAY THREE

Appendix C.1. Variables definition

This table presents definitions of all the variables.

	Variables	Definition
Dependent variable	R&D_Assets	The ratio of R&D expenditure to total assets multiply by 100.
Explanatory variable	CPU Index	Twitter based_Climate policy Uncertainty Index divide 1000, as developed by Lee and Cho (2023). It is constructed by averaging the values over the preceding 12 months relative to the firm's fiscal year-end.
	CU Index	Twitter based_Climate Uncertainty Index divide 1000, as developed by Lee and Cho (2023). It is constructed by averaging the values over the preceding 12 months relative to the firm's fiscal year-end.
Control variables	Size	Natural logarithm of the market value of equity.
	Lev	The ratio of total debt to total assets.
	ROA	Returns on assets, calculated as net income over total assets.
	Growth	The growth rate of sales.
	Tobin's Q	The ratio of market value to book value of assets.
	KZ	KZ Index; higher KZ index, higher financial constraints.
	Top1	The shareholding ratio of the top one major shareholder.
	ListAge	Natural logarithm of current year minus listed year and plus one, ln (current year-listed year+1).
	BoardSize	Natural logarithm of the number of board members.
	IndepR	The proportion of independent directors.
	Dual	The dummy variable equals 1 if chairman of the board and CEO are the same individual, and 0 if otherwise.
	Mshare	Management's shareholding
	Fixed	The ratio of fixed assets to total assets.
	Big 4	Dummy variable that equals 1 if the firm employs a Big Four auditor, and 0 otherwise.
	SOE	The dummy variable equals 1 if the firm is state - owned-enterprise (SOE), and 0 if otherwise.
	Political connection	The dummy variable equals 1 if the CEO has prior work experience in the government, and 0 otherwise
	Government Subsidy	The ratio is measured by government subsidy to total assets of each firm.

Data source:

- Twitter-based Chinese economic policy uncertainty index by Lee et al. (2023): https://twitterchnepu.github.io/.
- U.S. Climate policy uncertainty by Gavriilidis (2021) available from January 2000 to December 2021: https://www.policyuncerta inty.com

Appendix C.2. Correlation Matrix

This table reports the correlation coefficients between key variables. Definitions of variables are in Appendix C.1. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables		1	2	3	4	5	6	7	8	9
1	R&D_Assets	1.000								
2	CPU	0.097***	1.000							
3	size	-0.189*	0.048***	1.000						
4	roa	0.114***	0.001	-0.020***	1.000					
5	lev	-0.176***	0.026***	0.522***	-0.353***	1.000				
6	growth	0.049**	0.066***	0.041***	0.275***	0.024***	1.000			
7	tobinq	0.267***	0.014**	-0.295***	0.205***	-0.281***	0.088***	1.000		
8	KZ	-0.095***	0.075***	0.205***	-0.575***	0.545***	-0.088***	-0.045***	1.000	
9	top1	-0.150***	-0.047***	0.174***	0.140***	0.038***	-0.025***	-0.083***	-0.121***	1.000
10	board	-0.087***	-0.061***	0.261***	0.004	0.131***	-0.013***	-0.099***	0.042***	0.006***
11	indep	0.036***	0.019***	-0.018**	-0.011	-0.013*	-0.010	0.045***	-0.002***	0.055***
12	dual	0.097***	0.045***	-0.170***	0.051***	-0.127***	0.035***	0.070***	-0.088***	-0.018***
13	mshare	0.126***	-0.023***	-0.358***	0.175***	-0.268***	0.063***	0.016**	-0.245***	-0.069***
14	fixed	-0.223***	-0.068***	0.149***	-0.071***	0.127***	-0.069***	-0.104***	0.095***	0.128***
15	big4	-0.009	0.025***	0.359***	0.026***	0.120***	-0.006	-0.057***	0.009***	0.138***
16	listage	-0.124***	0.013*	0.445***	-0.259***	0.310***	-0.076***	-0.018**	0.359***	-0.108***
17	soe	-0.145***	-0.014*	0.383***	-0.083***	0.263***	-0.078***	-0.118***	0.165***	0.242***
18	polluter	-0.111***	-0.026***	0.076***	0.053***	-0.040***	-0.020***	-0.053***	-0.048***	0.057***

(Continuous)

Variables		10	11	12	13	14	15	16	17	18
1	R&D_Assets									
2	CPU									
3	size									
4	roa									
5	lev									
6	growth									
7	tobinq									
8	KZ									
9	top1									
10	board	1.000								
11	indep	-0.602	1.000							
12	dual	-0.175***	0.116**	1.000						
13	mshare	-0.187***	0.072***	0.198***	1.000					
14	fixed	0.133***	-0.042***	-0.087***	-0.178***	1.000				
15	big4	0.069	0.043***	-0.055***	-0.134***	0.047***	1.000			
16	listage	0.134***	-0.010***	-0.190***	-0.430	0.159***	0.052***	1.000		
17	soe	0.270***	-0.058***	-0.266***	-0.415***	0.186***	0.157***	0.325***	1.000	
18	polluter	0.077***	-0.055***	-0.028***	-0.055***	0.308***	0.006	0.095***	0.051***	1.000

Appendix C.3. Alternative baseline regressions: Climate policy uncertainty and corporate innovation investment

This table reports the results of the alternative baseline regressions. It shows the impact of climate policy uncertainty on corporate innovation investment. The dependent variable is *R&D_Assets*, measured by R&D expenditure to total assets of each firm. The main independent variable is Twitter-based Chinese climate policy uncertainty index (*CPU*) by Lee and Cho (2023). In the first column, we lag all control variables. In the second column, we lag all control variables and the independent variable. Definitions of variables are presented in Appendix C.1. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*R&D_Assets*	*R&D_Assets*
	(1)	(2)
CPU	1.170***	
	(4.01)	
L.CPU		7.263***
		(4.01)
L.Size	0.127**	0.127**
	(2.46)	(2.46)
L.ROA	0.804	0.804
	(1.63)	(1.63)
L.Lev	0.243	0.243
	(1.03)	(1.03)
L.Growth	0.062	0.062
	(1.16)	(1.16)
L.Tobin's Q	0.275***	0.275***
	(7.25)	(7.25)
L.KZ	-0.054***	-0.054***
	(2.72)	(2.72)
L.Top1	-1.006***	-1.006***
	(-4.18)	(-4.18)
L.Board	0.117	0.117
	(0.52)	(0.52)
L.IndepR	0.192	0.192
	(0.26)	(0.26)
L.Dual	0.064	0.064
	(0.97)	(0.97)
L.Mshare	0.069	0.069
	(0.38)	(0.38)
L.Fixed	-1.423***	-1.423***
	(-5.30)	(-5.30)
L.Big4	0.168	0.168
	(1.01)	(1.01)
L.List age	-0.177***	-0.177***

	(-3.64)	(-3.64)
L.SOE	0.136	0.136
	(1.31)	(1.31)
L.Polluter	-0.176**	-0.176**
	(-2.38)	(-2.38)
Constant	-1.736	-1.881
	(-1.41)	(-1.53)
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	13,048	13,048
Adj R-squared	0.303	0.303

Appendix C.4. Alternative baseline regressions: Climate policy uncertainty and corporate innovation investment

This table reports the results of alternative baseline regressions. It shows the impact of climate policy uncertainty on corporate innovation investment. The dependent variable is *R&D_Assets*, measured by R&D expenditure to total assets of each firm. The main independent variables are Twitter-based Chinese climate policy uncertainty index (*Chinese_CPU*) by Lee and Cho (2023) and the U.S. climate policy uncertainty index (*US_CPU*) by Gavriilidis (2021). Definitions of variables are presented in Appendix C.1. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*R&D_Assets*	*R&D_Assets*
	(1)	(2)
Chinese_CPU		1.100***
		(4.49)
US_CPU	34.967***	1.969***
	(4.34)	(2.50)
Size	0.124***	0.124***
	(2.72)	(2.72)
ROA	1.039**	1.039**
	(2.27)	(2.27)
Lev	0.029	0.029
	(0.14)	(0.14)
Growth	-0.010	-0.010
	(-0.20)	(-0.20)
Tobin's Q	0.300***	0.300***
	(9.12)	(9.12)
KZ	-0.005	-0.005
	(-0.27)	(-0.27)
Top1	-0.805***	-0.805***
	(-3.66)	(-3.66)
Board	0.138	0.138
	(0.68)	(0.68)
IndepR	0.081	0.081
	(0.12)	(0.12)
Dual	0.055	0.055
	(0.92)	(0.92)
Mshare	0.189	0.189
	(1.15)	(1.15)
Fixed	-0.129***	-0.129***
	(-5.28)	(-5.28)
Big4	0.193	0.193
	(1.27)	(1.27)
List age	-0.186***	-0.186***

	(-4.35)	(-4.35)
SOE	0.109	0.109
	(1.17)	(1.17)
Polluter	-0.157**	-0.157**
	(-2.29)	(-2.29)
GDP growth	-0.658	-0.658
	(-0.91)	(-0.91)
GDP per capita	-0.314	-0.314
	(-0.75)	(-0.75)
Constant	-7.267***	-2.106*
	(-4.18)	(-1.88)
Year	Yes	Yes
Industry	Yes	Yes
Province	Yes	Yes
S.E. Clustering	Firm	Firm
N	16,310	16,310
Adj R-squared	0.313	0.313

Appendix C.5. Alternative robustness check

This table presents the results of robustness checks for the baseline regressions. Observations from the year 2020 are excluded to account for potential impacts of COVID-19. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*R&D_Assets*	*R&D_Assets*	*R&D_Assets*
	(1)	(2)	(3)
CPU	1.900***	1.406***	1.156***
	(5.45)	(5.39)	(4.28)
GDP growth			-0.648
			(-0.91)
GDP per capita			-0.324
			(-0.75)
Constant	0.905***	-1.852	-1.798
	(3.12)	(-1.60)	(-1.64)
Controls	No	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Province	Yes	Yes	Yes
S.E. Clustering	Firm	Firm	Firm
N	15,530	15,530	15,530
Adj R-squared	0.245	0.312	0.312

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