THE IMPACT OF EXOGENOUS SHOCKS ON FIRM PERFORMANCE: THREE EMPIRICAL STUDIES

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The Impact of Exogenous Shocks on Firm Performance: Three Empirical Studies

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CERTIFICATE OF ORIGINALITY

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Abstract

In recent years, businesses have been confronted with unprecedented challenges arising from global disruptions such as public health crises, geopolitical instability, and climate change. These crises highlight the pressing need for a comprehensive reassessment of risk management frameworks. Despite the extensive literature on managing endogenous operational disruptions, existing studies have proven inadequate in addressing the increasingly complex and extreme nature of exogenous risks. Shocks such as extreme weather events, economic volatility, and regulatory changes are becoming more frequent and interconnected, often triggering cascading crises rather than isolated incidents. Consequently, companies must develop proactive strategies to navigate a broader spectrum of exogenous threats. Drawing on theoretical lens such as the natural-resource-based view, prospect theory, resource dependence theory, and information processing theory, this thesis consists of three interrelated studies that aim to fill this gap by examining how these emerging exogenous risks impact firm operations and financial outcomes, while also proposing tailored strategies to mitigate these effects. A thorough exploration of these issues not only contributes to the theoretical foundation of strategies for addressing exogenous risks but also provides valuable insights for practitioners and policymakers.

Study 1 examines the impact of extreme weather events on firm operational performance from the perspective of natural force risks and evaluates the effectiveness of three operational strategies in mitigating this impact. Utilizing panel data from 3,722 Chinese A-share listed firms between 2010 and 2020, and employing a staggered difference-in-differences (DID) approach, Study 1 identifies a significant negative casual effect of extreme weather shocks on firm labor productivity. Building on resource dependence theory and information processing theory, it further examines the moderating roles of operational slack, cash hedging, and digital technology. The results suggest that these buffering and bridging strategies can significantly

mitigate this negative effect by stabilizing material flows, facilitating information processing efficiency, and enhancing financial flexibility, respectively. A series of robustness checks and supplementary analyses are conducted to validate the consistency and reliability of the findings.

Study 2 delves into the impact of carbon emission risk on firms' financial performance from the perspective of transition risks. Drawing on the Natural Resource-Based View (NRBV), it examines how carbon risk influences firm value, utilizing a panel dataset comprising 691 firm-year observations from 298 unique firms between 2018 and 2022. The analysis reveals a significant negative relationship between carbon emission risk and firm value, supported by rigorous econometric techniques to strengthen causal inference. Furthermore, Study 2 investigates the moderating effects of three NRBV-aligned strategies: production efficiency, green innovation, and ESG performance. The results indicate that production efficiency and green innovation can effectively mitigate the adverse effects of carbon risk. However, while ESG performance does not exhibit a significant buffering effect across the full sample, further analysis indicates that firms with lower levels of greenwashing do benefit from ESG initiatives. Finally, Study 2 explores the motivations behind corporate carbon disclosure. While the market generally penalizes all carbon-emitting firms, the negative valuation effect is less severe for those that voluntarily disclose their emission information. This finding underscores the signaling role of carbon disclosure and provides insight into firms' motivations for transparency in managing transition risks.

While conventional views typically posit a monotonic negative relationship between Economic Policy Uncertainty (EPU) and firm investment based on real options theory, emerging anecdotal evidence suggests that firms' innovation activities may not always be adversely affected by EPU. Grounded in prospect theory, Study 3 investigates the impact of EPU on firm innovation performance from the perspective of man-made policy risk. Utilizing a dataset comprising 11,769 firm-year observations from Chinese listed firms between 2000

and 2019, the study uncovers an inverted-U relationship between EPU and innovation performance. Building on the complementary asset view, it further investigates the moderating roles of organizational capabilities, particularly operational and marketing capabilities, in shaping this relationship. The results indicate that these capabilities enable firms to better navigate and even leverage the uncertainty associated with EPU, with higher capability levels amplifying the inverted U-shaped effect and shifting the turning point rightward. To ensure the robustness of the findings and address potential endogeneity concerns, a range of econometric techniques is employed, with results demonstrating consistency across multiple specifications.

The theoretical contributions of this thesis are reflected in the following aspects. First, it broadens the scope of risk management literature by integrating a diverse range of exogenous risks into a unified framework. Second, the research highlights the heterogeneity of risks and emphasizes the need for tailored operational strategies. By recognizing that different types of risks require distinct management approaches, this thesis challenges the prevailing one-size-fits-all mindset in risk management research. Finally, the thesis employs advanced econometric methodologies to enhance the rigor of causal inferences, thereby improving the reliability of its findings. Through these contributions, this thesis offers valuable insights for both academics and practitioners in navigating the intricate and ever-evolving risks faced by firms in today's dynamic global landscape.

Keywords: exogenous risks; performance implications; operational strategies; extreme weather; carbon risk; EPU

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Chapter 1 Introduction

1.1 Research Background

In recent years, the global economic landscape has undergone significant upheaval, with persistent public health crises and escalating geopolitical tensions deeply disrupting firm operations and global supply chains. For instance, the COVID-19 pandemic nearly paralyzed global economic activities and social life, leaving enduring and profound impacts across all industries worldwide (Sodhi & Tang, 2021). This widespread disruption has exposed critical vulnerabilities in supply chains and highlighted the risks related to globalization, compelling companies to confront substantial challenges such as production halts, raw material shortages, and restrictions on the movement of human resources. The ongoing Russia-Ukraine war has further destabilized the global economic order, jeopardizing global energy and food security while driving up commodity prices and contributing to inflationary pressures globally (Korosteleva, 2022).

In addition to these immediate challenges, the long-term issue of climate change, driven by greenhouse gas emissions, has emerged as one of the most pressing global issues. Achieving climate goals and mitigating the impacts of global warming have become widely recognized imperatives (Zhang et al., 2024). To date, over 120 countries, including major industrial nations such as China, the European Union, the United Kingdom, Japan, South Korea, and Canada, have made binding commitments to achieve carbon neutrality between 2050 and 2060. As regulatory pressures intensify, businesses are no longer merely required to comply with stringent environmental regulations but are also expected to actively pursue green transformation. This transition involves adopting innovative strategies to enhance sustainability efforts, optimize resource utilization, and integrate environmentally friendly technologies (e.g., Ba et al., 2013; Li et al., 2020). Consequently, sustainability has become a central strategic priority for firms seeking to thrive in an increasingly environmentally conscious and regulation-driven global market.

These exogenous shocks have a profound impact on corporate production decisions and operational outcomes. While such disruptions have long been a part of the business environment, their frequency has increased notably in recent years, manifesting as cascading crises rather than isolated incidents (Beamish & Hasse, 2022; Ciravegna et al., 2023). In this “new normal”, companies, especially multinational corporations, are confronted with a more complex decision-making landscape. They must not only leverage internal tools, technologies, and strategies to identify, assess, manage, and monitor supply chain risks, but also foster external coordination and collaboration to reduce vulnerabilities (Manhart et al., 2020). While existing research has demonstrated that a variety of operations management (OM) resources and strategies can be effective in dealing with firm-specific, endogenous operations disruptions such as parts shortages, order changes, production problems, supplier misconducts, logistics interruptions, and ramp up issues (Braunscheidel & Suresh, 2009; Kleindorfer & Saad, 2005; Simangunsong et al., 2016; Sodhi et al., 2012), it remains unclear whether these same resources and strategies are equally effective in addressing exogenous shocks such as extreme weather events, carbon risk, and economic policy uncertainty (EPU). At the same time, the rapid advancement of digital technologies, such as artificial intelligence, blockchain, and cloud computing, provides new opportunities for businesses to develop innovative operational strategies. Whether the integration of these technologies can mitigate the adverse impacts of exogenous risks remains an area for further exploration. As such, both researchers and practitioners must reassess and refine existing risk management paradigm to better navigate an evolving and increasingly volatile external environment.

Theoretically, despite the substantial body of literature on strategies for managing supply chain disruptions, existing risk management frameworks remain inadequate in addressing the increasingly complex and extreme conditions that have emerged in recent years (Sodhi & Tang

2021). The concept of risk, as articulated by Knight (1921), is defined as the measurable probabilities of various potential outcomes. Within the operations and supply chain management (O&SCM) literature, risk is typically understood as the potential occurrence of adverse and unforeseen events that can disrupt normal operations or create imbalances in the coordination between supply and demand (Kleindorfer & Saad, 2005; Sodhi et al., 2012). In this context, implementing effective operational strategies to proactively address these risks before they materialize has become a critical issue. Risks are commonly categorized into two main types: endogenous and exogenous, based on whether their source originates within the supply chain (DuHadway et al., 2019; Trkman & McCormack, 2009). Specifically, endogenous risks arise primarily from market fluctuations, while exogenous risks are triggered by external events, such as terrorist attacks, epidemics, labor strikes, and inflation. In essence, endogenous risks are related to fluctuations in supply and demand within the supply chain, whereas exogenous risks are linked to external volatilities beyond the control of the supply chain itself (Wagner & Bode, 2008). Moreover, exogenous risks can be further subdivided into continuous risks, such as changes in price indices, and discrete risks, such as terrorist attacks, natural disasters, and technological failures, depending on whether they occur as random, one-off events or as ongoing incremental changes (Oetzel & Oh, 2014).

Prior research has predominantly concentrated on endogenous risks, demonstrating that firms can effectively mitigate these risks by fostering strong collaborative relationships with supply chain partners. Such collaborations typically include practices such as information sharing, relationship development, and joint reviews (e.g., Cheung et al., 2010; Trkman & McCormack, 2009; Yan & Dooley, 2013). For example, external integration among supply chain members can enhance flexibility and increase overall value by reducing risks associated with fluctuations in supply and demand (Davies & Joglekar, 2013). However, the increasing prevalence of novel challenges, such as epidemics, societal upheavals, and natural disasters induced by climate change, has shifted both academic and practical focus toward the effective management of external shocks. While these risks typically lie beyond the control of individual organizations, companies can still mitigate their adverse impacts by proactively allocating critical resources and implementing appropriate strategies (Manhart et al., 2020). Furthermore, existing literature often treats disruptions as homogeneous events that can be managed through universally applicable risk management strategies. This approach, however, overlooks the diverse sources and characteristics of these risks, thus undermining the development of tailored strategies for managing specific disruptions (DuHadway et al., 2019). This thesis aims to fill this gap by identifying exogenous risks from diverse sources and proposing tailored operational strategies that account for their distinct characteristics. Specifically, the thesis will explore strategies for managing three distinct types of exogenous risks: corporate carbon risk, extreme weather risk, and the risk associated with frequent adjustments in economic policies. These risk types can be categorized based on the degree of human involvement into human-induced and natural risks. Among these, EPU and carbon risk are primarily human-induced, whereas extreme weather risk is largely driven by natural forces, although human actions may exacerbate the frequency and intensity of such events (Gupta et al., 2016; Oh & Oetzel, 2022). For continuous risks such as EPU and carbon risk, firms can seek an optimal balance between the probability of occurrence and the costs of impact and prevention. In contrast, for discrete risks caused by natural forces, strategies such as risk transfer, mitigation, and monitoring may be more appropriate (Trkman & McCormack, 2009).

1.2 Research Objectives and Design

In summary, the primary objective of this thesis is to examine the impact of three emerging exogenous risks on both the operational and financial performance of firms, and to explore what operational management strategies can be leveraged to mitigate their potential adverse effects. The thesis is structured around three independent yet logically complementary studies, each designed to help companies develop tailored operational strategies to address specific risks and maintain their competitive advantage. Each sub-study not only enhances the understanding of individual exogenous risks but also, building upon its predecessor, collectively establishes a cohesive risk management framework from addressing natural risks to addressing policy risks. Through this series of studies, the thesis aims to provide in-depth insights for business managers, enabling them to navigate exogenous risks more effectively in an increasingly volatile global environment.

Study 1 aims to investigate how extreme weather events impact corporate operations and supply chain management, and to identify which operational and supply chain resources or strategies can effectively mitigate the potential adverse consequences of these events. China is selected as the research context due to its vast territory and diverse climate types, making it one of the countries most severely affected by extreme weather events. Additionally, as the world's second-largest economy, China plays a pivotal role in global supply chains. As such, extreme weather events may have cascading effects on both domestic and international firms and industries. Study 1 integrates large-scale secondary data from multiple reliable sources to construct the research sample. Specifically, it focuses on six major types of extreme weather events: droughts, extreme temperatures, wildfires, landslides, floods, and storms. A staggered difference-in-differences (DID) method is employed to establish the causal relationship between extreme weather events and labor productivity. To better understand how firms should respond to extreme weather, this study further assesses the moderating roles of operational slack, cash hedging, and digital technology deployment. Finally, a series of several robustness checks, including parallel trend analysis, estimation window adjustments, alternative measurements, Mahalanobis distance matching, and placebo tests are conducted to ensure the robustness of the findings.

Study 2 employs the Natural Resource-Based View (NRBV) as its theoretical lens to investigate the causal effect of carbon risk on firm value, while also examining the moderating effects of three NRBV-aligned OM strategies. The NRBV emphasizes the critical strategic role of environmental resources and sustainability in the creation of competitive advantage for firms (Hart, 1995). According to this theory, through effective management, environmental resources and capabilities can be transformed into valuable, rare, unique, and irreplaceable assets. Such distinctive resources and capabilities establish formidable competitive barriers, enabling firms to achieve superior performance and secure a dominant market position. The NRBV further identifies three key environmental strategies, pollution prevention, product stewardship, and sustainable development. Building on this foundation, Study 2 explores how the transformation and physical risks associated with carbon emissions affect firm financial performance and investigates the moderating effects of the three corresponding operational strategies. In terms of empirical design, this study utilizes panel data from Chinese listed companies and applies a two-way fixed effects model to quantify the economic impact of carbon risk on firm value. Additionally, it examines how practices such as production efficiency, green innovation, and ESG performance can alleviate these potential negative effects. To address potential endogeneity concerns and minimize the influence of confounding factors, a range of econometric strategies such as instrumental variable techniques, treatment effects models, system generalized method of moments (GMM) estimation, and quasi-natural experiments are employed to establish a causal relationship between carbon risk and firm performance. Finally, this study conducts additional analyses to consider the potential for greenwashing among firms and the associated consequences. It also investigates the motivations behind firms' decisions to voluntarily disclose carbon emissions, as opposed to concealing such information.

Study 3 adopts prospect theory as an analytical approach to examine the potential non-linear effects of Economic Policy Uncertainty (EPU) on corporate innovation. Existing literature predominantly draws on real options theory, which suggests that, in the face of uncertainty, firms are more likely to adopt a wait-and-see strategy, thereby reducing investment expenditures. However, real-world cases indicate that innovation activities, as a critical driver of competitive advantage, may not always be negatively impacted by EPU. Consequently, this study seeks to provide a novel perspective that bridges the gap between traditional theoretical paradigm and empirical observations. Kahneman & Tversky (1979) argue that individuals' actual decision-making processes may deviate from the principles of rational calculation. Based on the assumption of bounded rationality, prospect theory proposes that economic agents exhibit distinct risk preferences in different contexts. In the pursuit of gains, individuals are willing to take on greater risk despite potential losses within a certain threshold. In contrast to the conventional view, which assumes that EPU always diminishes innovation performance, this study hypothesizes an inverted U-shaped relationship between EPU and firm innovation. Specifically, it posits that a moderate level of EPU may encourage innovation by fostering risk-seeking behavior. The complementary asset view is further integrated to analyze the moderating role of complementary organizational capabilities. Empirically, this study utilizes longitudinal panel data from Chinese A-share listed companies and applies robust econometric methods, including a fixed effects model, alternative measures, instrumental variables (IV), and sub-sample analysis, to ensure the validity and reliability of the findings.

Overall, this thesis explores the impact of three exogenous risks on corporate operational and financial performance and develops targeted strategies for addressing different types of risks. By investigating these emerging exogenous shocks, including both natural and man-made risks, this thesis provides valuable insights to the literature on risk management.

Figure 1.1 presents a summary of the research framework of this thesis.

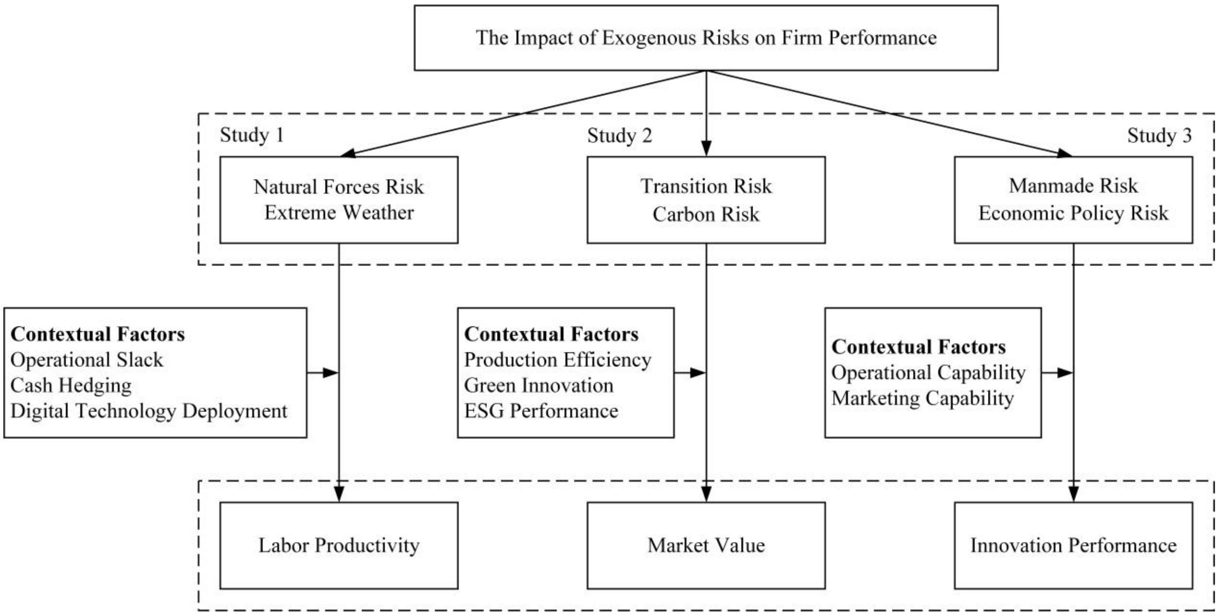

Figure 1.1 Research framework of the thesis

1.3 Research Question

This thesis aims to address the following three research questions (RQs):

RQs of Study 1: How do extreme weather events impact firm operational performance in terms of labor productivity? How do three buffering and bridging strategies, namely operational slack, cash hedging, and digital technology deployment, moderate this relationship?

RQs of Study 2: How does carbon risk impact firm financial performance measured by Tobin's *q*? How do the NRBV-aligned strategies such as production efficiency, green innovations, and ESG performance moderate this relationship?

RQs of Study 3: How does economic policy uncertainty impact firm innovation performance? How do two complementary capabilities (i.e., operational and marketing capability) moderate this relationship?

1.4 Research Significance

The contributions of this thesis can be encapsulated in several aspects, including expanding the research perspective, exploring novel research topics, and applying innovative research methods, each of which enriches our understanding of how firms can navigate the increasingly complex and volatile landscape of exogenous risks.

First, this thesis expands the research perspective and broadens the scope of risk management. Previous research has primarily focused on endogenous risks within firms and supply chains, with limited attention given to exogenous risks. While significant progress has been made in understanding and managing endogenous disruptions, such as those arising from supply chain glitches, product introduction delays, excess inventory etc. (Hendricks & Singhal, 2005, 2008, 2009), there has been insufficient exploration of exogenous risks that lie beyond a firm's direct control. Given the increasing frequency and severity of emerging exogenous risks driven by factors such as climate change, geopolitical tensions, and public health crises, it is critical to reassess and extend existing risk management frameworks to address these new challenges. This thesis addresses this gap by integrating three key exogenous risks (i.e., extreme weather risk, carbon risk, and economic policy risk) into a unified research framework. This approach not only provides a more comprehensive understanding of how firms can manage external risks but also marks a significant shift away from the traditional focus on endogenous disruptions that has dominated much of the existing literature. By synthesizing these diverse but interrelated risks, the thesis broadens the scope of risk management and contributes to the development of a more holistic approach to addressing exogenous threats.

In addition, the three distinct sub-studies within the thesis build upon one another, creating a coherent and comprehensive approach for managing exogenous risks. Study 1 enhances the understanding of extreme weather risks, which have become increasingly prevalent due to climate change. Study 2 focuses on carbon risk, emphasizing the strategic importance of carbon reduction in the context of global climate change goals. Finally, Study 3 examines the growing unpredictability of economic conditions and the resulting policy uncertainty, which has significant implications for firm strategy and decision-making. Each sub-study not only deepens the understanding of its specific risk but, collectively, they establish a comprehensive risk management framework that spans natural risks to policy-induced risks.

Second, this thesis contributes to the existing body of research by identifying the heterogeneity of risk sources, operational strategies, and firm performance. A key limitation of prior research is the tendency to treat different types of risks as homogeneous, and as a result, propose generic operational strategies. This "one-size-fits-all" approach fails to account for the diverse origins and distinct characteristics of different risks. By challenging this conventional view, this thesis recognizes the heterogeneity of both risks and the operational strategies required to manage them. It emphasizes that each type of risk has unique origins and impacts, necessitating tailored, context-specific strategies. For example, carbon risks, largely driven by economic and regulatory challenges arising from the global shift toward a low-carbon economy, require firms to adopt OM-related carbon reduction strategies. In contrast, extreme weather events demand flexibility and resilience in supply chains. Additionally, EPU, as a policy-induced risk, may require firms to adjust their innovation strategies. This nuanced approach to risk management is a significant contribution, as it enables firms to better align their strategies with the specific characteristics of each risk, thereby enhancing their ability to mitigate adverse impacts effectively.

Moreover, prior studies have largely focused on the financial impacts of risks, with limited attention given to their effects on operational and innovation performance. This thesis addresses this gap by exploring not only how exogenous risks affect firms' financial performance but also their operational efficiency and innovation capabilities. This broader perspective offers managers a more comprehensive understanding of the full scope of potential disruptions, allowing them to design more effective strategies to safeguard against a range of adverse effects, including those on day-to-day operations and long-term innovation capabilities.

The third major contribution of this thesis lies in its innovative research methodology, particularly in its approach to causal inference. Previous studies on risk management have often focused on the effects of internal risks, which are endogenous and closely related to a firm's specific characteristics. As a result, these studies are prone to endogeneity issues, making it difficult to establish clear causal relationships between disruptions and firm performance. For example, the relationship between excess inventory risks and firm performance may be influenced by factors such as corporate strategy, culture, or the personal characteristics of managers, which are difficult to control for using conventional methods. In contrast, exogenous risks are typically beyond a firm's control, which mitigates the potential for endogeneity issues. This thesis takes advantage of this distinction and employs a more robust empirical design to improve the credibility of causal inferences. Specifically, Study 1 utilizes the Difference-in-Differences (DID) method to analyze the impact of extreme weather events on labor productivity, which helps isolate the causal effect of the exogenous shock from other confounding factors by constructing a natural counterfactual group. Additionally, the study employs multiple econometric techniques, such as fixed effects models, instrumental variable strategies, Heckman's (1979) treatment effects model, the system generalized method of moments (GMM) estimation, and quasi-natural experiments, to address endogeneity concerns and strengthen causal claims. These rigorous methods enhance the overall quality of the research and contribute to more accurate and reliable conclusions.

In conclusion, this thesis contributes to the literature on risk management by expanding the research perspective to include exogenous risks, offering a nuanced view of risk heterogeneity and operational strategies, and employing innovative methodologies to improve causal inference. The tailored strategies developed in this research can help firms mitigate the adverse impacts of a wide range of external risks, from environmental challenges to economic policy fluctuations, thereby enhancing their resilience and long-term competitiveness.

Chapter 2 Study One: Combating extreme weather through operations management: Evidence from a natural experiment in China

2.1 Introduction

As global warming intensifies, the past decade has witnessed increasingly frequent extreme weather events. In 2022 alone, various regions around the world were hit by extreme weather shocks such as heat waves, heavy rains, floods, droughts, and wildfires, with temperatures frequently breaking records. Taking China as an example, a widespread 79-day-long heat wave occurred from June 13th to August 30th, 2022, with temperatures above 40 degrees Celsius in 23 provinces, covering an area of over 5 million square kilometers and affecting a population of over 900 million. The subsequent evaluation results showed that the comprehensive intensity of this heat wave was the strongest in China since complete meteorological observation records began in 1961[1]. An article in *New Scientist* also pointed out that the 2022 heat wave in China is the most severe ever recorded worldwide (LePage, 2022). According to the *Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes (1970–2019)* published in 2021 by the World Meteorological Organization (WMO), between 1970 and 2019, there were 11,072 disasters attributed to weather-, climate-, and water-related extremes, which resulted in 2.06 million deaths and US$ 3.64 trillion in losses[2].

In addition to its marked damage to health, economy, and social development, extreme weather also has significant effects on firms' operations and supply chain management (Bertrand & Parnaudeau, 2017). For instance, the extreme heat waves and droughts that occurred in China during the summer of 2022 resulted in a significant decrease in hydropower

[1] https://www.cma.gov.cn/2011xwzx/2011xqxxw/2011xqxyw/202301/t20230109_5247477.html
[2] https://reliefweb.int/report/world/atlas-mortality-and-economic-losses-weather-climate-and-water-extremes-1970-2019?gclid=EAIaIQobChMIytDZg4Px_QIVlH4rCh3uXwo0EAAYASAAEgJwuPD_BwE

capacity, with demand for air conditioning cooling far exceeding expected levels, leading to severe imbalances between electricity supply and demand. Multiple provinces and municipalities, including Sichuan and Chongqing, required companies to restrict electricity usage or even halt production to meet the electricity needs of residents. Sichuan and Chongqing are home to a large number of companies in the semiconductor, photovoltaic, and display industries (e.g., BOE, TCL, Foxconn). As is well known, the production of semiconductors needs a significant amount of electricity to meet the requirements of precision manufacturing equipment and clean rooms which must keep a constant temperature and humidity and very low levels of contaminants (Ding *et al*., 2021). Power outages may also result in the sudden termination of wafer manufacturing or prolonged delays in a particular process, causing irreparable damage and resulting in component failure. Due to the inability to provide stable power supply, many companies are unable to operate their equipment properly, resulting in delayed deliveries. This is also a challenge for the entire supply chain, as semiconductor is an essential component of many electronic products like smartphones, televisions, computers, and automobiles. Numerous cases can be found in many other industries, such as agriculture, retail, transportation, banking, and construction, where extreme weather disturbs normal business operations and causes supply chain disruptions (Battiston *et al*., 2021; Lesk *et al*., 2016; Venturini, 2022). It can be said that firms need to consider the impact of extreme weather and climate change more than ever before.

In the scientific circle, climate change science is offering more and more findings to show that human activities such as burning fossil fuels like coal, oil, and gas are the most significant sources of climate change and frequent extreme weather shocks (e.g., Lynas *et al*., 2021). On the other hand, the economic and management literature has also started to investigate extreme weather's negative implications for various economies, societies, industries, organizations, and individuals. An increasing number of studies have provided rigorous evidence that extreme weather is closely associated with macro-level consequences such as agricultural output decline, political instability, mortality, migration, conflict, violence, and crime, among others, based on the settings of developed countries (e.g., Barreca *et al*., 2016; Deschenes & Moretti, 2009; Hsiang *et al*., 2013; Maccini & Yang, 2009; Miguel *et al*., 2004). Compared with a wealth of studies focusing on the socioeconomic implications of extreme weather events, limited efforts have been devoted to investigating extreme weather's impacts on micro-level firms' behaviors and outcomes. While a small number of firm-level studies do exist, they primarily focus on financial variables like capital structure, cost of debt or equity capital, earnings forecasts, stock price crash risk, and financial reporting quality (e.g., Bourveau & Law, 2021; Huynh *et al*., 2020; Massa & Zhang, 2021).

Turning to the operations management (OM) field, scholars have long investigated diverse climate change-related issues, such as green supply chain management, carbon neutrality, sustainable operations, and corporate environmental initiatives. However, very little attention has been specifically paid to extreme weather implications so far, with just a few exceptions such as Bag *et al*. (2022), Cho *et al*. (2018), Fang *et al*. (2023); Gupta *et al*. (2022); Keleş *et al*. (2018), Pan *et al*. (2020), and Pu *et al*. (2021). As OM researchers, we naturally hope to learn more about the impact of extreme weather on firms' operational outcomes and how firms could leverage operational resources or strategies to mitigate potential negative impacts. Specifically, in this study, we first examine the impact of extreme weather on firms' operational performance in terms of labor productivity in the context of China. We then investigate the moderating roles of firms' operational slack, digital technology deployment, and cash hedging.

Our motivation for conducting this study is threefold. First, little empirical evidence on extreme weather's operational performance implications in emerging markets has been presented to date. China provides a suitable research context for investigating extreme weather's impacts. With vast territory and complex climate types, China is one of the countries most severely affected by extreme weather events worldwide. Sixteen of the top 20 regions most vulnerable to climate change globally are located in China[3]. Also, compared with developed markets, as an emerging economy, China's infrastructure is more vulnerable and its disaster resilience is relatively lower. Chinese firms thus may suffer more severely in the face of extreme weather shocks (He *et al*., 2022). Furthermore, as the world's second-largest economy, China plays a crucial role in the global supply chain. Extreme weather events may have a ripple effect on firms and industries both within and outside of China (Dolgui & Ivanov, 2021; Mishra *et al*., 2021). Second, OM is fundamentally concerned with productivity, as its *raison d'être* is to efficiently and effectively manage processes that transform inputs into outputs (Jacobs *et al*., 2016). Demeter *et al*. (2011) also point out that labor productivity is one of the main sources of business success. Our choice to concentrate on labor productivity is consistent with prior empirical OM studies dealing with operational performance (e.g., Lo *et al*., 2014; Sartal *et al*., 2020). Third, while a number of studies have well documented that many OM resources and strategies are effective in dealing with firm-specific, endogenous operations disruptions such as parts shortages, order changes, production problems, supplier misconducts, logistics interruptions, and ramp up issues, it remains unclear as to whether these resources and strategies are still effective for exogenous shocks with significant impacts such as extreme weather events. The prior literature suggests that the field of OM recognizes that material, information, and financial flows are three fundamental elements for managing operations within a firm or across firms along a supply chain (Wuttke *et al*., 2013; Zhang *et al*., 2020). Thus, we select the aforementioned moderators from these three aspects to make them not only relevant to OM but also adoptable by practitioners. In addition, the extant studies indicate that buffering and bridging are two best-suited coping strategies for firms responding to disruptions or risks (Bode *et al*., 2011). Buffering helps managers protect their firms and

[3] https://rfi.my/9AzV

supply chains from disruptions by keeping slack resources, such as huge inventories, sufficient cash, flexible production processes, and diversified suppliers, which may serve as "shock absorbers" (Bode *et al*., 2011). Bridging aims to establish strong linkages with exchange partners (e.g., joint risk management system, strengthening information sharing) (Flynn & Flynn, 1999). Researchers usually employ information processing theory to view bridging as a way to mitigate disruptions by providing easy access to timely and authentic information about emergencies and their outcomes (Mishra *et al*., 2016). In this study operational slack and cash hedging are buffering strategies, which may help firms stabilize material flow and financial flow, respectively, in the context of extreme weather. The deployment of digital technologies can be regarded as a bridging strategy, which aims to strengthen data analytics and information exchanges.

We collect and combine large-scale secondary data from multiple reliable sources to construct the sample. Our natural experiment setting and staggered difference-in-differences (DID) approach show that extreme weather does have significant negative influences on firms' labor productivity. Our results further indicate that firms with high levels of operational slack, digital technology deployment, and cash hedging are less significantly affected by extreme weather shocks. Also, different types of extreme weather events present heterogenous adverse impacts on firms' operations, and in our sample, we find that droughts and landslides are two primary threats to Chinese listed firms' labor productivity. These findings are still valid after a battery of robustness checks such as parallel trend analysis, alternative measures, Mahalanobis distance matching approach, placebo test, and adjustment of estimation window.

Our research contributes to the literature on multiple fronts. First, this study contributes to the growing extreme weather literature by providing direct evidence on the negative impact of extreme weather on firms' operational performance in terms of labor productivity. This investigation direction may inspire future OM studies to further explore extreme weather's influences on other operational outcomes. Second, we respond to recent calls (e.g., Hendricks *et al*., 2020; Sodhi & Tang, 2021) that more OM efforts should be devoted to investigating the implications of and solutions to various exogenous major shocks or extreme conditions such as natural disasters, pandemics, trade disagreements, and national conflicts by examining the effectiveness of various OM resources in mitigating productivity losses caused by extreme weather. We confirm the value of these OM resources in making firms respond more resiliently towards extreme weather risks. Finally, from the methodological perspective, the natural-experimental design employed in this study demonstrates the possibility and advantage of conducting secondary data-based, causal inference-oriented empirical research on addressing disruption-related issues in the OM field.

We organize the rest of the study as follows: Section 2.2 briefly reviews the literature on climate change, extreme weather events, and disaster management. Then, we propose our hypotheses. In Section 2.3 we describe the data, sample, measures, and identification strategy. Section 2.4 presents the empirical results and a series of robustness checks. Finally, in Section 2.5, we summarize the whole paper and discuss in detail the theoretical contributions, practical implications, limitations, and future research directions.

2.2 Literature Review and Hypothesis Development

2.2.1. Climate Change, Extreme Weather Events, and Organizational Consequences

Our study is closely related to two research streams: one is climate change and extreme weather's implications and another is firms' disaster management. In this section, we provide a brief literature review in both streams and position our study at the point of their intersection.

Climate change refers to long-run shifts in weather conditions and patterns of extreme weather events (Wu *et al*., 2016). These shifts can be broadly attributed to two main causes. One is nature, such as through changes in solar activity cycles. Another is human activity, such as burning fossil fuels, cutting down forests, using land improperly, and farming livestock. A wealth of evidence shows that since the 1800s, human activities have been the primary driver of climate change, mainly due to burning fossil fuels like coal, oil, and gas. Lynas *et al*. (2021) analyze a data set of 88,125 climate-related papers published since 2012 and find that more than 99 per cent of peer-reviewed scientific articles believe that it is human activities that lead to contemporary climate change. An extreme weather event is a time and place in which weather conditions rank above a threshold value near the upper or lower ends of the range of historical measurements (usually the highest or lowest 5 or 10 per cent) (Herring, 2020). Research has demonstrated that climate change has made many extreme weather events more likely, more intense, longer lasting, or larger in scale than they would have been without it (Herring, 2020; Stott, 2016).

Although climate change and extreme weather have been extensively discussed and debated in the scientific community for many years, the economics and management literature has started to focus on their implications only since the seminal work of Nordhaus (1977). Following Nordhaus (1977), a large number of subsequent studies explored how extreme weather substantially affects the economy, society, industry, organization, and individual. Extant studies have shown that extreme weather is closely related with crop production losses, cities' production factor efficiency reduction, political instability, deterioration of health, migration, conflict, violence, and crime, among others (e.g., Barreca *et al*., 2016; Billings *et al*., 2022; Deschenes & Moretti, 2009; Hornbeck & Naidu, 2014; Hsiang *et al*., 2013; Jia, 2014; Maccini & Yang, 2009; Miguel *et al*., 2004; Song *et al*., 2023). For instance, Miguel (2005) provides novel evidence that extreme rainfall (drought or flood) leads to a large increase in the murder of elderly women who killed by relatives in rural Tanzania. One plausible mechanism is that extreme rainfall may cause a sharp decline in household income, with household heads responding to this negative income shock by weeding out elderly female members who lack productive capacity. In particular, agriculture-related research accounts for a large proportion of studies on the consequences of extreme weather (e.g., Fisher *et al*., 2012; Hornbeck, 2012). The reason is that weather variables such as temperature, precipitation, relative humidity, wind speed, sunshine time, and evaporation rate directly enter the agricultural production functions. Lesk *et al*. (2016) shows that nearly one-quarter of all damage and losses from weather-related disasters has been in the agricultural sector in developing countries.

Compared with the large number of macro-level extreme weather outcomes paper, studies on the impacts of extreme weather on firm-level consequences are still relatively scarce. From a practical perspective, managers tend to be more concerned with what firms should do before, during, and after extreme weather events to minimize losses and ensure supply chain stability (Gupta *et al*., 2016). Thus, the investigation of the influences of extreme weather on firm-level outcomes is of great significance for understanding firm behavior under the extreme weather condition and providing the corresponding practical implications for decision-makers (Huang *et al*., 2018; Huang *et al*., 2022). Prior empirical studies in this domain concentrates on firms' financial variables such as capital structure, financing choice, cost of equity capital, earnings forecasts, stock price crash risk, financial reporting quality, and stock returns (e.g., Bourveau & Law, 2021; Huynh *et al*., 2020; Javadi & Masum, 2021; Massa & Zhang, 2021) as summarized in Table 2.1. For example, Huynh *et al*. (2020) document a significant positive association between drought risk and firms' cost of equity capital, and the cost of equity capital is 92 basis points higher for firms influenced by serious drought situations. Likewise, Nguyen *et al*. (2022) find that drought risk has adverse impacts on both leverage and the speed of leverage adjustment. Employing Indian monsoon data, Rao *et al*. (2022) show that rain-sensitive companies experience significant declines in their market value as a direct consequence of both excess and deficit rainfall circumstances.

Our study is also relevant to disaster management and humanitarian operations, and extreme weather-related research in general can be placed into this category (Gupta *et al*., 2016). Although OM researchers have long explored a variety of climate change-related issues such as green supply chain management, sustainable operations management, and corporate environmental initiatives (e.g., Fu & Su, 2020; Hardcopf *et al*., 2021; Henao & Sarache, 2022; Khuntia *et al*., 2018; Lam *et al*., 2016; Li *et al*., 2020; Zhan *et al*., 2021; Zhu & Sarkis, 2004), very limited attention has been specifically paid to firm- or supply chain-level extreme weather influences and the corresponding mitigation strategies, with a few exceptions such as Bag *et al*. (2022), Cho *et al*. (2018), Fang *et al*. (2023); Gupta *et al*. (2022); Keleş *et al*. (2018), Pan *et al*. (2020), and Pu *et al*. (2021). Here, we point out that although earthquakes are also purely exogenous natural disaster shocks and have been analyzed in detail in prior studies (e.g., Carvalho *et al*., 2021; Ding *et al*., 2021; Hendricks *et al*., 2020; Son *et al*., 2021), they are geological activities, not extreme weather events, and are therefore outside the scope of our study. These studies provide significant implications for firms dealing with uncertainty stemmed from a single extreme weather event or one specific type of extreme weather (e.g., hurricane, extreme temperature). The central question of interest to OM community is how extreme weather may affect firms' operations and supply chain management and what operations and supply chain resources or strategies could contribute to mitigating the adverse impacts derived from extreme weather events. According to Lee (2004), agility, adaptability, and alignment (also known as the triple-A framework) are the three most important attributes of the best-performing supply chains. Then, a number of studies follow this logic to investigate various operational measures firms could take (e.g., buffering and bridging strategies) to become more agile, adaptable, and aligned to efficiently and effectively tackle endogenous, firm-specific operational glitches or disruptions such as parts shortages, order changes, production problems, supplier misconducts, logistics interruptions, ramp up issues etc. (Braunscheidel & Suresh, 2009; Kleindorfer & Saad, 2005; Simangunsong *et al*., 2016;

Table 2.1 A summary of extreme weather's firm-level implications

Articles	Extreme weather events	Extreme weather data sources	Dependent variables	Findings
Morrice *et al*. (2016)	Hurricane	National Hurricane Center	Sales	The authors establish a robust correlation between the temporal aspect of the hurricane weather forecast, the projected landfall location of the storm, and the resultant hurricane sales.
Hsu *et al*. (2018)	37 major disasters such as blizzards, earthquakes, floods, and hurricanes, with a duration of less than thirty days and an estimated total damage exceeding $1 billion (in 2013 constant dollars) occurred in the United States from 1987 to 2013.	The Spatial Hazard Events and Losses Database	ROA	Firms operating in states affected by natural disasters experience a significant decline in profitability. However, firms that possess diversified technologies are found to be less vulnerable to the impact of natural disasters.
Huang *et al*. (2018)	Extreme weather in general	Global Climate Risk Index compiled and published by Germanwatch	Financial performance (ROA and cash flows from operations)	The probability of incurring losses due to major weather events such as storms, floods, and heat waves is positively associated with lower and more volatile earnings and cash flows.
Addoum *et al*. (2020)	Extreme temperature in the US	PRISM Climate Group (the U.S. Department of Agriculture's official climatological database)	Sales; Productivity	The authors did not observe any evidence suggesting that exposure to temperature significantly impacts sales or productivity at the establishment level, even among industries commonly categorized as "heat sensitive".
Huynh *et al*. (2020)	Droughts in the US	National Centers for Environmental Information; National Oceanic and Atmospheric Administration	Cost of equity capital	The cost of equity capital tends to increase for firms impacted by droughts, particularly those with higher local institutional holdings.
Pan *et al*. (2020)	Four US continental hurricanes between 2008 and 2014	National Hurricane Center Atlantic Basin Best Tracks HUR-DAT2 database	Consumer stockpiling propensity; In-store product availability	The propensity of consumers to stockpile as hurricanes approach is significantly influenced by supply-side, demand-side, and disaster characteristics. The resultant increase in consumer stockpiling has both immediate and longer-term effects on in-store product availability.
Bourveau & Law (2021)	Hurricanes occurred between 1996 and 2009 in the US	The Spatial Hazard Events and Losses Database	Analysts' forecast optimism relative to consensus forecasts	Analysts in states affected by hurricanes are found to issue less optimistic forecasts for non-affected firms after the hurricanes, in

				comparison to non-affected analysts.
Massa & Zhang (2021)	Hurricane Katrina	National Hurricane Center; 2005 special report on Hurricane Katrina provided by the Holborn Corporation	Bond holdings; Bond prices	The adverse impact on bonds prompts companies to transition from bond financing to bank-based borrowing and to reduce the maturity of their debt.
Oetzel & Oh (2021)	Natural disasters in general	EM-DAT database	Firm disaster preparedness	Experience of previous natural disasters within an organization enhances preparedness for subsequent hazards. This preparedness is further facilitated by organizational learning from other businesses and institutions.
Pu *et al*. (2021)	Typhoon Rumbia	N.A.	ROA	In the context of emergency, the authors identified an inverted U-shaped relationship between lean manufacturing and financial performance.
Celil *et al*. (2022)	Natural disasters in general	EM-DAT database	Loan growth	The authors' findings suggest that Chinese regional state-owned City-Commercial Banks (CCBs) that are restricted to operate within a specific city are more effective in responding to natural disasters by expanding credit more aggressively, particularly to corporate borrowers.
Huang *et al*. (2022)	Natural disasters in general	CDP survey; SHELDUS database	Bank loan terms	Climate risk is associated with unfavorable corporate financing terms for bank loans.
Huang *et al*. (2022)	Natural disasters in general	The Spatial Hazard Events and Losses Database	ESG disclosure	The proximity of natural disasters to firms leads to an increase in environmental, social, and governance (ESG) disclosure transparency in neighboring counties over the following period.
Nguyen *et al*. (2022)	Droughts in the US	National Centers for Environmental Information; National Oceanic and Atmospheric Administration	Capital structure and the adjustment speed of capital structure	The risk of drought has a negative impact on both a firm's leverage and the speed of leverage adjustment.
Rao *et al*. (2022)	Extreme rainfall in India	IMD (Ministry of Earth Sciences website)	Firm value	Rain-sensitive firms experience a substantial decrease in their market value in the immediate aftermath of both excess and deficit rainfall conditions.

Sodhi *et al.*, 2012). However, it is still unclear whether these implications could be generalized to and applied in exogenous shocks such as extreme weather events. Also, there is still little empirical evidence on this issue from emerging economies (e.g., China).

In short, prior climate change and extreme weather-related research mainly focuses on the impacts of a single extreme weather event or one specific type of extreme weather on macro-level socioeconomic outcomes in developed countries (e.g., the US, UK, Germany, Australia, Japan). Firm-level operational performance implications from extreme weather in emerging markets are still scarce and it is unclear whether the mitigation strategies dealing with firm-specific endogenous operations disruptions could be successfully applied in extreme weather contexts.

2.2.2 Hypothesis Development

Our first hypothesis considers the direct impact of extreme weather on firms' labor productivity. First, extreme weather could disrupt firms' material flows by inflicting physical destruction of firms' fixed assets (e.g., plant, warehouse, property, equipment), which will not only decrease the value of these assets *per se*, but also force firms to halt production and operations activities, especially for those that require outdoor operations (e.g., construction, transportation, logistics, sanitation) (Huang *et al.*, 2018). For example, hurricanes or heavy snows can make transportation difficult, causing delays in the delivery of raw materials and finished goods (Markolf *et al.*, 2019). Even indoor businesses can also be affected by extreme weather. For instance, the power constraints caused by extreme heat waves will restrict the operations of a considerable portion of firms. These disruptions to the material flow process may lead to delays in production and increased downtime, and employees may be idle or unable to perform their jobs if they do not have access to the necessary materials or equipment, which can negatively impact firms' labor productivity.

Moreover, extreme weather may lead to breakdown or slowdown of information transmission within a firm and across firms along the supply chain, which in turn leads to delays, errors, and misunderstandings. Also, studies suggest that the fit between a firm's information processing capability and information processing needs has significant impacts on organizational outcomes. The higher the fit between the two, the better a firm's performance will be (Premkumar *et al*., 2005). The information processing needs of firms come from the uncertainty and ambiguity of internal and external environment. One of the great challenges that extreme weather poses to firms is that it is difficult for firms to predict the scale and costs of the impact that extreme weather will have on their operating environment (Mehta *et al*., 2019). This means that when extreme weather strikes, firms will face great environmental uncertainty, i.e., extreme weather uncertainty, and the needs for information processing will rise rapidly. It is believed that firms faced with extreme weather events have to handle more complex operational issues than usual. The dilemma between the increasing needs for information processing and the relative lack of information processing capability under extreme weather conditions will do harm to firms' operations. For example, firms may feel difficult to handle complex information of sharp fluctuations in supply, demand, and price as well as recovery plans brought about by extreme weather shocks (Haile *et al*., 2017). Also, extreme weather-induced power outages can cause a company's data center to fail to provide services, which means that managers may have difficulty accessing critical information such as inventory levels, sales figures, customer satisfactions, project timelines, safety protocols, and work instructions stored on computers and other electronic devices in a timely manner. This can impede firms' information processing, decision-making and planning, resulting in productivity losses. Moreover, employees who are worried about their safety or their families may be distracted and unable to focus on their work, which may lead to errors or delays. The stress and anxiety caused by extreme weather may also affect employees' ability to process information effectively, leading to reduced labor productivity (Karthick *et al*., 2023).

Furthermore, extreme weather may impact labor productivity through the mechanism of financial flows. Damage to physical assets will result in repair and replacement costs, and firms may face higher operating costs (e.g., energy and transportation costs) in extreme weather conditions, which will lead to financial constraints. Reduced financial flow may limit a firm's ability to hire and retain skilled workers, provide training and development opportunities, or invest in new technology or equipment that could enhance productivity. Additionally, financial strain may lead to cost-cutting measures such as layoffs, which can further lower labor productivity.

Finally, from the labor supply perspective, extreme weather could cause a reduction in labors' working hours and productivity. For instance, both in laboratory and observational data settings, a number of studies have well documented the biological effects of extreme temperatures on workers' discomfort, fatigue, and cognitive impairment (e.g., Graff Zivin *et al*., 2018; Seppänen *et al*., 2006). Workers may strategically choose not to work or to cut working hours on these days. Integrating individual worker productivity data from personnel records with weather data, Cai *et al*. (2018) provide novel evidence from a Chinese manufacturing firm that there exists an inverted-U relationship between daily maximum temperature and indoor workers' productivity, and this link is fairly homogeneous across populations (males vs. females, young vs. old, migrants vs. local workers). Similarly, Zhang *et al*. (2018) employ detailed production data from a half million Chinese manufacturing firms between 1998 and 2007 to examine the influences of temperature on firms' total factor productivity, factor inputs, and outputs. The authors also detect an inverted-U association between temperature and firm-level total factor productivity. One of the main implications from the above studies is that both too high and too low temperatures (extreme temperatures) could significantly lower labor productivity.

Based on the above discussion, extreme weather will lead to productivity losses through disrupting firms' material-, information- and financial flows as well as decreasing the labor supply. Accordingly, we propose the first hypothesis:

H1: Extreme weather has negative impact on firms' labor productivity.

Our second hypothesis considers the moderating role of operational slack. Operational slack represents firms' access to buffer resources which could support operational activities and make it possible for firms to better match variations between supply and demand and deal with environmental dynamism and operational disruptions (Hendricks *et al*., 2009; Kovach *et al*., 2015). Operational slack usually manifests itself as having spare physical inventory, surplus capacity, extra time, and excess labor in a firm's production processes (Azadegan *et al*., 2013). Given the prevalence of lean philosophy, studies on lean manufacturing/just-in-time have highlighted the significant costs associated with maintaining slack and holds that firms should enhance operational efficiency and effectiveness by reducing slack and redundancy (Gligor *et al*., 2015; Inman & Mehra 1993; Karlsson & Åhlström, 1997).

However, recent studies have recognized that while efficiency-oriented operations may enhance firms' profitability (Eroglu & Hofer, 2011; Modi & Mishra, 2011), it may also make firms less able to adjust to dynamic markets and can have adverse influences on firms' ability to cope with disruptions and uncertainties (Kovach *et al*., 2015; Wood *et al*., 2017). For instance, Azadegan *et al*. (2013) examine the relationship between operational slack and venture survival and how three types of environmental uncertainty (i.e., dynamism, complexity, and lack of munificence) moderate the operational slack-venture survival link. While the authors acknowledge the fact that operational slack could be expensive and may even reduce the venture's financial performance, they argue that survival is the top priority of a venture and financial loss could play a secondary role to warding off possibly damaging environmental threats. Empirical results of this study show that operational slack does lower the likelihood of venture failure with an increase in three kinds of environmental uncertainty. In the extreme weather context, as we have discussed above, main threats to firms in the face of extreme weather events are damage to assets, logistics disruptions and lack of production materials. In this extreme case, the important goals of firms are to ensure continuity of material flow and undiminished productivity. Operational slack is often maintained in firms' internal operations in the form of excess inventory or capacity (Essuman *et al*., 2022), which could help firms achieve the above goals as it provides firms with needed materials, resources and capacities in this condition. The above discussions suggest that firms need to build more operational slack as a buffer to respond more resiliently to the lack of production materials and capacity caused by extreme weather shocks in mitigating their productivity losses. We thus propose the following hypothesis:

H2: The impact of extreme weather on labor productivity is less negative for firms with high levels of operational slack.

Our third hypothesis considers the moderating role of digital technology deployment. Studies show that firms can develop digital capabilities and build digital resilience through the employment of digital technologies (e.g., IoT, big data, AI, cloud computing, 3D printing) to mitigate major shocks, adapt to disruptions and convert to the new state (Boh *et al*., 2023; Sousa-Zomer *et al*., 2020). This establishment of digital capabilities and resilience allows firms to survive when facing shocks and may even take advantage of opportunities from the adversity to improve their structures and processes (Boh *et al*., 2023). This is partly because the use of digital technologies could enhance a firm's operational adjustment agility, which means that firms are more flexible to adjust their original processes supported by digital technologies (Li *et al*., 2022; Lu & Ramamurthy, 2011). Even in some cases where slack resources are not easy to access to, cloud infrastructures can enable firms to have low switching costs and fast scalability, which provides redundancy (Boh *et al*., 2023).

Moreover, different from traditional IT, digital technologies enable a real-time information flow and the massive amount of data that can be exchanged, integrated and processed to increase data analytics and prediction capacity (Enrique *et al*., 2022), which could to a certain extent help firms lower the unfit between information processing needs and information processing capacity when facing adverse shocks (Li *et al*., 2020). For example, data from social media platforms and satellite imagery could be used to map the spread of extreme weather. An AI platform that could detect water rise from social media posts has already been successfully developed and put into use by scientists (Gupta, 2018). If a company has suppliers in the location of a weather disaster, such digital technologies can help this firm obtain timely risk information and make adjustments to avoid loss of productivity. In addition, the adoption of digital technologies offers employees both temporal and geographic flexibility, which means employees can work from home or even work from anywhere (Bai *et al*., 2021). Ge *et al*. (2023) suggest that work from home backed by digital remote working significantly increases firms' resistance capacity during the COVID-19 pandemic. The above discussions indicate that digital technologies improve firms' operational adjustment agility, strengthen information processing capacity and make it easier for employees to perform their duties, which will ultimately protect firms' productivity in the context of extreme weather. Thus, the study hypothesizes that:

H3: The impact of extreme weather on labor productivity is less negative for firms with high levels of digital technology deployment.

Our fourth hypothesis considers the moderating role of cash hedging. Cash hedging means that firms can buy (sell) commodity in the spot market and at the same time sell (buy) the same commodity in the financial market by carefully choosing a suitable financial derivative such as futures, forwards, option or swap (Xing *et al*., 2022). Because opposite trades are made in the spot and financial markets, cash flow losses in the spot market can be compensated by gains in the financial market, and vice versa (Liu *et al*., 2023). Studies show that firms can effectively obtain stable cash flow and avoid profit variability risk by adopting cash hedging strategy (Sun *et al*., 2017; Xing *et al*., 2022). For example, Liu *et al*. (2023) point out that remanufacturing firms often face the risk of high production costs which originate from the price changes of commodities (e.g., steel, aluminum, plastics, and natural gas) and fluctuations of interest and exchange rates. Remanufacturers thus often choose to use cash hedging to protect firms from the cash flow volatility risk and provide firms with stable cash flow to successfully invest in cost-reduction technologies. Their empirical result confirms the value of cash hedging in enhancing remanufacturing firms' profits as well as environmental performance. In particular, Brusset & Bertrand (2018) conduct case study to illustrate the approach for manufacturers to employ weather-indexed financial instruments to transfer weather risks to risk takers and reduce cash flow uncertainty and potential losses induced by adverse weather.

As our discussion in the first hypothesis, extreme weather can negatively impact a firm's labor productivity through the financial flow mechanism (i.e., financial constraints). By adopting cash hedging, firms can have stable financial flows in the face of extreme weather, which will not only help themselves recover from disruptions as quickly as possible, but also enable them to help their supply chain partners (e.g., suppliers) who may also be affected by adverse weather. For instance, a number of Ford's parts suppliers experienced financial distress that limited their ability to supply parts to Ford during the 2008 global financial crisis. Ford thus responded this circumstance by adopting cash hedging strategy and using its cash reserves to provide suppliers with a range of financial supports such as extending temporary financing to suppliers which ultimately "burning through" $7.7 billion during the third quarter of 2008 (Kulchania & Thomas, 2017). This move allowed Ford to eventually avoid bankruptcy like its rivals General Motors and Chrysler. The above discussions indicate that firms can benefit from cash hedging to stabilize their financial flows in extreme weather conditions, which will ease the financial constraints of the focal firm and its supply chain partners and make firms more flexible in investing productivity-enhancement projects. This leads to the following hypothesis:

H4: The impact of extreme weather on labor productivity is less negative for firms with high levels of cash hedging.

2.3 Methodology

2.3.1 Data and Sample

We collect and combine longitudinal secondary data from multiple sources to examine the impact of extreme weather events on operational outcomes, and the role of operational resources and strategies in combating extreme weather events. First, we obtain extreme weather data from the EM-DAT database (The Emergency Events Database), which is a free international database of natural disasters and other emergency events, maintained by the Centre for Research on the Epidemiology of Disasters (CRED) based in Brussels, Belgium. It was established in 1988 and is considered one of the most comprehensive and authoritative sources of information on disasters. EM-DAT is compiled from different sources, including UN agencies, non-governmental organizations, insurance companies, research institutes, and press agencies, which contains data on the locations, date, types, and impacts of natural disasters and other emergencies, such as epidemics, industrial accidents, and complex humanitarian emergencies, worldwide. In particular, EM-DAT encompasses more than 22,000 worldwide major disaster events since 1900 and has been extensively used in the prior literature (e.g., Bena *et al*., 2022; Celil *et al*., 2022; Kaplanski & Levy, 2010). The database provides comprehensive information on various types of hazards, including geophysical (e.g., earthquake, volcanic activity), meteorological (e.g., storm, extreme temperature, and fog), hydrological (e.g., flood, landslide, and wave action), climatological (e.g., drought, glacial lake outburst, and wildfire), biological (e.g., epidemic, insect infestation, animal accident), and extraterrestrial events. We extract three categories of natural hazards from EM-DAT as proxies for extreme weather: meteorological, hydrological, and climatic events. As our sample is limited to the A-share listed firms in mainland China, where some climate-related natural hazards do not occur within our analysis period, the six main extreme weather events in our study are droughts, extreme temperatures, wildfires, landslides, floods, and storms. The accounting data and headquarter addresses for public firms are collected from China Stock Market & Accounting Research (CSMAR) database. We merge the city-level extreme weather information with firms' longitudinal financial data based on the city in which each firm is headquartered. Our initial sample includes all Chinese A-share listed companies from 2010 to 2020 with 33,133 firm-year observations. As our analysis period is the subsequent three years following an extreme weather event (further explained below), we advance the starting time of extreme weather data three years ahead to incorporate the impact of weather shocks on observations in earlier years. Following prior literature, we exclude firms in financial industries due to their distinct regulatory policies and market trading mechanisms (Dessaint & Matray, 2017; Zhu *et al*., 2021), which leads to the reduction of 733 firm-year observations. Furthermore, we lose 3,702 firm-year observations with missing values for the variables used in the regression. After these two steps, our final sample contains 3,722 unique firms with 28,698 firm-year observations between 2010 and 2020. The estimated economic losses due to extreme weather events range from $2.3 million to $18 billion during our sampling period. Some examples of extreme weather events are presented in Table 2.2.

Table 2.2 Sample examples

Disaster Number	City	Disaster Subgroup	Disaster Type	Start	End	Total Damages ('000 US$)
2008-0263-CHN	Wuhan	Hydrological	Flood	2008.05.02	2008.05.05	19000
2016-0023-CHN	Harbin	Meteorological	Extreme temperature	2016.01.20	2016.01.26	1600000
2016-0162-CHN	Sanming	Hydrological	Landslide	2016.05.04	2016.05.11	700000
2019-0134-CHN	Liangshan Yi	Climatological	Wildfire	2019.04.01	2019.04.01	N.A.
2019-0472-CHN	Zhoushan	Meteorological	Storm	2019.10.02	2019.10.02	263000

2.3.2 Measures

Labor Productivity. In the existing OM literature, labor productivity reflects a firm's total output that can be produced from a given level of labor inputs and is therefore a good indicator for operational effectiveness (e.g., Levine & Toffel, 2010; Lo *et al*., 2013; Sartal *et al*., 2020). Drawing on previous studies, we use the natural logarithm of the ratio of operating income to number of employees to capture labor productivity (Heim & Peng, 2010; Lo *et al*., 2014; Sartal *et al*., 2020; Yang *et al*., 2021).

Moderators and controls. We derive the operational slack indicator based on the cash-to-cash cycle. Specifically, the cash-to-cash cycle equals the sum of days of inventory and accounts receivables minus days of accounts payables (Hendricks *et al*., 2009; Wiengarten *et al*., 2017). Digital technology deployment is operationalized based on the frequency of digital transformation keywords extracted from firms' annual report using textual analysis. Drawing on the approach employed in prior research to construct a firm-level focus on digital technologies (e.g., Mishra *et al*., 2022; Niu *et al*., 2023; Zhou & Li, 2023), we first use Python to collate the annual reports of our sample firms between 2010 and 2020, and then find the terms that characterize a firm's digitalization (e.g., artificial intelligence, big data, cloud computing, blockchain, and practical digital applications) and calculate their frequencies to reflect a firm's digitalization level. We take the logarithm of one plus a firm's digital transformation word frequency to measure digital technology deployment. Cash hedging is measured by the natural logarithm of a firm's financial derivative investments to capture its ability to respond to cash flow fluctuations (Liu *et al*., 2023). In the robustness check section, we use the inventory dimension of operational slack and the ratio of financial derivative investments to current assets as alternative measures for operational slack and cash hedging, respectively. In line with prior studies (e.g., Brav *et al*., 2015; Datta *et al*., 2005; Jacob, 2021; Li & Valentini, 2023; Stuebs & Sun, 2010; Yang, 2022), our estimation includes a series of firm-specific control variables that are suggested to be related with a firm's operational performance, including return on assets (ROA, net income divided by total asset), firm size (the natural logarithm of a firm's total assets), firm age (the natural logarithm of the number of years since a firm was founded), leverage (the ratio of the book value of debt to assets), sales growth (a firm's sales for the current year divided by last year's sales then minus one), capital investment (capital expenses divided by total assets), technology intensity (intangible assets divided by total assets), and state ownership (equals one if state-owned and 0 otherwise). High financial performance and large-scale operations are commonly associated with superior productivity. However, the impact of firm age on productivity is uncertain *ex ante*, as the positive effect of the learning curve on productivity may be offset by the adverse impact of organizational rigidity due to the reluctance of established firms to undertake changes. Moreover, capital and technology intensity are important factors to control for because they could be utilized to either substitute or leverage labor (Datta *et al*., 2005; Sartal *et al*., 2020). Table 2.3 provides the measures, data sources, and references for the variables used in the regression analysis.

2.3.3 Identification Strategy

We believe that the extreme weather events appear to be exogenous, which provides a favorable natural experiment for our identification. As extreme weather events occur in different years, we perform a staggered DID estimation to assess the impact of extreme weather shocks on firms' operational performance. We first identify the treatment group as firms located in cities hit by extreme weather, while the control group consists of companies located in those cities that have not experienced extreme weather throughout our sample period. Using this DID approach, we are able to compare the difference in operational performance between companies in the treatment and control groups before and after extreme weather and thus

Table 2.3 Measurement of variables

Variable type	Variable name	Measurement	Data source	Reference
Dependent variable	*Labor productivity*	Natural logarithm of the ratio of operating income to number of employees	CSMAR	Lo *et al*. (2014)
Explanatory variable	*After × Treated*	A dummy variable	EM-DAT	Bena *et al*. (2022)
Moderators	*Operational slack*	Sum of days of inventory and accounts receivables minus days of accounts payables	CSMAR	Wiengarten *et al*. (2017)
	Digital deployment	Natural logarithm of one plus a firm's digital transformation word frequency	Hand-collected	Mishra *et al*. (2022)
	Cash hedging	Natural logarithm of a firm's financial derivative investments	CSMAR	Liu *et al*. (2023)
Control variables	*ROA*	Net income divided by total asset	CSMAR	Datta *et al*. (2005)
	Size	Natural logarithm of a firm's total assets	CSMAR	Stuebs & Sun (2010)
	Age	Natural logarithm of the number of years since a firm was founded	CSMAR	Yang (2022)
	Leverage	The ratio of the book value of debt to assets	CSMAR	Jacob (2021)
	Sales growth	A firm's sales for the current year divided by last year's sales then minus one	CSMAR	Datta *et al*. (2005)
	Capital investment	Capital expenses divided by total assets	CSMAR	Brav *et al*. (2015)
	Technology intensity	Intangible assets divided by total assets	CSMAR	Li & Valentini (2023)
	State ownership	A dummy variable equals one if state-owned and 0 otherwise	CSMAR	Zhang *et al*. (2001)

estimate the causal effect of extreme weather exposure on firm labor productivity. Our baseline model is as follows:

$$Labor\ Productivity_{i,t} = \beta_0 + \beta_1 After_t \times Treated_i + \beta_2 Treated_i + \beta_3 Controls_{i,t} + \eta_t + \delta_j + \varepsilon_{i,t}$$

where the subscripts i and t represent firm and year, respectively. *Treated* is a dummy variable that takes the value of 1 if the firm is in the treatment group and 0 if the firm is in the control group. *After* equals 1 if the year of observation falls within the three-year period (t+1 to t+3) following the extreme weather, and 0 otherwise. We determine this time window by referring to previous studies on natural disasters such as droughts, floods, high temperature and hurricanes (Dessaint & Matray, 2017; Duqi *et al.*, 2021; Huang *et al.*, 2022). Our interest is to estimate the interaction term between *After* and *Treated* in the model. The coefficient β_1 is the treatment effect and captures the causal impact of extreme weather events on firm labor productivity. $Controls_{i,t}$ is a set of firm-level control variables. η_t and δ_j are vectors of dummy variables that control for year and industry fixed effect, respectively. $\varepsilon_{i,t}$ is the error term. Before running the analysis, all the continuous variables are winsorized at the 1st and 99th percentiles to mitigate the potential impact of outliers.

A key assumption of the DID estimation is the parallel trend, which means that there is no systematic difference between the samples in treatment and control group before extreme weather events occur. Drawing on prior literature (Beck *et al.*, 2010; Lam *et al.*, 2022), we construct the model below to compare the differences in firm performance between the two groups over time.

$$Labor\ Productivity_{i,t} = \beta_0 + \sum_t \beta_t Year_t \times Treated_i + \beta_2 Treated_i + \beta_3 Controls_{i,t} + \eta_t + \delta_j + \varepsilon_{i,t}$$

where t is the relative year compared to the occurrence of extreme weather. $Year_t$ is a binary variable that takes the value of 1 in year t and 0 otherwise. Five years or earlier before the weather disturbance are lumped together as the "Year -5", representing five or more years before the event happens. *Treated* equals 1 for the treatment group and 0 for the control group.

Figure 2.1 plots the result of the parallel trend analysis with 90 per cent confidence intervals. The result shows that the coefficients of the interaction term are not significantly different from zero prior to the weather event. In contrast, in the three years following an extreme weather shock, the coefficients are negative and statistically significant ($p < 0.1$). Therefore, there is insufficient evidence to suggest a difference in pre-trends between the treatment and control firms.

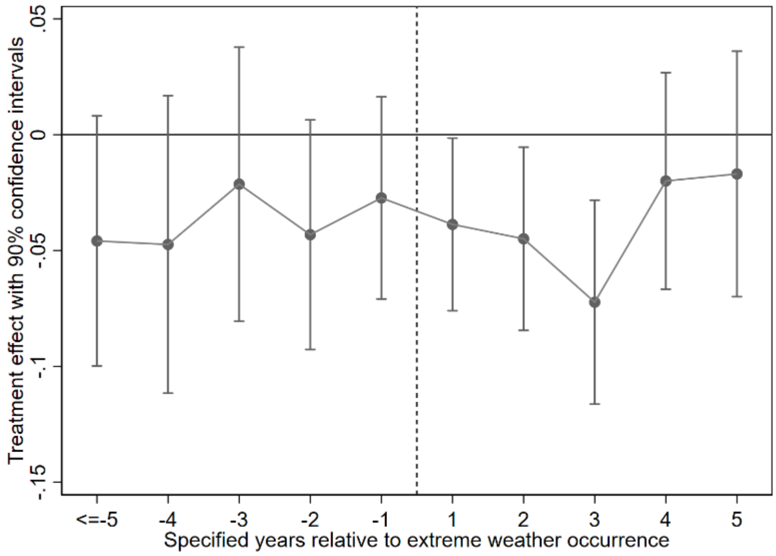

Figure 2.1 Parallel trend test plot

2.4 Empirical Results

2.4.1 Descriptive Statistics and Baseline Results

After combing the data from multiple sources and dropping the observations with missing data, we finally obtain a full sample of 3,722 unique firms (1,017 in treated group and 2,705 in control group) with 28,698 firm-years between 2010 and 2020. Table 2.4 presents the distribution of our sample. We see that the majority of observations are in the manufacturing sector, which accounts for 64.63 per cent of the entire sample. All the dependent and independent variables' means, medians, standard deviations, minimum and maximum values can be found in Table 2.5. In particular, *After* × *Treated* is a binary indicator with the mean value of 0.104, which suggests that around 10.4 per cent of the total observations are affected by extreme weather events in our analyzing period. Table 2.6 documents the correlation matrix. It can be seen that the absolute values of the correlation coefficients between all the variables are less than 0.5. Also, the correlation coefficient between *After* × *Treated* and *Labor Productivity* is significantly negative (-0.048, $p < 0.01$), which gives us a prediction that extreme weather may negatively impacts firms' labor productivity. In addition, the mean and largest values of Variance Inflation Factor (VIF) are 1.24 and 1.57, respectively, which are far less than the threshold of 10, indicating that multicollinearity is not a major concern in this study.

Table 2.7 presents the DID test results. The dependent variable is labor productivity (Models 1 and 2). In Model 1, we just include the explanatory variable (*After* × *Treated*) and year and industry fixed effects. We see that the coefficient of *After* × *Treated* in Model 1 is negative and significant. Model 2 is the full model that includes all the control variables, and year and industry fixed effects. In consistent with Model 1, we also find that the coefficient of explanatory variable is significantly negative in Model 2, demonstrating that extreme weather does negatively influence operational performance in terms of labor productivity. Thus, our hypothesis 1 (H1) is supported.

2.4.2 The Moderating Effects of Operational Resources and Strategies

To further understand how firms should react to extreme weather, we examine the roles that multiple operational resources and capabilities play in extreme weather conditions. Specifically, for each of the four variables proposed in H2-H4, we divide the entire sample into two sub-samples based on the median value of the moderating variable in the three-digit industry each year (e.g., Ge *et al*., 2023; Lam *et al*., 2022). As a result, one sub-sample includes firms with higher resources and capabilities than the industry median, and the other sub-sample is composed of firms with insufficient resources relative to their peers in the same industry. W

Table 2.4 Distribution of sample firms

Panel A: Distribution of sample firms across industries

CSRC industry code	Industry	Frequency	Percentage (%)
A	Agriculture, forestry, animal husbandry and fishery	430	1.50
B	Mining	733	2.55
C	Manufacturing	18,548	64.63
D	Electricity, heat, gas and water production and supply	962	3.35
E	Construction	759	2.64
F	Wholesale and Retail	1,553	5.41
G	Transportation, warehousing and postal services	881	3.07
H	Accommodation and catering	113	0.39
I	Information transmission, software and information technology services	1,799	6.27
K	Real estate	1,219	4.25
L	Leasing and business services	360	1.25
M	Scientific research and technical services	252	0.88
N	Water conservancy, environment and public facilities management	341	1.19
O	Residential service, repair and other services	19	0.07
P	Education	28	0.1
Q	Health and social work	67	0.23
R	Culture, sports and entertainment	362	1.26
S	Comprehensive	272	0.95
Total sample size		28,698	100.00

Panel B: Distribution of sample firms across years

Year	Frequency	Percentage (%)
2010	1,597	5.56
2011	1,963	6.84
2012	2,207	7.69
2013	2,334	8.13
2014	2,375	8.28
2015	2,476	8.63
2016	2,671	9.31
2017	2,943	10.26
2018	3,287	11.45
2019	3,339	11.63
2020	3,506	12.22
Total sample size	28,698	100.00

Table 2.5 Summary statistics

	N	Mean	Median	Std. Dev.	Min	Max
Labor Productivity	28,698	13.80	13.70	0.927	7.697	19.91
After × Treated	28,698	0.104	0.000	0.305	0.000	1.000
ROA	28,698	0.033	0.035	0.072	-0.370	0.207
Size	28,698	22.16	22.00	1.295	19.36	26.08
Age	28,698	2.866	2.890	0.350	0.693	4.796
Leverage	28,698	0.439	0.430	0.213	0.049	0.952
Sales Growth	28,698	0.188	0.104	0.525	-0.652	3.866
Capital Investment	28,698	0.049	0.035	0.047	0.000	0.228
Technology Intensity	28,698	0.048	0.034	0.052	0.000	0.326
State Ownership	28,698	0.375	0.000	0.484	0.000	1.000

Table 2.6 Correlation matrix

		1	2	3	4	5	6	7	8	9	10
1	*Labor Productivity*	1.000									
2	*After × Treated*	-0.048***	1.000								
3	*ROA*	0.069***	-0.019***	1.000							
4	*Size*	0.428***	-0.012**	0.025***	1.000						
5	*Age*	0.144***	0.021***	-0.100***	0.164***	1.000					
6	*Leverage*	0.277***	0.029***	-0.356***	0.450***	0.175***	1.000				
7	*Sales Growth*	0.127***	-0.004	0.196***	0.032***	-0.047***	0.032***	1.000			
8	*Capital Investment*	-0.167***	0.000	0.145***	-0.044***	-0.201***	-0.093***	0.042***	1.000		
9	*Technology Intensity*	-0.145***	0.003	-0.050***	-0.008	-0.000	0.007	-0.012*	0.144***	1.000	
10	*State Ownership*	0.154***	0.035***	-0.050***	0.346***	0.161***	0.274***	-0.054***	-0.086***	0.058***	1.000

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 2.7 Baseline results-Extreme weather and firms' labor productivity

	Labor Productivity	
	(1)	(2)
After × Treated	-0.062***	-0.045***
	(-3.53)	(-2.83)
Treated	-0.108***	-0.126***
	(-9.19)	(-11.74)
ROA		1.390***
		(16.25)
Size		0.212***
		(44.15)
Age		0.008
		(0.59)
Leverage		0.325***
		(10.27)
Sales Growth		0.175***
		(14.20)
Capital Investment		-2.114***
		(-19.96)
Technology Intensity		-1.501***
		(-14.27)
State Ownership		0.004
		(0.32)
Constant	13.396***	8.852***
	(174.01)	(67.99)
Year F.E.	Included	Included
Industry F.E.	Included	Included
N	28,698	28,698
R-squared	0.280	0.406

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

then implement a DID estimation for each of these sub-samples and document the test results in Table 2.8. Since we have identified an inverse relationship between extreme weather events and firm performance across the full sample, comparing the differences between the two sub-samples makes it possible for us to more intuitively understand whether these resources can offset this adverse influence.

Our sub-sample analysis suggests that the impact of extreme weather on firms' labor productivity is still significantly negative for firms with low levels of digital technology deployment, low operational slack, and low cash hedging. In contrast, the adverse effect of extreme weather shocks is no longer significant for firms with high levels of digital technology deployment, high operational slack, and high cash hedging level. The opposite results obtained from the two sub-samples are consistent with our conjecture that these OM resources and strategies can provide firms with a buffer and insurance-like protection against adverse external conditions, therefore supporting H2-H4.

2.4.3 Robustness Checks and Additional Analysis

A series of robustness tests are performed to consolidate our findings. We first utilize a Mahalanobis distance matching approach to identify a control sample. This matching approach could minimize the observable variation across multiple observable dimensions that might affect labor productivity between the treatment and control groups and thus allow us to estimate the causal effect of extreme weather on firm labor productivity as far as possible (Morandi *et al*., 2020). Intuitively, observations in treatment and control groups with similar firm-level characteristics constitute an ideal counterfactual, as they are similar in most aspects, differing only in whether affected by extreme weather events or not. Specifically, we impose the condition that the paired firms belong to the same one-digit Standard Industrial Classification (SIC) industry, thereby yielding two advantages. Firstly, this condition guarantees that the matched firms share similar industry-specific attributes. Secondly, it enables a substantial pool of eligible control firms to be considered for matching. Next, from the pool of candidates, we select the nearest neighbor with replacement to match each treatment firm to a control firm, according to the following characteristics: return on assets, firm size, firm age, leverage, sales growth, capital investment, and technology intensity. Similar to Flammer (2015) and Huang *et al*. (2022), we require that the matched firms have the closest Mahalanobis distance across these matching characteristics prior to treatment. This matching procedure ensures that control firms are as similar as possible to the treated firms ex ante along each dimension. As previously noted, the variables included in the matching process are considered to be closely related to corporate labor productivity. Panel A of Table 2.9 suggests that our matching minimizes the differences in covariates between the treatment and control firms. The regression result of DID

Table 2.8 Sub-sample test results

	Labor Productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
	Low operational slack	High operational slack	Low digital deployment	High digital deployment	Low cash hedging	High cash hedging
After × Treated	-0.078***	-0.016	-0.070**	-0.038	-0.089***	-0.008
	(-3.35)	(-0.74)	(-2.25)	(-1.61)	(-3.83)	(-0.37)
Treated	-0.104***	-0.128***	-0.077***	-0.165***	-0.108***	-0.138***
	(-6.72)	(-8.72)	(-3.66)	(-10.54)	(-6.88)	(-9.48)
Control variables	Included	Included	Included	Included	Included	Included
Year F.E.	Included	Included	Included	Included	Included	Included
Industry F.E.	Included	Included	Included	Included	Included	Included
N	13,955	14,326	8,530	11,932	13,508	15,190
R-squared	0.415	0.429	0.429	0.430	0.389	0.418

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

analysis based on the matched firms is presented in Panel B of Table 2.9. The coefficient of our interest remains negative and pronounced after the employment of Mahalanobis distance matching approach.

Table 2.9 Robustness check-Identify control firms with Mahalanobis distance matching approach

Panel A: Covariate balance check of the matched samples

	Mean			
	Treated group	Control group	bias (%)	*p* values
ROA	0.028	0.029	-1.9	0.188
Size	22.19	22.20	-0.6	0.683
Age	2.896	2.890	1.5	0.305
Leverage	0.459	0.457	1.0	0.516
Sales Growth	0.199	0.186	2.4	0.106
Capital Investment	0.048	0.048	1.8	0.208
Technology Intensity	0.048	0.047	2.4	0.117

Panel B: Regression results with matched firms

	Mahalanobis distance matching	
	Labor Productivity	
After × Treated	-0.059***	-0.046***
	(-3.40)	(-2.84)
Treated	-0.091***	-0.121***
	(-6.36)	(-9.23)
ROA		1.388***
		(12.17)
Size		0.193***
		(28.43)
Age		0.009
		(0.49)
Leverage		0.409***
		(9.26)
Sales Growth		0.182***
		(11.23)
Capital Investment		-2.431***
		(-16.72)
Technology Intensity		-1.124***
		(-8.15)
State Ownership		0.022
		(1.51)
Constant	13.391***	9.221***
	(205.59)	(61.14)
Year F.E.	Included	Included
Industry F.E.	Included	Included
N	15,301	15,301
R-squared	0.293	0.414

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the *p*-values are two-tailed. *t* statistics in parentheses.

To provide additional insight into how firms react to diverse extreme weather events, we separate the events by extreme weather type, i.e., droughts, extreme temperatures, landslides, floods, and storms. Wildfire is not included due to insufficient variant observations. Table 2.10 reports the regression results by our classification. Overall, all five types of extreme weather exert a significant negative impact on firm labor productivity. Among them, droughts and landslides are the two main threats to labor productivity, with larger coefficients significant at a 1% level ($p < 0.01$). For the sub-sample of extreme temperature, flood, and storm, their negative effects are still significant, although the coefficients are slightly smaller than those of the first two hazards. The above analysis indicates that the operational outcomes caused by extreme weather events may vary across various weather types.

Next, we perform multiple robustness tests to check the sensitivity of our findings. The results of the robustness tests are shown in Table 2.11, which will be discussed in detail below. First, we no longer use the three-year period interval ($t + 1$ to $t + 3$) but adjust the time window to two alternative periods: the two-year period ($t + 1$ to $t + 2$) and the four-year period ($t + 1$ to $t + 4$). The former captures the relative short-term effect of extreme weather shocks, whereas the latter can better reflect their influence on affected firms over a longer horizon. After adjusting the estimation window, we arrive at a similar result as before. To verify the captured relationship is sensitive to different measures of dependent variables, the ratio of a firm's operating income to its number of employees (without taking logarithm) serves as a substitute for labor productivity. Additionally, we further investigate the impact of extreme weather shocks on the firm market performance. Tobin's q is a substitute of dependent variable, which is a forward-looking, capital market-based value measurement. The coefficient of the interaction term is still negative, once again proving the adverse effect of extreme weather events on firms' operational outcomes as well as market performance. We also adopt alternative measures of three moderating variables. Operational slack is computed as the inventory divided by the cost of goods sold (Kovach *et al*., 2015; Lam & Zhan, 2021). Cash hedging is replaced by the ratio of financial derivative investments to current assets. The sub-sample test results show that the negative impact of extreme weather is largely mitigated or even eliminated for firms with high operational slack and cash hedging. The alternative measure for digital technology deployment is a dummy variable that equals to 1 if a firm holds patents related to digitization during our sample period and 0 otherwise. The empirical result reconfirms that companies with strong digital technology deployment are more likely to mitigate the negative impact of extreme weather on labor productivity. In short, our findings remain valid after a series of checks.

Finally, we conduct a placebo test to exclude the influence of confounding factors beyond severe weather on our principal findings. If the previously observed decline in labor productivity is indeed due to the extreme weather suffered by the city where a firm is headquartered, then most of the estimated coefficients of *After* × *Treated* based on a random selection of falsified treatment firms should not be statistically significant (Lam *et al*., 2022). Following Amiram *et al*. (2019), we randomly generate the same number of pseudo-treatment cities as the number of real treated cities and randomly assign a spurious treatment year to each pseudo-treated city. Subsequently, we perform the DID analysis incorporating all control variables and repeat the above process 500 times. The distributions of the estimated coefficients and *t*-values of the falsified *After* × *Treated* are plotted in Figure 2.2. As the kernel density plot in Figure 2.2 shows, most of the estimated coefficients are clustered around zero, with few exceptions smaller than -0.045 (true coefficient as presented in Table 2.7), and the majority of the *p*-values are larger than those of the real coefficients ($p > 0.005$). The *t*-values of these estimated coefficients largely lie within the range of -2 to 2, indicating that extreme weathers' negative impacts become no longer significant when using randomly (pseudo) allocated cities. In the second placebo test, we retain the real treatment and control group and only randomly assign a "false" occurrence year to the cities in the treatment group. We repeat this process 500 times and obtain the similar results aforementioned. These placebo test results further reinforce the validity of our previous findings and suggest that our captured relationship is not driven by chance. As such, our results are unlikely to be affected by potential confounding or other extraneous factors.

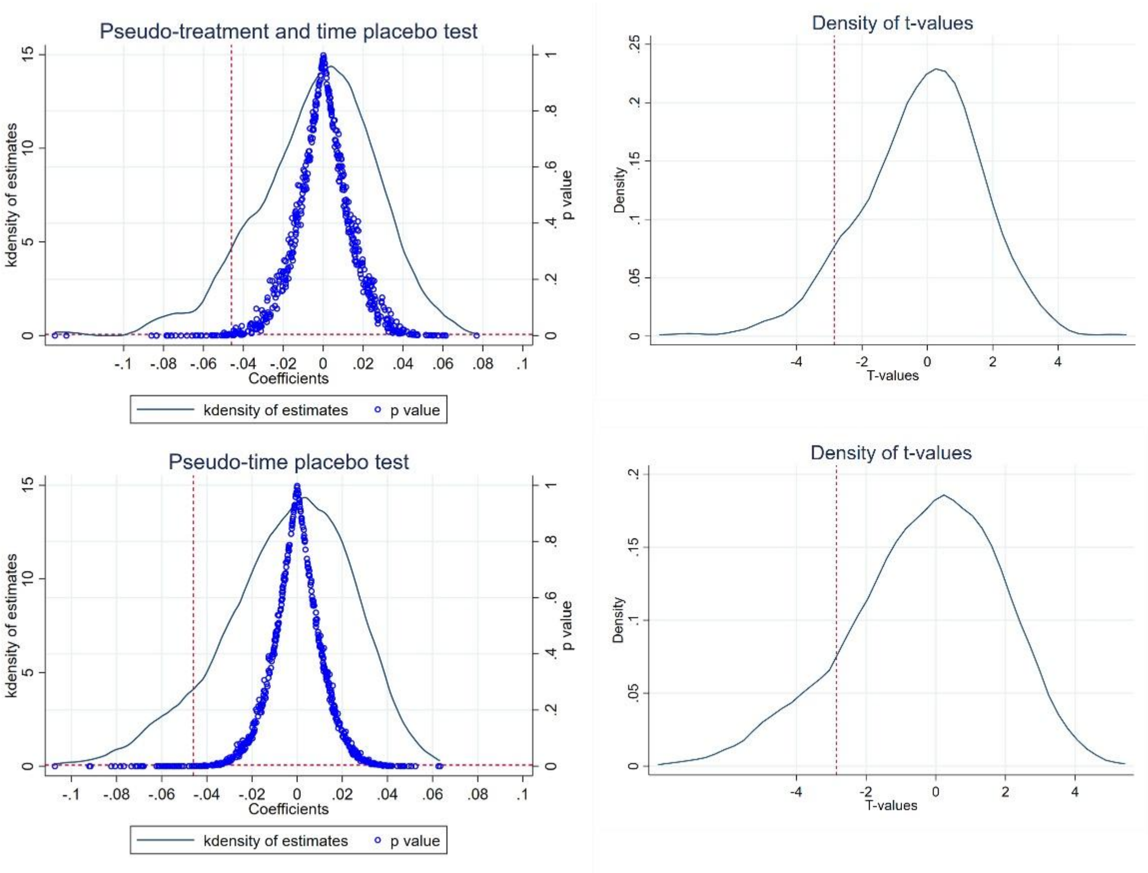

Figure 2.2 Placebo test plot

Table 2.10 Different types of extreme weather on firms' labor productivity

	Labor Productivity				
	(1)	(2)	(3)	(4)	(5)
	Drought	Extreme temperature	Landslide	Flood	Storm
After × Treated	-0.657***	-0.143***	-0.164***	-0.146***	-0.088***
	(-2.87)	(-3.49)	(-4.15)	(-8.36)	(-3.86)
Control variables	Included	Included	Included	Included	Included
Year F.E.	Included	Included	Included	Included	Included
Industry F.E.	Included	Included	Included	Included	Included
N	28,698	28,698	28,698	28,698	28,698
R-squared	0.4015	0.4015	0.4016	0.4027	0.4016

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

Table 2.11 Robustness check-Adjustment of estimation window and alternative measures

Panel A: baseline model

	Labor Productivity			
	(1)	(2)	(3)	(4)
	(t+1, t+2)	(t+1, t+4)	Alt_Labor Productivity	Tobin's q
After × Treated	-0.036**	-0.036**	-232685***	-0.132**
	(-2.00)	(-2.36)	(-3.14)	(-2.57)
Treated	-0.132***	-0.126***	-269855***	0.174***
	(-12.93)	(-11.20)	(-3.99)	(4.44)
Control variables	Included	Included	Included	Included
Year F.E.	Included	Included	Included	Included
Industry F.E.	Included	Included	Included	Included
N	28,698	28,698	28,698	28,005
R-squared	0.406	0.406	0.116	0.205

Panel B: moderating effect

	Labor Productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
	Alt_low operational slack	Alt_high operational slack	Alt_low digital deployment	Alt_high digital deployment	Alt_low cash hedging	Alt_high cash hedging
After × Treated	-0.093***	0.006	-0.052***	-0.026	-0.078***	0.002
	(-3.95)	(0.28)	(-3.02)	(-0.65)	(-3.79)	(0.08)
Treated	-0.114***	-0.132***	-0.115***	-0.181***	-0.122***	-0.128***
	(-7.36)	(-9.32)	(-9.82)	(-6.92)	(-8.47)	(-8.03)
Control variables	Included	Included	Included	Included	Included	Included
Year F.E.	Included	Included	Included	Included	Included	Included
Industry F.E.	Included	Included	Included	Included	Included	Included
N	13,977	14,307	25,596	3,102	16,098	12,600
R-squared	0.434	0.425	0.408	0.376	0.390	0.424

Notes: *p < 0.1, **p < 0.05, ***p < 0.01. All the p-values are two-tailed. t statistics in parentheses.

2.5 Summary, Discussion, and Future Research

2.5.1 Summary and Principal Findings

In recent years, the frequent occurrence of extreme weather events has had serious impacts on firms' products and services, adaptation activities, supply chain, investments, and production and operations (Huang *et al*., 2022). More and more firms are taking extreme weather into consideration in formulating their strategies and trying to employ measures to combat the adversity induced by extreme weather exposure. Although an increasing number of studies have investigated extreme weather's macro-level socioeconomic consequences as well as firm-level financial implications, there is still a lack of understanding on how extreme weather influences firms' operational performance and what operational resources or strategies firms could leverage to mitigate potential adverse effects. Employing the staggered DID approach and analyzing a large-scale panel dataset of Chinese publicly traded firms, we provide one of the first empirical evidence that extreme weather does have significant negative impacts on firms' operational performance in terms of labor productivity. The results further show that operational slack, digital technology deployment, and cash hedging can help firms stabilize material-, information-, and financial flow respectively, which ultimately allows firms to experience fewer productivity losses under extreme weather conditions. Also, different extreme weather events have heterogenous effects on firm operations. In our sample, we find that droughts and landslides are the two primary threats to Chinese listed firms. Our findings hold after a series of robustness checks such as parallel trend analysis, alternative measures, mahalanobis distance matching approach, placebo test, and adjustment of estimation window. The implications of these findings for research and practice are discussed below.

2.5.2 Implications for Research

This study has some implications for research. First, while many studies have well documented the potential impacts of extreme weather, most of these studies have concentrated on developed markets to investigate the macro-level socioeconomic consequences of a single extreme weather event or one specific type of extreme weather (e.g., Baylis & Boomhower, 2022; Groen & Polivka, 2008; McIntosh, 2008). Some recent studies have started to explore extreme weather's firm-level implications, but these efforts primarily focus on financial outcomes such as bank loan financing, cost of equity capital, capital structure, and earnings forecasts (e.g., Huang *et al*., 2022; Huang *et al*., 2018; Rao *et al*., 2022). Our work contributes to extreme weather literature by providing one of the first direct evidence that extreme weather has negative impact on firm-level operational performance in terms of labor productivity in an emerging market context. This study may inspire operations and supply chain management researchers to further investigate extreme weather's other operational implications such as firm risk, stock returns, market value, working capital, innovation performance, supply chain structure, etc. at different levels and/or in diverse contexts, which could enhance our understanding of the impacts of extreme weather on firms' operations and supply chain activities.

Moreover, this study contributes to disaster management literature by specifically focusing on how a firm could leverage operational slack, digital technology, and cash hedging to stabilize its material-, information-, and financial flow respectively to mitigate extreme weather's negative effect on labor productivity. Although existing disruptions-related OM research has demonstrated that some operational and supply chain resources or strategies (e.g., slack resources, diversification, vertical relatedness) are effective in mitigating the adverse effects of disruptions on firm performance, these studies mainly focus on firm-specific, endogenous operational glitches or disruptions such as parts shortages, order changes, production problems, supplier misconducts, logistics interruptions, ramp up issues etc. (Braunscheidel & Suresh, 2009; Kleindorfer & Saad, 2005; Simangunsong *et al*., 2016; Sodhi *et al*., 2012). It is still unclear whether these resources or strategies can be successfully generalized to and applied in exogenous shocks with significant impacts such as extreme weather. Our study goes one step further by examining the moderating roles of some operational resources aforementioned, which confirms the value of operations management in navigating extreme weather shocks.

In addition, lean/just in time manufacturing have been prevalent and sourced much of the research on how to manage and improve operations over the past four decades (Browning & de Treville, 2021). The debate over the operational slack has been ongoing. Some scholars view slack as a form of waste and firms thus should minimize redundancy and slack to improve operational efficiency (Beamon, 1999; Hines *et al*., 2004), while others demonstrate that slack resources make firms less sensitive to threats and challenges (Kleindorfer & Saad, 2005; Kovach *et al*., 2015). We join this debate and complement this research stream by showing that operational slack safeguards firms' productivity in emergency situations (i.e., extreme weather shocks). Also, while prior OM studies traditionally focus on operational hedging (e.g., Sting & Huchzermeier, 2014; Weiss & Maher, 2009), a new research trend is to incorporate financial hedging into operational problems as well as study the relationship between operational hedging and financial hedging (e.g., Chen *et al*., 2014; Shantia *et al*., 2019; Xing *et al*., 2022). In fact, transactions and payments accompany the movement of physical goods along the supply chain, creating significant operational and financial interdependence between supply chain partners (Kouvelis *et al*., 2019). To effectively and efficiently manage supply chains, firms need to properly handle both of material flow and cash flow as they are closely related and affect each other. Our study indicates that firms could use cash hedging to stabilize financial flow and make labor productivity less affected by extreme weather, which may inspire further empirical OM studies to investigate the role of cash hedging in mitigating other adverse conditions. In doing so, this article responds to the recent calls that more OM efforts need to be devoted to studying the implications of and solutions to various exogenous major shocks or extreme conditions such as natural disasters, pandemics, trade disagreements, and national conflicts (Chen *et al*., 2023; Hendricks *et al*., 2020; Jacobs *et al*., 2022; Sodhi & Tang, 2021). Both academia and industry are increasingly finding that these exogenous shocks have important impacts on firms' production and operations activities. We respond their calls and join this research stream to attempt to answer the question about what impacts extreme weather have on operational performance and how firms could use OM measures to handle the adversity.

Finally, in the methodology aspect, our natural experiment setting and staggered DID approach demonstrate the possibility and advantages of conducting causal inference-oriented empirical OM research on disruption issues based on secondary data collected and combined from multiple sources, which is also advocated in recent empirical OM studies (e.g., Dhanorkar & Muthulingam, 2020; Lam *et al*., 2022).

2.5.3 Implications for Practices

The results of this study also provide several practical implications. First, our findings reveal that extreme weather significantly reduces firms' labor productivity. Firms thus are suggested to incorporate extreme weather factors and climate change issues into their company-wide strategic planning. For example, companies could consider setting a special committee that takes direct responsibility to plan and supervise firms to implement climate-related policies and practices, which will better help firms resist extreme weather shocks (Bloom *et al*., 2010; Huang *et al*., 2022). In addition, Kleindorfer & Saad (2005) point that prevention is always better than cure, which means loss avoidance and preemption are better than mitigation of losses after the fact. We thus suggest firms regularly take a full inventory of their entire infrastructure to ensure the security of both physical and digital infrastructure. If a data center or office is located in a place that have been impaired by extreme weather, these facilities must be reinforced. Similarly, software and data stored at these sites should be prepped for migration to other data centers long before actual crisis alerts are raised. Preparing for unpredictable extreme weather ahead of time pays dividends when emergencies strike.

Furthermore, by examining the moderating roles of operational slack, digital technology deployment and cash hedging, this study enhances our understanding of how firms could employ diverse operational resources and strategies to stabilize material-, information- as well as financial flow and mitigate the productivity losses resulted from extreme weather. Thus, overemphasizing operational leanness may not be an appropriate strategy for firms operating in areas with high risk of extreme weather. Instead, firms should be aware of the important role of operational slack in extreme weather and find a balance between the benefits and costs of holding slack (Modi & Mishra, 2011). Also, firms should embrace digitalization, automation and orchestration of the recovery processes, which creates pre-determined plans to retrieve critical data in an extreme weather event and strengthens firms' ability to manage its material and information flows. For example, Cloud Resiliency Orchestration developed by IBM can be customized for any firm size and in any environment, which aims to simplify disaster recovery management and achieve multiple specific recovery goals such as the protection of labor productivity. Finally, firms could consider taking cash hedging strategy to mitigate the exposure to extreme weather effects. For instance, climate risk management companies such as The Demex Group has developed an innovative options which helps distribute the monetary risk that extreme weather events pose (Freedman, 2021). Firms could use such weather derivatives to hedge the cost of extreme weather and obtain a smooth financial flow. We also notice that extreme weather has a substantial negative impact on firms' Tobin's q, a measure reflecting market valuation and perceived future prospects. Disruptions to operations, supply chains, and assets caused by extreme weather may erode investor confidence, lower earnings expectations, and increase perceived risk (Huang *et al.*, 2018), leading to a decline in firms'

Tobin's *q*. To counter these effects, managers should prioritize resilience-building measures, such as risk management, stakeholder communication, and financial preparedness. By proactively addressing the challenges posed by extreme weather, firms can mitigate the adverse effects on their Tobin's *q* and enhance their long-term value proposition in the eyes of investors and stakeholders.

2.5.4 Limitations and Future Research Directions

As with any research, this work is subject to several limitations, which also provide promising directions for future studies. The first limitation comes from the sample of firms used in this study. Like other secondary data-based empirical OM studies, although we construct our sample based on multiple objective and reliable data sources such as EM-DAT and CSMAR, this approach inevitably limits the generalizability of our findings to publicly traded firms only (Cheung *et al*., 2020; Geng *et al*., 2022). In fact, the number of listed companies is only a small proportion nationwide. Non-listed firms and small and medium-sized enterprises account for around 91.8 per cent and provide approximately 80 per cent of the employment opportunities in China (National Bureau of Statistics, 2019). Also, compared with large, listed firms, small and medium-sized enterprises are more vulnerable to extreme weather shocks due to limited resources and poor governance. We thus encourage future studies to employ other methods (e.g., survey, case study, interview, simulation) or multi-methods to explore other private and small firms to replicate our findings (Choi *et al*., 2016).

The second limitation concerns the measures used in our research. For instance, our measure of extreme weather is a binary variable, i.e., if a city was affected by an extreme weather event in a certain year, the variable will be recorded as 1 for the years following that year, otherwise it is 0. Although this approach allows us to more objectively document the occurrence of extreme weather events and facilitate subsequent data analysis, it does not give us a more specific understanding of diverse characteristics of extreme weather events such as wind speed, precipitation, maximum temperature, and other specific dimensions. Future research could consider adding more dimensions of extreme weather events in the empirical analysis. For instance, in terms of hurricanes, future studies may consider applying the Wind Field Model (WFM) in meteorology and publicly available data from the Met Office to more accurately quantify the local destructive power of hurricanes (Emanuel, 2011). WFM can calculate the wind speed generated by the hurricane in the subject area by comprehensively considering the hurricane center pressure, travel direction, displacement velocity, and the relative position information of the affected area to the hurricane center, and further quantify the hurricane damage by this wind speed data.

Third, due to data limitation, we only consider the influence of extreme weather on listed firms' headquarters and neglect other domestic branches and overseas subsidiaries in this study (Huang *et al*., 2018). This may to some extent underestimate the negative impact of extreme weather on firms. Future research could use more detailed firm-, supply chain-, or supply network-level data to explore the operational implications of extreme weather. Moreover, future studies may consider additional operational and financial resources or strategies (e.g., diversification, catastrophe insurance) to better help firms cope with extreme weather risks.

Chapter 3 Study Two: Carbon Risk and Firm Value: A Revisit and Extension

3.1 Introduction

Climate change is widely regarded as one of the most pressing challenges of our time (Ardia *et al*., 2023), with profound environmental, economic, and societal repercussions, such as an increasing frequency of extreme weather events, biodiversity loss, disruptions to agricultural systems, market volatility, and public health challenges (Blanco, 2021; Ginglinger & Moreau, 2023; Liang *et al*., 2024). Central to this crisis is the issue of greenhouse gas (GHG) emissions, particularly carbon dioxide, which has garnered significant attention from policymakers, investors, and businesses (Zhang *et al*., 2024). While leading firms in developed economies, such as Amazon, Apple, and Daimler, have made substantial efforts to reduce carbon emissions and pledged to achieve carbon neutrality in the near future, many companies in emerging markets and developing economies (EMDEs) continue to expand their carbon footprints despite escalating climate risks (Liu *et al*., 2024; Roemer *et al*., 2023). According to a recent report by the World Economic Forum (WEF, 2022), EMDEs accounted for over 95% of the increase in carbon emissions over the past decade, with this share projected to rise further in the coming years. This disparity highlights a critical issue: the economic viability of low-carbon strategies in EMDEs remains uncertain due to differing regulatory frameworks, institutional dynamics, and market pressures (Lam *et al*., 2016; Su *et al*., 2024). Addressing this issue is of great practical relevance, as it directly relates to firms' incentives to pursue carbon reduction initiatives in EMDEs and is vital to achieving global decarbonization targets.

Environmental issues have long been integrated into mainstream operations management (OM) literature and other business research domains (Angell & Klassen, 1999; de Burgos Jiménez & Céspedes Lorente, 2001; Etzion, 2007). A prominent research stream within this literature explores the relationship between firms' environmental performance and financial or operational outcomes, addressing the critical question of whether firms can "do well by doing good." This inquiry has been pivotal in building the business case for sustainable OM practices (de Burgos-Jiménez *et al*., 2013; Jacobs *et al*., 2010; Jeong & Lee, 2022; Lo *et al*., 2018; Pil & Rothenberg, 2003). Building upon this foundation, recent studies have shifted toward carbon-specific issues, particularly investigating the financial implications of carbon risk as well as potential mitigation and adaptation strategies (Bai & Ru, 2024; Blanco, 2021; Liu *et al*., 2024; Song *et al*., 2024). However, empirical findings remain inconclusive. While some studies suggest that reducing carbon emissions could enhance financial performance, measured by ROA or Tobin's *q* (Jung *et al*., 2018; Lee *et al*., 2015; Matsumura *et al*., 2014), others identify a positive association between carbon risk and financial returns, indicating the existence of a carbon premium (Bolton & Kacperczyk, 2021; Busch *et al*., 2022; Oestreich & Tsiakas, 2015). Notably, most of these studies are conducted concerning developed economies, leaving significant gaps in understanding this relationship within the context of EMDEs, which are characterized by distinct challenges and opportunities in addressing climate change. For these reasons, we reexamine the relationship between firms' carbon risk and financial performance in China, a leading EMDE and a critical player in global decarbonization efforts.

While theories such as stakeholder theory, legitimacy theory, and institutional theory have been extensively employed to explain firms' motivations for pursuing carbon neutrality (Zhang *et al*., 2024), these frameworks primarily focus on external pressures such as stakeholder expectations, societal norms, and institutional demands and provide limited guidance on actionable strategies for mitigating the adverse impacts. This limitation is particularly evident in the OM literature, where studies addressing effective approaches to managing carbon risk are relatively scarce. To fill this gap, this paper adopts the natural-resource-based view (NRBV) (Hart, 1995) as its theoretical foundation. With the concepts of NRBV, we identify three interconnected strategies, i.e., pollution prevention, product stewardship, and sustainable development, that not only minimize environmental impact but also serve as sources of sustainable competitive advantage. From an OM perspective, these strategies could be operationalized through practices such as enhancing production efficiency, fostering green innovation, and implementing environmental, social, and governance (ESG) initiatives (Ye *et al.*, 2023). These discussions lead to the second research question: Are NRBV-aligned OM strategies effective in mitigating the financial impacts of carbon risk?

To address the aforementioned research questions, this study utilizes data from various sources, including the Institute of Public and Environmental Affairs (IPE), the Chinese Research Data Services Platform (CNRDS), the China Stock Market & Accounting Research (CSMAR) database, the WIND database, and the National Carbon Trading Market Information Network. After excluding financial sector firms and observations with incomplete data, the final dataset comprises 691 firm-year observations from 298 distinct firms over the period 2018–2022. Employing a two-way fixed effects (TWFE) model, the findings reveal a significant and negative relationship between carbon risk and firm value, as measured by Tobin's q. This effect is also economically substantial: a one-standard-deviation increase in carbon risk is associated with a 0.464 decrease in firm value, equivalent to 24.3% of the average firm value. Furthermore, we find that production efficiency and green innovation positively moderate the main effect, indicating that these two OM strategies effectively mitigate the adverse financial impacts of carbon risk. While the pooled regression model does not reveal a significant moderating effect of ESG performance, we conduct further analysis by splitting the sample based on greenwashing behavior provides additional insights. Specifically, for firms with low greenwashing behavior, ESG performance exhibits a significant positive moderating effect, suggesting that investors consider the alignment between carbon emissions risk and ESG performance when making investment decisions. Finally, we find that the market, in general, penalizes all the firms for their carbon emissions. However, firms that voluntarily disclose emissions information experience a less significant decline in firm value compared with those that do not disclose, underscoring the importance of transparency in addressing carbon risk. The results still hold across various robustness tests, including the use of alternative measures, the instrumental variable (IV) method, a selection model, system generalized method of moments (GMM) estimation, and a quasi-natural experimental design.

Our study contributes to the sustainable OM literature broadly and to the understanding of the firm value implications of carbon risk in EMDEs specifically. While prior research has examined the relationship between carbon risk and financial performance, the findings remain inconsistent, and most studies have been conducted in the context of developed economies. By reexamining this relationship in the Chinese context, our study provides new empirical evidence on how contextual factors, such as regulatory dynamics and investor expectations, influence the financial consequences of carbon risk. This approach helps enhance the robustness and contextual relevance of previous findings. Furthermore, we validate the effectiveness of three NRBV-aligned OM strategies in mitigating the adverse financial impacts of carbon risk. This directly responds to the calls by Lam *et al*. (2022) and George *et al*. (2016) for OM researchers to address societal grand challenges, such as climate change, by examining the role of OM-related factors. Lastly, our study extends the environmental disclosure literature by shedding light on how investors interpret and respond to carbon-related disclosures, including greenwashing behavior and voluntary disclosure, within the context of emerging markets. Collectively, these findings provide empirical support for the value of reducing carbon emissions and offer actionable insights for firms, investors, and policymakers seeking to align environmental and financial objectives.

3.2 Literature Review and Hypothesis Development

3.2.1 Related Literature

Our study primarily relates to two research streams: carbon risk and its economic outcomes, and firms' carbon reduction strategies. While there is no universal definition of carbon risk to date, several studies conceptualize it within the broader context of environmental risk, encompassing both transitional and physical risks (Borghei, 2021; Velte *et al*., 2020; Wang, 2023). Transitional risks arise from changes in policies, legal frameworks, technologies, and market dynamics associated with the transition to a low-carbon economy (Nguyen & Phan, 2020; Shu *et al*., 2023). In contrast, physical risks arise from the tangible impacts of climate change, such as extreme weather events, elevated sea levels, and prolonged disturbances to organizational operations and supply chain activities (Liang *et al*., 2024; Pu *et al*., 2021; Shu & Fan, 2024).

With respect to the economic implications of carbon risk, prior studies primarily focus on its financial repercussions, including effects on performance metrics, valuation significance, cost of capital, and risk profiles (Wang, 2023). Research examining the link between carbon risk and financial performance—captured through short-term accounting-based measures (e.g., ROA, ROE) and long-term market-based indicators (e.g., Tobin's *q*)—has produced mixed results. While a majority of studies find a negative association between carbon risk and financial performance (e.g., Aggarwal & Dow, 2012; Wang *et al*., 2021), others reveal positive or nonlinear relationships, contingent on factors such as sample characteristics, study period, geographic context, methodological approaches, and firm-specific attributes (e.g., Broadstock *et al*., 2018; Ganda, 2018; Wang *et al*., 2014). Additionally, investors are increasingly integrating carbon emissions information into their decision-making frameworks, underscoring its importance for valuation (Bolton & Kacperczyk, 2021). This growing emphasis highlights the critical role of capital markets in shaping research on the interplay between carbon risk and corporate valuation. Empirical evidence generally supports a negative association between carbon risk and valuation metrics, such as market value of equity or stock returns (e.g., Bose *et al.*, 2021; Choi & Luo, 2021; Cooper *et al.*, 2018; Griffin *et al.*, 2017; Matsumura *et al.*, 2014). Furthermore, carbon risk has been linked to increased costs of equity and debt. For instance, Jung *et al.* (2018) and Kim *et al.* (2015) find significant positive relationships between carbon risk and the cost of debt and equity, respectively, with these effects being economically meaningful. Carbon risk has also been associated with heightened default risk and tail risk, underscoring its financial significance (Kabir *et al.*, 2021; Neudorfer, 2022).

In practice, firms adopt various OM-related carbon mitigation strategies aligned with the tenets of NRBV (Hart, 1995) to address carbon risk. These strategies are broadly categorized into three types: pollution prevention, product stewardship, and sustainable development. Pollution prevention focuses on minimizing emissions and waste at the source through cleaner production technologies and operational efficiency. Studies suggest that such measures could enhance resource utilization and strengthen stakeholder relationships (King & Lenox, 2002). Product stewardship extends this focus across the product lifecycle, emphasizing sustainable design, production, and disposal, thereby reducing regulatory compliance costs and fostering brand loyalty. Sustainable development, the most comprehensive strategy, involves long-term investments in ESG initiatives. Research shows that firms prioritizing sustainable development not only improve their environmental footprint but also bolster their resilience to market and regulatory shocks (Ye *et al.*, 2023). Collectively, these strategies enable firms to balance short-term economic pressures with long-term environmental objectives. However, their effectiveness is context-dependent, with most research focusing on developed economies, leaving the dynamics in EMDEs underexplored.

In summary, while prior studies have enhanced our understanding of the financial implications of carbon risk, critical gaps remain, particularly concerning its long-term impacts and context-specific dynamics. Similarly, although research on carbon reduction strategies underscores their potential to improve firm resilience and market performance, their varying effectiveness across industries and regions requires further investigation. By synthesizing these two research streams, this study aims to provide a nuanced perspective on how carbon risk impacts financial performance and whether NRBV-aligned OM strategies are effective in navigating carbon risk for firms in EMDEs. This approach contributes to theoretical and practical insights into both sustainability and operational strategy.

3.2.2 The Impact of Carbon Risk on Firm Value

As an extension of the traditional RBV of the firm, NRBV emphasizes the interplay between an organization and its natural environment. Specifically, NRBV highlights the strategic importance of environmental resources and sustainability in achieving and maintaining competitive advantage (Hart, 1995; Hart & Dowell, 2011). According to this perspective, well-managed environmental resources and capabilities can evolve into valuable, rare, inimitable, and non-substitutable assets, thereby contributing to superior firm performance. Conversely, poor environmental management, particularly high levels of carbon emissions, undermines firm value by exposing firms to physical and transition risks.

In this study, we define carbon risk as an overarching construct that encompasses both physical risk and transition risk. Physical risk arises from the direct impacts of climate change, such as extreme weather events, which pose significant threats to firms' operations and infrastructure (Benincasa *et al*., 2024; Liang *et al*., 2024). High-emissions industries, including energy, manufacturing, and resource extraction, often locate their capital-intensive facilities in regions vulnerable to climate-related disruptions, such as coastal areas prone to hurricanes and flooding (Balakrishnan *et al*., 2022; Pu *et al*., 2021). For instance, oil refineries and coal-fired power plants are heavily exposed to operational disruptions caused by severe weather events (An *et al*., 2021). These facilities require continuous operation to maximize profitability, and any downtime due to extreme weather can lead to production delays, revenue losses, and increased costs for repairs and operational adjustments (Ginglinger & Moreau, 2023; Huang *et al*., 2018). In addition, firms in such industries often face higher insurance premiums and significant costs associated with fortifying infrastructure against future climate risks, further eroding their financial stability and market valuation.

Transition risk, on the other hand, encompasses economic and regulatory challenges stemming from the global shift toward a low-carbon economy, including changes in policies, technological advancements, market dynamics, and reputational pressures (Bolton & Kacperczyk, 2021; Matsumura *et al*., 2014). Stricter environmental regulations, such as carbon pricing mechanisms, carbon taxes, and emissions trading systems, have progressively internalized the externalities of carbon emissions into firms' operational costs (Bai & Ru, 2024; Martinsson *et al*., 2024). For example, under the European Union Emissions Trading System (EU ETS), firms exceeding their carbon allowances must purchase additional permits or face penalties. Industries with inherently high emissions, such as cement production and steel manufacturing, are particularly affected by these mechanisms, leading to higher operating costs and reduced profitability if they fail to adopt cleaner technologies or enhance energy efficiency (Dewaelheyns *et al*., 2023). Such costs diminish profit margins, constrain cash flows, and negatively impact Tobin's *q*, as investors reassess their expectations for future financial performance.

Moreover, firms failing to respond to market demand for sustainable products may lose competitiveness. The automotive sector illustrates this dynamic, as traditional manufacturers face growing pressure to develop electric vehicles (EVs) in response to regulatory mandates and consumer preferences for low-emissions alternatives. Industry leaders such as Tesla and BYD have leveraged their advancements in EVs and emissions reduction to achieve superior market performance, while firms lagging in technological adaptation risk losing market share. Transition risks also extend to stranded assets, such as fossil fuel reserves, which may become economically unviable as the market shifts away from carbon-intensive energy sources. Finally, reputational risk and stakeholder engagement exacerbate the impact of carbon risk. Companies with high carbon emissions may face reputational damage, reduced stakeholder trust, and heightened scrutiny from regulators, investors, and consumers. For instance, Jacobs & Singhal (2020) demonstrate the significant shareholder value losses experienced by Volkswagen and its ecosystem following the emissions scandal in 2015. Such reputational setbacks not only damage investor confidence but also reduce customer loyalty, amplifying the negative impact on firm value.

Taken together, carbon risk adversely affects firm value by reducing the magnitude and stability of cash flows. Firms with elevated carbon risk face operational disruptions, increased regulatory costs, shifting market dynamics, and reputational challenges, all of which diminish profitability and market valuation. Based on this reasoning, we propose the following hypothesis:

H1: Carbon risk is negatively associated with a firm's value.

3.2.3 Moderating Roles of NRBV-Aligned OM Strategies

Production efficiency reflects a firm's ability to achieve maximum output with minimal input while reducing waste (Lam *et al*., 2016; Li *et al*., 2022). Higher production efficiency could attenuate the negative effects of carbon risk on firm value by alleviating the financial and operational burdens imposed by both physical and transition risks. From the perspective of physical risk, firms with higher production efficiency are better equipped to withstand disruptions caused by extreme weather events, such as floods, hurricanes, and heatwaves (Liang *et al*., 2024). Efficient production systems often incorporate advanced technologies and adaptive processes, enabling firms to recover more quickly from climate-related disruptions (Pu *et al*., 2021). For example, energy-efficient facilities with robust contingency planning can reduce downtime and limit revenue losses during extreme weather events, thereby safeguarding profitability and firm valuation (Gupta *et al*., 2024; Kim *et al*., 2024). Conversely, firms with lower production efficiency are more likely to face prolonged operational interruptions, which could lead to significant financial losses and erode firm value (Xu *et al*., 2024).

With respect to transition risk, high production efficiency enhances firms' ability to adapt to regulatory pressures and market dynamics associated with the shift to a low-carbon economy. Regulatory frameworks, such as carbon taxes and emissions trading systems, increase operating costs for carbon-intensive firms (Martinsson *et al*., 2024; Timilsina, 2022). However, firms with efficient production systems often operate with lower carbon intensity, reducing their exposure to such costs (Luo *et al*., 2022). In addition, high production efficiency can strengthen a firm's reputation as an environmentally responsible entity, thereby attracting environmentally conscious investors and customers, which supports firm valuation (Lee & Kwon, 2019). We therefore hypothesize:

H2: The negative association between carbon risk and firm value is weaker for firms with higher production efficiency.

Green innovation encompasses the creation and application of novel or substantially enhanced products, processes, practices, or business models designed to mitigate environmental harm, improve resource efficiency, and advance sustainability objectives (Ye *et al*., 2023; Zolotoy *et al*., 2022). Within the realm of OM, green innovation mitigates firms' exposure to physical risks by enabling the integration of renewable energy systems, energy-efficient technologies, and infrastructure resilient to climate-related challenges. Such innovations decrease firms' dependence on carbon-intensive inputs, ensuring continuity of operations during disruptions caused by extreme events (Marín-Vinuesa *et al*., 2020). For example, advanced water management systems or renewable energy integration allows firms to safeguard production continuity and minimize financial losses during climate-induced crises.

Beyond in-house innovation, green innovation often necessitates an integrated and collaborative approach, emphasizing strong partnerships with suppliers and customers (Song *et al*., 2023). Firms engaged in green innovation establish collaborative relationships with suppliers specializing in eco-materials, green technologies, and environment-friendly practices (Yang *et al*., 2024). These partnerships not only facilitate the co-development of sustainable solutions but also enhance the firm's supply chain resilience, reducing the operational risks posed by climate change. In addition, green innovation fosters trust and stronger relationships with customers who increasingly demand sustainable products. These enhanced relationships mitigate potential reputational risks associated with carbon-intensive operations and bolster firm value through improved stakeholder loyalty and market competitiveness (Bag *et al*., 2022; Xue & Wang, 2024).

Moreover, green innovation offers firms opportunities to proactively respond to market dynamics, differentiating themselves by developing innovative sustainable products (Ba *et al*., 2013). For example, the success of firms like Tesla in electric vehicles or BYD in renewable energy solutions highlights how green innovation allows firms to align with shifting consumer preferences while maintaining competitive advantages in emerging markets. These firms not only mitigate carbon risk but also unlock new revenue streams, thereby enhancing their overall market valuation. In short, green innovation serves as a multi-faceted buffer against the detrimental effects of carbon risk, addressing operational vulnerabilities, regulatory compliance, supply chain integration, and market opportunities. By enhancing adaptive capabilities and fostering collaborative networks, green innovation could mitigate the negative impact of carbon risk on firm value. Based on this reasoning, we hypothesize that:

H3: The negative association between carbon risk and firm value is weaker for firms with more green innovations.

ESG performance reflects a firm's commitment to sustainable and socially responsible practices while adhering to robust governance standards (Starks, 2023). This multifaceted construct has gained prominence as stakeholders increasingly prioritize ethical, environmental, and societal concerns. Environmentally, firms with high ESG performance proactively address carbon emissions by adopting renewable energy, improving energy efficiency, and implementing advanced carbon management systems. These practices lower regulatory compliance costs and mitigate operational disruptions, helping firms maintain stability and value despite carbon risks (Li *et al*., 2025). From a social perspective, strong ESG performance fosters robust relationships with key stakeholders, including employees, customers, and local communities. Firms committed to social sustainability often exhibit greater employee engagement, brand loyalty, and customer trust (Dai & Tang, 2022; Gillan *et al*., 2021). For instance, a company with inclusive workplace policies and community engagement programs is more likely to retain talent and maintain positive public perceptions, countering the potential reputational losses associated with high carbon emissions.

Moreover, firms with superior governance frameworks are more adept at integrating carbon risk management into their strategic decision-making processes (Luo & Tang, 2021). Transparent reporting, ethical practices, and effective risk management structures help these firms anticipate and adapt to evolving regulatory landscapes, thereby mitigating carbon risk's financial impacts (Huang *et al*., 2022). For instance, firms with well-structured ESG committees may be better equipped to navigate carbon trading systems or carbon taxes, minimizing regulatory burdens and preserving firm value (Burke *et al*., 2019; Fu *et al*., 2020). These dynamics suggest that ESG performance could attenuate the adverse impact of carbon risk on firm value. Accordingly, we hypothesize that:

H4: The negative association between carbon risk and firm value is weaker for firms with better ESG performance.

3.3 Methodology

3.3.1 Data and Sample

We assemble a longitudinal panel dataset of Chinese A-share listed firms by integrating information from multiple secondary sources. First, we construct our sample by collecting carbon emissions data from the Institute of Public and Environmental Affairs (IPE) database, which provides firm-level carbon emissions information from 2018 to 2022. Similar to the Carbon Disclosure Project (CDP) database used in prior carbon-related research (Ilhan *et al.*, 2021; Matsumura *et al.*, 2014), the IPE has established a comprehensive information disclosure platform that encourages firms to voluntarily release their carbon emissions data to the public. Firms making such disclosures are required to submit supporting documentation, including business licenses, records of electricity and fossil fuel consumption, and relevant receipts. Unlike the CDP database, which collects data through surveys targeting major corporations within specific timeframes, the IPE platform allows firms to report their emissions data at any time. Moreover, the public can access this information via the IPE website, thereby enhancing transparency and accessibility.

We also collect corporate patent information from CNRDS database, ESG performance from Wind, financial and accounting data from CSMAR database, and carbon trading information from National Carbon Trading Market Information Network. The final matching process yields 1,417 firm-year observations from 2018 to 2022. Firms in the financial sector are excluded due to their distinct regulatory environment, and observations with incomplete data for key variables are also omitted (Liang *et al*., 2024; Zhu *et al*., 2021). Consequently, our baseline sample consists of 691 firm-year observations pertaining to 298 distinct firms. One limitation of the IPE dataset is that only a subset of firms voluntarily disclose their carbon emissions, which may introduce self-selection bias into our analysis. We address this issue through a series of methodologies, which will be discussed in detail later in the

Table 3.1 Descriptive statistics of sample firms

Panel A: Distribution of sample firms across industries

CSRC industry code	Industry	Frequency	Percentage (%)
B	Mining	50	7.24
C	Manufacturing	421	60.93
D	Utilities	42	6.08
E	Construction	12	1.74
F	Wholesale and retail	10	1.45
G	Transportation, warehousing, and postal services	69	9.99
I	Information transmission, software, and IT services	25	3.62
K	Real estate	17	2.46
L	Leasing and business services	5	0.72
M	Scientific research and technical services	18	2.60
N	Water conservancy, environment, and public facilities management	7	1.01
Q	Health and social work	9	1.30
R	Culture, sports and entertainment	5	0.72
S	Comprehensive	1	0.14
Total sample size		691	100.00

Panel B: Distribution of sample firms across years

Year	Frequency	Percentage (%)
2018	30	4.34
2019	101	14.62
2020	136	19.68
2021	215	31.11
2022	209	30.25
Total sample size	691	100.00

paper. Table 3.1 provides the sample distribution, with Panel A detailing the breakdown by industry and Panel B by year. Notably, 60.93% of the observations are derived from the manufacturing sector.

3.3.2 Measures

Firm Value. Consistent with prior research (e.g., Dotzel & Shankar, 2019; Jacobs *et al*., 2016; Yiu *et al*., 2020), we employ Tobin's *q*, a financial market-based metric, to quantify firm value. Tobin's *q* is defined as the ratio of a firm's capital market value to the replacement cost of its tangible assets. A significant advantage of Tobin's *q* is that it is derived from stock market prices, providing a forward-looking measure that reflects the firm's future prospects (Dotzel & Shankar, 2019; Yiu *et al*., 2020). The numerator of Tobin's *q*, the firm's market value, offers an estimate of the present value of its expected cash flows (Lang & Stulz, 1994). Tobin's *q* is particularly appropriate for our study, as the physical and transition risks associated with carbon exposure are anticipated to impact a firm's future cash flows. Tobin's *q* is calculated by dividing the sum of a firm's market equity value and the book value of total debt by its total assets' book value (Lin & Su, 2008).

Carbon Risk. The greenhouse gas (GHG) Protocol is an extensively recognized framework that delineates a firm's GHG emissions into three distinct categories (Blanco, 2021). Scope 1 emissions refer to direct emissions arising from the combustion of fossil fuels or from releases during production processes. Scope 2 emissions refer to indirect emissions resulting from the use of purchased electricity, heat, or steam. Scope 3 emissions encompass all other indirect emissions across a firm's value chain, covering both upstream and downstream activities (Ilhan *et al*., 2021). This research emphasizes the combined Scope 1 and Scope 2 emissions, as these are under the direct management and control of the firm. Moreover, Scope 3 emissions are rarely reported by sample firms to IPE, primarily due to the difficulties in estimating and verifying indirect emissions from external sources, such as employee business travel, waste disposal, and outsourced activities (Zhang *et al*., 2024). All the emissions are reported in terms of carbon dioxide equivalents. Following the prior literature (Bose *et al*., 2021; Ilhan *et al*., 2021; Jung *et al*., 2018), carbon risk is proxied by the ratio of a firm's annual carbon emissions (in tCO2e) to its total revenue (in ten thousand RMB). We use a normalized metric of carbon emissions to evaluate a firm's carbon risk, as this approach adjusts for firm size and reflects emissions per unit of output. As global warming exacerbates climate-related uncertainties for carbon-intensive firms, those with higher carbon intensity are broadly perceived to bear greater transition risks (Ilhan *et al*., 2021). For example, companies with higher carbon intensity are perceived as having business models that heavily rely on greenhouse gas emissions. This perception may result in a decreased demand for their products, services, and investments, thus increasing market risk (Jung *et al*., 2018; Wang, 2023).

Moderators and controls. Consistent with previous studies (Chen *et al*., 2024; Xu *et al*., 2024), we use a firm's registered green patents as a measure of its green innovation activities. Green patents are identified using the IPC Green Inventory created by the World Intellectual Property Organization (WIPO), which classifies patents associated with Environmentally Sound Technologies (ESTs) into seven categories: alternative energy production, transportation, energy efficiency, waste management, agriculture and forestry, administrative, regulatory, and design aspects, and nuclear energy generation. A patent is classified as a green patent if at least one of its IPC codes falls within these categories. We record patents based on the year of application rather than the year of grant, as the application year more accurately reflects the timing of actual innovation activities (Fang *et al*., 2014). To measure a firm's green innovation performance, we utilize the natural logarithm of one plus the count of its green invention and utility patents. Production efficiency is assessed using the natural logarithm of the ratio of operating income to the total number of employees, capturing the output a firm generates relative to a given level of labor input (Jacobs *et al*., 2016; Sartal *et al*., 2020). We also perform the stochastic frontier estimation approach in the robustness test to incorporate various manufacturing inputs, i.e., cost of goods sold, capital expenditure, and labor, that operations managers can manipulate to optimize firm outputs as an alternative measure of production efficiency (Jacobs *et al*., 2016). We use the Huazheng ESG ratings to assess a firm's disclosed ESG initiatives in the baseline model and the CNRDS ESG score for robustness checks, both of which have been employed in prior ESG-related research (He *et al*., 2023; Zhang, 2023). The Huazheng ESG rating system categorizes corporate ESG performance into nine hierarchical levels, i.e. C, CC, CCC, B, BB, BBB, A, AA, and AAA, with scores ranging from 1 to 9 assigned accordingly in our study.

To address potential concerns regarding confounding factors and omitted variable bias, we incorporate a variety of CEO and firm-specific characteristics that may influence firm value. These controls include firm size, measured as the natural logarithm of total assets; ROA, calculated as the ratio of net income to total assets; leverage, defined as the proportion of the book value of debt to total assets; sales growth, represented by the year-over-year percentage change in sales; and firm age, expressed as the natural logarithm of the years since the firm's inception. While firms with superior earnings and higher financial leverage are expected to exhibit more favorable growth prospects, firm size may be negatively correlated with Tobin's q due to the typically underperformed stock returns of large companies (Lang & Stulz, 1994; Yiu *et al*., 2020). We also use dummy variables to account for CEO duality and international experience, as international knowledge may positively influence firm performance and green practices (Le & Kroll, 2017; Quan *et al*., 2023). In addition, the theoretical implications of dual governance structures for financial outcomes are significant, despite a lack of empirical consensus among researchers (Krause *et al*., 2014). Furthermore, we control whether a firm actively participates in carbon emissions trading schemes and implement ISO 14001 standards.

The carbon trading scheme serves as an effective tool for addressing climate change by establishing a cap on emissions, allocating emissions permits to companies, and allowing the trading of these allowances as commodities (Bai & Ru, 2024). As a result, firms with higher carbon emissions may face diminished competitiveness and an urgent need to transition toward green production. As an environmental proactivity strategy, ISO 14001 certification can further assist firms in enhancing operational performance through continuous process optimization and the reduction of unnecessary emissions (Treacy *et al.*, 2019).

3.3.3 Model Specification

We introduce a two-way fixed effect (TWFE) model to examine whether carbon risk enhances or impedes firm value, and to assess the moderating effect of distinct operational strategies. The firm fixed effects control for time-invariant characteristics at the firm level, while the year fixed effects capture the intertemporal trends that affect firm performance. Robust standard errors are clustered by firms to address potential autocorrelation of the error terms within firms over time, thereby preventing inflating the *t*-statistics (Fang *et al.*, 2014). The TWFE model is as follows:

$$FirmValue_{i,t} = \beta_0 + \beta_1 Carbon\ Risk_{i,t} + \beta_2 Moderators_{i,t} \times Carbon\ Risk_{i,t} + \beta_3 X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad (1)$$

The subscripts *i* and *t* denote the firm and year indices, respectively. The terms μ_i, τ_t, and $\varepsilon_{i,t}$ refer to the firm fixed effects, year fixed effects, and error term, respectively. $X_{i,t}$ is a vector of the control variables discussed above. The corresponding coefficient β_1 quantifies the impact of carbon risk on firm performance, with a negative value indicating detrimental effects of carbon risk. To minimize the potential influence of the outliers, all the continuous variables are winsorized at the bottom and top 1% levels.

3.4 Results

3.4.1 Descriptive Statistics and Correlation

Table 3.2 presents the descriptive statistics and correlation matrix for the variables used in the baseline analysis. The mean value of Tobin's q is 1.910, with a range spanning from 0.780 to 9.540, reflecting substantial variation in the market-to-book ratios across the sample. Carbon risk has an average of 1.220 and a standard deviation of 3.340, highlighting notable differences in carbon emissions intensity among the firms. Furthermore, carbon risk is negatively correlated with Tobin's q in the absence of control variables, offering initial support for our hypothesis. To examine potential multicollinearity, we calculate the variance inflation factor (VIF) for all variables. The average VIF is 1.37, with a maximum value of 2.36, both well below the conventional threshold of 10, indicating that multicollinearity does not pose a concern in this study.

3.4.2 Baseline Results

Table 3.3 presents empirical results pertinent to the research hypotheses. Model 1 reveals a significant negative correlation between carbon risk and firm value, as measured by Tobin's q. Economically, a one-standard-deviation increase in carbon risk leads to a 0.464 reduction in firm value, which accounts for 24.3% of the average firm value (β_1 = -0.139, standard deviation of carbon risk = 3.340, mean of Tobin' q = 1.910), highlighting the considerable economic implications of carbon risk. Further analysis of the moderating effects of green innovation and production efficiency in Models 2 and 3 shows

Table 3.2 Correlation matrix and descriptive statistics

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1	*Tobin's q*	1.000													
2	*Carbon Risk*	-0.148***	1.000												
3	*Firm Size*	-0.363***	0.201***	1.000											
4	*ROA*	0.484***	-0.020	-0.173***	1.000										
5	*Leverage*	-0.363***	0.073*	0.491***	-0.518***	1.000									
6	*Sales Growth*	0.177***	-0.045	-0.052	0.324***	-0.0190	1.000								
7	*Firm Age*	-0.139***	0.044	0.016	-0.139***	0.127***	-0.193***	1.000							
8	*CEO Duality*	0.132***	-0.062	-0.158***	0.042	-0.056	0.071*	-0.092**	1.000						
9	*CEO International Experience*	0.067*	0.012	0.162***	0.039	-0.029	0.052	-0.089**	0.063	1.000					
10	*Carbon Trading*	-0.006	0.076**	0.083**	-0.078**	0.050	-0.098***	0.091**	0.007	0.005	1.000				
11	*ISO14001*	0.066*	-0.073*	-0.179***	0.118***	-0.165***	0.031	-0.049	0.104***	-0.059	0.070*	1.000			
12	*Green Innovation*	-0.215***	0.136***	0.571***	-0.086**	0.329***	-0.020	-0.107***	-0.105***	0.035	-0.042	0.007	1.000		
13	*Production Efficiency*	-0.255***	0.105***	0.406***	0.027	0.230***	0.139***	-0.011	-0.137***	-0.001	-0.081**	0.030	0.227***	1.000	
14	*ESG Performance*	0.055	-0.035	0.241***	0.146***	-0.013	0.008	-0.040	-0.011	0.068*	0.064*	0.102***	0.202***	0.046	1.000
	Mean	1.910	1.220	24.28	0.050	0.500	0.200	3.090	0.220	0.780	0.140	0.410	2.190	14.47	5.130
	Median	1.280	0.160	24.19	0.040	0.520	0.140	3.140	0.000	1.000	0.000	0.000	1.950	14.38	5.000
	Standard deviation	1.620	3.340	1.570	0.060	0.180	0.340	0.290	0.420	0.410	0.340	0.490	1.810	0.810	1.140
	Minimum	0.780	0.000	20.72	-0.140	0.080	-0.490	1.950	0.000	0.000	0.000	0.000	0.000	12.59	1.000
	Maximum	9.540	27.90	28.61	0.220	0.940	1.920	3.780	1.000	1.000	1.000	1.000	7.180	18.25	7.000

significantly positive interaction terms, suggesting that these operational strategies effectively mitigate the adverse effects of carbon risk. In contrast, the interaction term between carbon risk and ESG performance in Model 4 is negative and statistically insignificant. Model 5 is the full model. Overall, the findings in Table 3.3 substantiate the detrimental effect of carbon risk on firm value while emphasizing the mitigating role of green innovation and production efficiency. However, the results do not support the hypothesis that ESG initiatives buffer against carbon risk, an issue that will be explored further in the following section.

Table 3.3 Results of fixed-effects regression analysis

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Carbon Risk × ESG Performance				-0.008	-0.000
				(-0.80)	(-0.01)
Carbon Risk × Production Efficiency			0.162^{***}		0.136^{***}
			(4.21)		(3.38)
Carbon Risk × Green Innovation		0.027^{***}			0.012^{**}
		(2.75)			(2.34)
Carbon Risk	-0.139^{***}	-0.108^{***}	-0.065^{**}	-0.140^{***}	-0.063^{**}
	(-2.99)	(-3.53)	(-2.47)	(-3.04)	(-2.47)
Firm Size	-0.692^{**}	-0.717^{**}	-0.670^{**}	-0.700^{**}	-0.685^{**}
	(-2.27)	(-2.34)	(-2.21)	(-2.30)	(-2.25)
ROA	3.629^{**}	3.696^{***}	3.371^{**}	3.618^{**}	3.443^{**}
	(2.56)	(2.62)	(2.38)	(2.54)	(2.43)
Leverage	1.484	1.671	1.482	1.477	1.567
	(1.30)	(1.44)	(1.31)	(1.29)	(1.38)
Sales Growth	-0.152	-0.144	-0.144	-0.158	-0.142
	(-1.10)	(-1.06)	(-1.08)	(-1.13)	(-1.05)
Firm Age	0.512	0.582	-0.097	0.406	0.033
	(0.18)	(0.21)	(-0.04)	(0.14)	(0.01)
CEO Duality	0.202	0.215	0.199	0.205	0.206
	(0.95)	(1.03)	(0.93)	(0.97)	(0.97)
CEO International Experience	-0.043	-0.056	-0.079	-0.040	-0.079
	(-0.21)	(-0.27)	(-0.40)	(-0.19)	(-0.39)
Carbon Trading	0.260	0.185	0.158	0.265	0.140
	(1.54)	(1.20)	(1.39)	(1.61)	(1.13)
ISO14001	0.067	0.060	0.053	0.065	0.052
	(0.51)	(0.46)	(0.41)	(0.49)	(0.40)
Green Innovation	-0.045	-0.055	-0.037	-0.046	-0.043
	(-0.86)	(-1.00)	(-0.69)	(-0.87)	(-0.79)
Production Efficiency	0.034	0.045	0.148	0.040	0.135
	(0.20)	(0.25)	(0.82)	(0.23)	(0.75)
ESG Performance	-0.002	0.000	-0.002	-0.003	-0.001
	(-0.04)	(0.00)	(-0.05)	(-0.07)	(-0.03)
Constant	15.775	15.916	15.273	16.214	15.425
	(1.18)	(1.22)	(1.19)	(1.22)	(1.20)
Firm F.E.	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES
N	691	691	691	691	691
Within R^2	0.219	0.231	0.241	0.220	0.243

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$ in two-tailed tests. *t* statistics in parentheses.

3.4.3 Robustness Checks

We perform several robustness tests using alternative measurement of core variables to check the sensitivity of our baseline results. First, we normalize a firm's annual carbon emissions by its total asset as an alternative metric for carbon risk. As shown in Model 1 of Table 3.4, the negative association between carbon risk and firm value remains statistically significant. Next, to account for market performance, we adjust the book value of total assets by excluding intangible assets to derive a revised Tobin's q value (Peters & Taylor, 2017). The result in Model 2 indicates that, even after adjusting for intangible assets, carbon risk continues to exert a negative effect on firm value, further supporting the conclusion that future profitability is adversely impacted. With regard to alternative measures for the moderators, we first exclude green utility patents and focus exclusively on green invention patents as proxies for a firm's green innovation. Unlike utility models, which are exempt from novelty and non-obviousness examinations, invention patents are subject to rigorous scrutiny and must demonstrate significant advancements over existing technologies (Liang *et al.*, 2024; Liu & Ma, 2020). Moreover, we employ an alternative measure of production efficiency based on stochastic frontier estimation (SFE) to assess a firm's efficiency in utilizing production resources, i.e., cost of goods sold, capital expenditure, and number of employees, to generate output (Lam *et al.*, 2016; Liang *et al.*, 2024). The model specification is as follows:

$$In(Operating\ Income)_{ijt} = \beta_0 + \beta_1 In(Employees)_{ijt} + \beta_2 In(COGS)_{ijt} + \beta_3 In(CAEX)_{ijt} + \epsilon_{ijt} - \gamma_{ijt} \quad (2)$$

where ϵ_{ijt} denotes the stochastic random error term, while γ_{ijt} represents the relative inefficiency score of firm i within industry j in year t, as compared to its peers in the same three-digit industry. The inefficiency score γ_{ijt} ranges from 0 to 1, where higher values signify more significant efficiency losses. Operational efficiency is calculated by subtracting the inefficiency score from 1, thereby reflecting a firm's capability to transform production resources into outputs effectively (Lam *et al.*, 2016; Yiu *et al.*, 2020). Lastly, we utilize the

ESG dimensions provided by the CNRDS database as an alternative measure for assessing ESG activities. The test outcomes presented in Models 3 to 5 indicate that the moderating effects observed with alternative measures align with those reported in the baseline model.

3.4.4 Endogeneity Tests

In this section we examine several potential sources of endogeneity, including issues related to estimation strategies, omitted variables, and self-selection, all of which could introduce bias into our estimation results. To address these identification challenges, we employ a range of econometric strategies to establish a causal relationship between carbon risk and firm performance. Overall, our results provide robust evidence that the carbon risk exerts a causal impact on firm value after accounting for endogeneity.

Table 3.4 Robustness test-Alternative measure of core variables

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Carbon Risk × ESG Performance					-0.001	0.000
					(-1.27)	(0.71)
Carbon Risk × Production Efficiency				1.992^{**}		1.901^{*}
				(2.13)		(1.91)
Carbon Risk × Green Innovation			0.028^{**}			0.023^{**}
			(2.56)			(2.54)
Carbon Risk	-0.201^{***}	-0.155^{***}	-0.112^{***}	-0.155^{***}	-0.127^{***}	-0.139^{***}
	(-5.29)	(-2.95)	(-3.76)	(-4.23)	(-3.40)	(-4.65)
Firm Size	-0.850^{***}	-0.867^{**}	-0.616^{*}	-0.635^{**}	-0.624^{**}	-0.631^{**}
	(-2.78)	(-2.51)	(-1.95)	(-2.01)	(-1.98)	(-2.00)
ROA	4.014^{***}	3.960^{**}	4.267^{**}	3.928^{**}	4.193^{**}	3.967^{**}
	(2.80)	(2.44)	(2.45)	(2.22)	(2.36)	(2.25)
Leverage	1.675	1.817	1.346	1.360	1.289	1.412
	(1.43)	(1.42)	(1.10)	(1.11)	(1.05)	(1.15)
Sales Growth	-0.135	-0.168	-0.175	-0.186	-0.190	-0.173
	(-1.01)	(-1.10)	(-1.22)	(-1.29)	(-1.31)	(-1.21)
Firm Age	0.086	0.739	1.067	0.539	0.685	0.791
	(0.03)	(0.24)	(0.38)	(0.20)	(0.25)	(0.29)
CEO Duality	0.226	0.231	0.145	0.188	0.171	0.172
	(1.12)	(1.04)	(0.72)	(0.92)	(0.83)	(0.84)
CEO International Experience	-0.079	-0.016	-0.132	-0.122	-0.121	-0.134
	(-0.41)	(-0.06)	(-0.64)	(-0.59)	(-0.58)	(-0.65)
Carbon Trading	0.143	0.285	0.170	0.218	0.211	0.180
	(1.28)	(1.49)	(0.96)	(1.22)	(1.24)	(0.93)
ISO14001	0.066	0.089	0.106	0.115	0.106	0.113
	(0.51)	(0.65)	(0.76)	(0.82)	(0.75)	(0.81)
Green Innovation	-0.055	-0.050	-0.018	-0.027	-0.020	-0.024
	(-1.05)	(-0.84)	(-0.43)	(-0.66)	(-0.47)	(-0.58)
Production Efficiency	0.100	0.090	-2.657^{**}	-2.809^{**}	-2.562^{**}	-2.837^{**}
	(0.54)	(0.46)	(-2.45)	(-2.37)	(-2.31)	(-2.32)
ESG Performance	-0.004	-0.005	-0.009^{*}	-0.010^{**}	-0.010^{**}	-0.009^{*}

	(-0.10)	(-0.09)	(-1.82)	(-1.98)	(-1.99)	(-1.84)
Constant	19.861	18.558	15.552	17.722	16.843	16.866
	(1.57)	(1.30)	(1.21)	(1.38)	(1.32)	(1.33)
Firm F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
N	691	691	618	618	618	618
Within R^2	0.238	0.212	0.240	0.241	0.234	0.246

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$ in two-tailed tests. *t* statistics in parentheses.

Instrumental Variable Approach

Although the TWFE model controls for unobservable time-invariant factors that may influence corporate performance, our findings could still be confounded by omitted time-variant factors that simultaneously affect both carbon intensity and firm performance. To address this potential endogeneity, we apply a two-stage least squares (2SLS) instrumental variable approach to strengthen our casual inference. Similar to Bose *et al*. (2021), who use the ten-year average mortality rate from air pollution to instrument carbon risk, we use the proportion of days over the past five years during which urban air quality grade reach level 2 (moderate) as our instrumental variables (IV) to alleviate endogeneity concerns arising from omitted variables.

Our chosen IV is valid for two reasons. First, poor air quality may compel regulators to prioritize the carbon exposure of local firms, thereby increasing their carbon risk. Second, weather-induced exogenous shocks influence corporate value only through their impact on heightened carbon risk. As such, our IV satisfies both the relevance and exclusion restriction criteria (Angrist & Pischke, 2014). Table 3.5 provides the estimates based on IV regression. Consistent with our predictions, the first-stage regression reveals a significant negative correlation between our IV and carbon risk, indicating that poor air quality indeed exacerbates the carbon risk faced by local firms. The significant *Kleibergen-Paap rk LM* statistic and *Kleibergen–Paap rk Wald F* statistic confirm the reliability and full identification of our IV. The second-stage results further support the hypothesis that carbon risk continues to negatively affect firm performance after isolating the exogenous component of carbon risk, thereby reinforcing the robustness of our findings.

The Selection Model

A potential endogeneity issue arises when a company selectively discloses its carbon emissions to the public (Lennox *et al.*, 2012). In other words, carbon emissions data can only be observed if a company voluntarily chooses to disclose its carbon footprint. Such voluntary disclosure may be driven by strategic considerations and is often closely related to firm-specific characteristics. To address the potential bias in estimated coefficients resulting from the non-random selection of firms, we implement the treatment effects model developed by Heckman (1979), which allows us to simultaneously estimate both the decision to disclose carbon emissions and the effect of carbon exposure on firm performance. In particular, we pool data from all the A-share listed firms and create a binary endogenous indicator variable (*Disclose*), which equals one if a firm discloses its carbon emissions during our sample period, and zero otherwise. The decision to disclose is then estimated using a binary choice model that includes a vector of control variables from the baseline model ($X_{i,t}$), along with an additional *Air Quality* regressor ($Z_{i,t}$) referred to as "exclusion restrictions" (Lennox *et al.*, 2012). Specifically,

$$Disclose_i^* = \alpha_0' Z_{i,t} + \alpha_1' X_{i,t} + \upsilon, \tag{3}$$

$$MILLS = \begin{cases} \varphi(\alpha_0' Z_{i,t} + \alpha_1' X_{i,t}) / \Phi(\alpha_0' Z_{i,t} + \alpha_1' X_{i,t}) & if\ Disclose = 1 \\ -\varphi(\alpha_0' Z_{i,t} + \alpha_1' X_{i,t}) / \left(1 - \Phi(\alpha_0' Z_{i,t} + \alpha_1' X_{i,t})\right) & if\ Disclose = 0 \end{cases} \tag{4}$$

where $\varphi(.)$ And $\Phi(.)$ Are the normal density and cumulative distribution functions, respectively. The inverse Mills' ratio (*IMR*) is constructed using Eq. 4 and subsequently incorporated into the baseline model to correct for the self-selection bias (Ilhan *et al.*, 2021; Lennox *et al.*, 2012). As shown in Table 3.5, the negative relationship between carbon risk and firm value remains statistically significant after correcting for self-selection bias.

Table 3.5 Endogeneity tests

	IV		Heckman		GMM		DID
	(1) First Stage	(2) Second Stage	(3) First Stage	(4) Second Stage	(5) GMM	(6) OLS	(7) DID
Carbon Risk		-0.400*		-0.133***	-0.117*	-0.009	
		(-1.70)		(-3.29)	(-1.82)	(-1.55)	
Lagged Tobin's q					0.533***	0.677***	
					(8.19)	(15.69)	
Air Quality	-4.582**		-0.371*				
	(-2.16)		(-1.72)				
IMR				0.216			
				(0.14)			
Treat × After							-0.077***
							(-3.03)
Firm Size	-0.112	-0.695**	0.441***	-0.396	-0.255**	-0.161***	-1.255***
	(-0.38)	(-2.12)	(24.08)	(-0.74)	(-2.20)	(-4.82)	(-24.64)
ROA	1.827	3.570**	2.794***	2.399	6.724***	4.354***	2.498***
	(0.98)	(2.00)	(7.52)	(0.71)	(3.22)	(3.16)	(7.19)
Leverage	2.504	2.164	-0.212*	1.362	0.970	0.434	1.244***
	(1.43)	(1.48)	(-1.73)	(1.14)	(0.77)	(1.45)	(8.35)
Sales Growth	-0.275	-0.218	0.138***	-0.092	-0.212	-0.036	0.037*
	(-1.31)	(-1.58)	(2.83)	(-0.44)	(-1.19)	(-0.28)	(1.82)
Firm Age	-5.904	-1.763	-0.069	0.789	-0.208	-0.176	1.050***
	(-0.52)	(-0.48)	(-1.12)	(0.24)	(-1.00)	(-1.38)	(5.53)
CEO Duality	-0.152	0.192	-0.016	0.167	0.304	0.058	-0.022
	(-0.92)	(1.07)	(-0.39)	(0.75)	(1.30)	(0.59)	(-0.54)
CEO International Experience	0.425	0.062	0.290***	-0.023	0.324*	0.198***	0.024
	(1.02)	(0.27)	(7.60)	(-0.06)	(1.83)	(2.65)	(0.74)
Carbon Trading	1.116	0.445	0.327***	0.230	0.431	0.051	-0.297***
	(1.32)	(1.11)	(5.45)	(0.62)	(1.40)	(0.50)	(-4.04)
ISO14001	0.007	0.062	0.232***	0.129	-0.132	-0.045	-0.057**
	(0.03)	(0.45)	(6.10)	(0.46)	(-1.00)	(-0.61)	(-2.02)
Green Innovation	-0.080	-0.062	0.053***	-0.025	0.058	0.015	-0.029*
	(-0.63)	(-0.91)	(3.98)	(-0.31)	(0.99)	(0.86)	(-1.81)
Production Efficiency	-0.762*	-0.117	-0.043*	0.195	-0.071	-0.078*	0.031
	(-1.83)	(-0.40)	(-1.85)	(0.89)	(-0.46)	(-1.71)	(1.09)
ESG Performance	-0.037	0.003	0.122***	0.022	-0.026	0.037	-0.028**
	(-0.26)	(0.04)	(7.75)	(0.16)	(-0.39)	(1.15)	(-2.15)
Constant	34.720*	24.997	-11.43***	5.130	7.938***	5.439***	25.754***
	(1.90)	(1.58)	(-26.12)	(0.32)	(2.85)	(5.03)	(22.94)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	No	Yes	Yes	No	Yes
N	554	554	16,026	653	649	649	16,141
Kleibergen-Paap rk LM statistic	5.06**						
Kleibergen-Paap rk Wald F statistic	4.66						
Wald Chi-square					257.22***		
Hansen test					$p = 0.576$		
AR(1)					$p = 0.015$		
AR(2)					$p = 0.801$		

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$ in two-tailed tests. *t* statistics in parentheses.

System Generalized Method of Moments (GMM) Estimation

Although static panel models are typically used to evaluate the effectiveness of carbon reduction initiatives (Bose *et al.*, 2021; Ilhan *et al.*, 2021; Jung *et al.*, 2018), firm performance often exhibits path dependence and persistence over time, indicating a significant correlation between past and current performance (Lam *et al.*, 2016; Yiu *et al.*, 2020). Therefore, we construct a dynamic panel data (DPD) model that incorporates a one-year lag of Tobin's q as an additional regressor to provide a more precise and robust estimation of the impact of carbon risk.

$$FirmValue_{i,t} = \beta_0 + \beta_1 Carbon\ Risk_{i,t} + \beta_2 FirmValue_{i,t-1} + \beta_3 X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad (5)$$

By incorporating a firm's historical financial returns, our model accounts for the enduring effects of past performance. However, the correlation between the lagged dependent variable and the error term gives rise to dynamic panel bias, which results in inconsistent estimates when using conventional two-way fixed effects (TWFE) models (Lam *et al.*, 2016; Nickell, 1981). To address this issue, we employ a system Generalized Method of Moments (GMM) estimation strategy that constructs instrumental variables through transformations of existing variables within the DPD model. This approach overcomes the challenges of obtaining suitable exogenous instruments from external sources (Arellano & Bover, 1995; Blundell & Bond 1998; Wintoki *et al.*, 2012). Following Yiu *et al.* (2020), we treat all the independent and control variables as potential endogenous variables, using lagged and differenced values as instruments for the difference and level equations, respectively. Before proceeding with the analysis, we perform several specification tests to ensure the prerequisites for system GMM estimation are satisfied (Chung, *et al.*, 2019; Lam *et al.*, 2016). First, we apply the Hansen statistic to test the validity of the instruments. The test results do not reject the null hypothesis of orthogonality between the specific instruments and the error term, thus affirming their exogeneity ($p = 0.576$). Next, we assess autocorrelation in the idiosyncratic disturbances. The insignificant second-order correlation in differences (*AR2*) does not reject the null hypothesis of no serial correlation in the idiosyncratic disturbances (Roodman, 2009). Taken together, these two tests indicate that our model specification is appropriate. The system GMM test results in Table 3.5 further corroborate the negative relationship between carbon risk and firm value following the DPD model estimation. Notably, the coefficient of the lagged dependent variable in the GMM model exhibits an upward bias compared with that in the OLS model, a finding consistent with previous DPD studies (Lam *et al*., 2016; Roodman, 2009).

The Implementation of Low-Carbon City Initiatives: A Quasi-Natural Experiment

Since regulatory risk is a primary source of carbon risk, we employ a quasi-natural experiment to ascertain the causal relationship between carbon reduction risk and corporate performance. Specifically, in 2010, the Chinese government imposed a low-carbon city pilot program that encourages local firms to undertake carbon reduction responsibilities while offering them corresponding financial incentives (Chen *et al*., 2022). The initial batch of pilot projects included five provinces and eight cities, followed by an expansion in 2012 to include Hainan Province and an additional 28 cities. We leverage the staggered introduction of these low-carbon city initiatives as an exogenous shock to identify the effect of carbon reduction risk under regulatory pressure, which ideally divides our sample into treatment and control groups. The treatment group consists of firms located in cities where low-carbon pilot programs are launched, while the control group includes firms headquartered in cities where such programs are not introduced. Consistent with prior studies (e.g., Chen *et al*., 2022; Huang *et al*., 2021), our analysis focuses on the first two batches of pilot projects and utilizes A-share listed companies from 2007 to 2016 to perform a difference-in-difference (DID) specification. The DID model is specified as follows:

$$FirmValue_{i,t} = \beta_0 + \beta_1 After_t \times Treat_i + \beta_2 X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \tag{6}$$

where $Treat_i$ is a dummy indicator that equals 1 for the treatment group and 0 for the control group and $Post_t$ equals 1 if the year of observation falls within the three years following the initiation of the pilot programs. The coefficient of the interaction term $Post_t * Treat_i$ captures the causal effect of low-carbon initiatives on firm performance. Figure 3.1 examines the validity of the parallel trend assumption, indicating that the treatment group does not exhibit a significant downward trend in performance compared with the control group prior to the initiation of the pilot programs. The DID test results presented in Table 3.5 further confirm that carbon emissions reduction risks have a negative and causally significant impact on firm value.

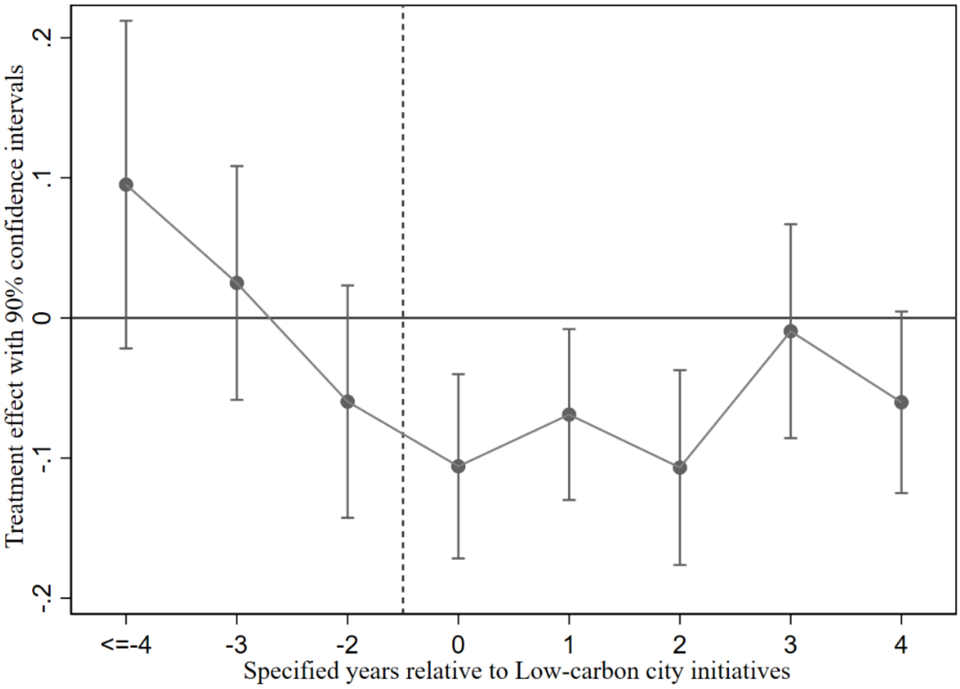

Figure 3.1 Parallel trend test plot.

3.4.5 Further Analysis

Our preceding analysis elicits two compelling questions that warrant further exploration. First, although prior research has established that ESG endeavors can function as an insurance-like mechanism that effectively safeguards shareholder value from negative events (e.g., Bose *et al*., 2021; Godfrey *et al*., 2009), our empirical findings do not support such a buffering effect. It remains unclear why the protective role of ESG indicators does not manifest across our entire sample, and under what specific conditions a company's accumulated ESG reputation can mitigate the adverse effect of carbon risk on firm value. Second, given that higher carbon emissions intensity represents a greater threat to corporate value, what motivates companies to voluntarily disclose rather than conceal carbon-related information? We address these questions in greater depth in this section.

Alignment Between Carbon Emissions Risk and ESG Performance

Previous research has demonstrated that ESG initiatives can mitigate punitive sanctions from stakeholders regarding carbon footprints by cultivating moral capital or goodwill, thereby preserving economic value (e.g., Bose *et al*., 2021; Godfrey *et al*., 2009; Treepongkaruna *et al*., 2024). Companies with high ESG scores are particularly favored by environmentally conscious investors, who prioritize them in their investment decision-making (Treepongkaruna *et al*., 2024). However, these scores reflect externally rated performance based primarily on disclosed information and may not always represent the authenticity of a firm's ESG actions. That is, firms may receive high ESG scores through symbolic communication rather than through substantive environmental improvements. For instance, although some companies receive high ESG scores from rating agencies, signaling a strong commitment to societal and environmental concerns, they fail to meet the ESG criteria they claim to uphold and continue to produce substantial carbon emissions. A plausible explanation for this discrepancy is that these companies derive significant publicity from their symbolic ESG reporting, which diminishes their incentive to undertake substantive actions. As a result, a decoupling occurs between their conveyed commitments and actual practices, a phenomenon widely referred to as greenwashing (Huang *et al*., 2024; Treepongkaruna *et al*., 2024). Walker & Wan (2012) provide a comprehensive definition of greenwashing as a strategy in which companies engage in symbolic communication about environmental and other issues without making substantial efforts to address these issues in practice. This definition extends beyond mere information disclosure and instead emphasizes the disparity between "walk" and "talk", laying the foundation for the development of quantitative metrics to measure greenwashing (Huang *et al*., 2024). To address this, we distinguish between ESG disclosure (symbolic/verbal commitment) and actual carbon performance (measurable actions). Following prior literature (Bothello *et al*., 2023; Long *et al*., 2024; Huang *et al*., 2024), we develop a greenwashing index to quantify this gap and isolate the effect of ESG authenticity on carbon risk mitigation. To quantify greenwashing, we standardize both the ESG disclosure scores and carbon intensity based on the mean and standard deviation within each three-digit industry on an annual basis and calculate the degree of decoupling between the two indices. Specifically, the greenwashing index is calculated as follows:

$$Greenwashing_{i,t} = \left[\frac{ESG_{Disclosurei,t} - \overline{ESG_{Disclosure}}}{\sigma_{ESG_{Disclosure}}}\right] - \left[-\frac{Carbon_{i,t} - \overline{Carbon}}{\sigma_{Carbon}}\right] \quad (7)$$

In this index, the first term captures symbolic ESG disclosure, while the second term (including the negative sign) reflects tangible progress in carbon reduction. A higher value of the index indicates a larger discrepancy between what is communicated and what is implemented, which enables us to separate firms with credible ESG actions from those with inflated ESG signaling. The results presented in Table 3.6 suggest that ESG performance effectively buffers the negative impact of carbon risks only when ESG practices are authentic. In contrast, firms that exhibit a high degree of greenwashing experience diminished or even negative market responses to ESG disclosures, due to perceived hypocrisy or disillusionment effects. In the DID analysis, a company is classified into the greenwashing group if its ESG score exceeds the industry median for the year while simultaneously engaging in an environmental violation. Similar empirical results are reported in Column 3 of Table 3.6. Our study contributes to the ongoing debate in the literature regarding whether sustainability initiatives exacerbate or mitigate the consequences of greenhouse gas emissions (Cooper *et al*., 2018). Specifically, our findings suggest that a disillusionment effect arises when companies, once perceived as ESG-friendly, fail to effectively implement their pledged carbon reduction measures. This decoupling of commitment from action undermines their ability to realize the intended benefits of ESG initiatives, ultimately eroding their corporate value.

Table 3.6 Regression results in subsamples

	Huazheng ESG		CNRDS ESG		DID	
Variables	Low GW	High GW	Low GW	High GW	Low GW	High GW
Carbon Risk × ESG Performance	0.122*	-0.004	0.030**	-0.000		
	(1.66)	(-0.20)	(2.20)	(-0.97)		
Carbon Risk	0.272*	-0.161***	0.361*	-0.095***		
	(1.86)	(-5.02)	(1.96)	(-4.80)		
Treat × After × ESG Performance					0.059***	0.101
					(2.68)	(1.18)
Treat × After					-0.309***	-0.301
					(-3.15)	(-0.65)
Firm Size	-0.730*	-0.026	-0.638*	-0.246	-1.306***	-0.798***
	(-1.75)	(-0.05)	(-1.80)	(-0.41)	(-24.38)	(-5.79)
ROA	0.336	2.857**	2.704	1.663	2.299***	3.618***
	(0.11)	(2.09)	(0.83)	(0.77)	(6.54)	(3.28)
Leverage	-1.263	3.418*	-0.544	3.061*	1.312***	0.963**
	(-0.57)	(1.81)	(-0.27)	(1.83)	(8.38)	(2.07)
Sales Growth	-0.167	-0.247	-0.070	-0.157	0.033	0.113
	(-0.64)	(-0.96)	(-0.37)	(-0.78)	(1.56)	(1.24)
Firm Age	-3.842	2.652	-4.447	4.307	0.955***	-0.467
	(-1.50)	(0.46)	(-1.31)	(0.76)	(4.83)	(-0.28)
CEO Duality	0.449	-0.055	0.327	-0.099	-0.020	-0.093
	(1.57)	(-0.47)	(1.21)	(-0.86)	(-0.44)	(-0.78)
CEO International Experience	-0.150	-0.118	-0.313	0.048	0.020	0.121
	(-0.80)	(-0.60)	(-0.98)	(0.42)	(0.60)	(1.16)
Carbon Trading	0.011	0.285	-0.189	0.105	-0.286***	-0.226
	(0.05)	(1.29)	(-0.51)	(0.64)	(-3.77)	(-0.56)
ISO14001	0.177	-0.104	0.104	-0.096	-0.060**	0.067
	(0.91)	(-0.44)	(0.58)	(-0.39)	(-2.04)	(0.96)
Green Innovation	-0.002	0.038	-0.028	0.040	-0.025	-0.119**
	(-0.02)	(0.44)	(-0.34)	(0.37)	(-1.46)	(-2.15)
Production Efficiency	0.703**	0.079	-0.046	0.084	0.033	0.015
	(2.48)	(0.23)	(-0.11)	(0.32)	(1.17)	(0.12)
ESG Performance	0.052	0.022	0.028**	-0.005	-0.040***	0.016
	(0.73)	(0.20)	(2.05)	(-0.53)	(-2.63)	(0.48)
Constant	20.757	-8.059	30.564*	-7.779	27.036***	19.805***
	(1.43)	(-0.31)	(1.92)	(-0.27)	(22.94)	(3.30)
Firm F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
N	335	356	338	353	15,105	1,036
Within R^2	0.236	0.306	0.231	0.192	0.408	0.296

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$ in two-tailed tests. *t* statistics in parentheses.

Penalty for non-disclosure

Our baseline analysis provides compelling evidence of the significant economic implications of increased carbon risk on firm value. However, it does not address the broader question of how capital markets incorporate both carbon intensity and voluntary self-reported disclosure practices into firm valuations. In China, despite the strong connection between carbon emissions and climate transition risks, emissions remain largely unregulated, with companies voluntarily disclosing this information. On the one hand, disclosing carbon information incurs substantial direct costs, such as those associated with calculation and measurement. Sharing carbon emissions data with competitors, coupled with the potential risk of divestment driven by investor panic, may also lead to indirect costs (Choi *et al*., 2024). On the other hand, carbon emissions disclosure enhances transparency by reducing information asymmetry with external stakeholders, enabling disclosing companies to differentiate themselves from competitors. Furthermore, companies that disclose their carbon footprints demonstrate their capacity to measure emissions, a critical prerequisite for effective management (Matsumura *et al*., 2014). Consequently, further investigation is necessary to understand why companies choose to disclose rather than conceal such information.

To explore this issue, we employ a propensity score matching approach followed by regression analysis to assess the market value relevance of carbon-related disclosure practices. Non-disclosing firms with comparable firm-level characteristics serve as an ideal counterfactual for disclosing firms, as they are similar across a range of observable dimensions that influence the likelihood of carbon disclosure, differing only in their decision to disclose this information. The matched pairs must come from the same year and have the closest propensity scores, as determined through nearest-neighbor matching without replacement. Panel A of Table 3.7 illustrates that the disparities in covariates between the treatment and control groups are notably diminished following our matching procedure. In Panel B of Table 3.7, we exclude firm fixed effects from the estimation, opting instead to incorporate fixed effects for industry, year, and province, given that the decision to disclose remains constant over time. Robust standard errors are clustered at the firm level. The findings demonstrate that the decision to disclose carbon footprints has a substantial positive effect on firm value, resulting in an 18.82% increase in firm value in economic terms (β_1 = 0.345, mean of Tobin' q = 1.833). Figure 3.2 visually illustrates the substantial enhancement in firm value resulting from carbon emissions disclosure. It demonstrates that, while firm value generally decreases as reported carbon risk increases, companies that disclose their emissions consistently outperform those that have never disclosed this information (To enhance the clarity of the Figure 3.2, the range of carbon risk is scaled between 0 and 5, as the carbon risk at the 95th percentile is below 5.37). In summary, our findings suggest that, although capital markets penalize all the firms for their carbon emissions risk, with more severe penalties for higher emissions intensities, companies that fail to disclose their emissions incur an additional penalty. This implies that capital markets factor both carbon intensity and the act of carbon disclosure into firm valuations, underscoring the importance of voluntary carbon disclosure in enhancing transparency.

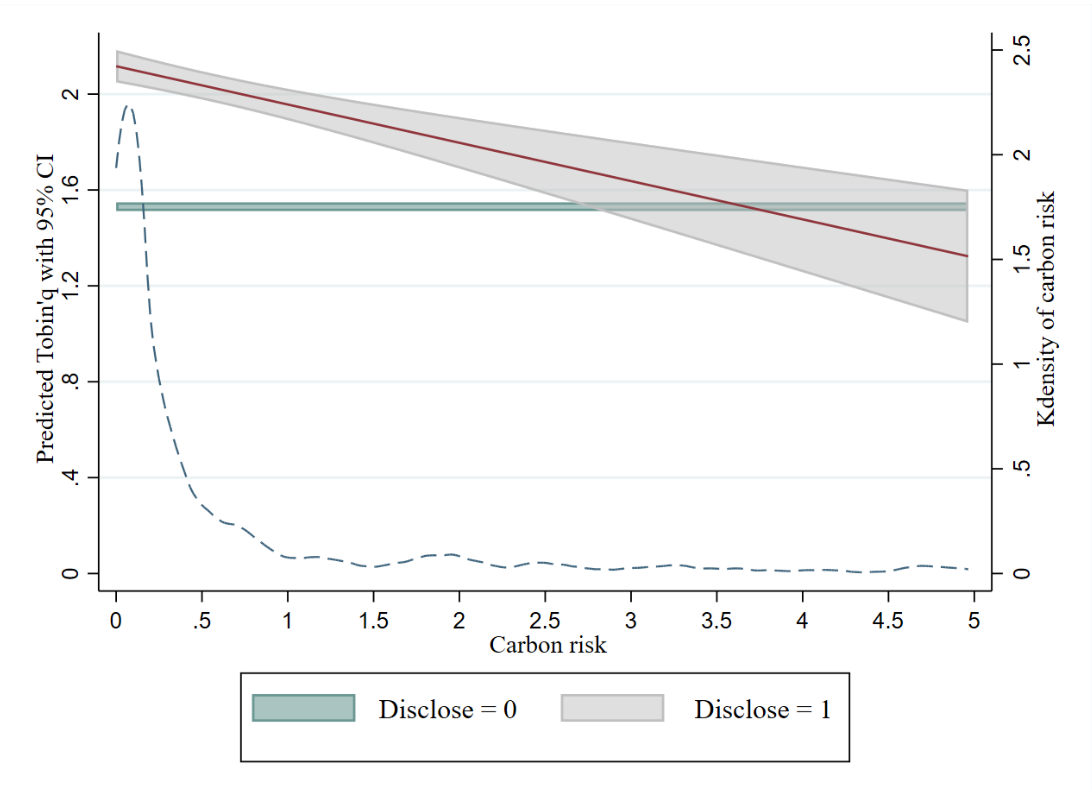

Figure 3.2 Firm-value effects of carbon disclosure.

Table 3.7 Firm-value effects of decision to disclose carbon emissions

Panel A: Covariate balance check of the matching

	Before matching			After matching		
	Treated	Control	*p*-value in the bias	Treated	Control	*p*-value in the bias
Firm Size	23.90	22.10	0.000***	23.63	23.66	0.608
ROA	0.053	0.026	0.000***	0.054	0.051	0.229
Leverage	0.490	0.412	0.000***	0.485	0.487	0.865
Sales Growth	0.205	0.128	0.000***	0.211	0.209	0.931
Firm Age	3.042	3.020	0.000***	3.064	3.061	0.773
CEO Duality	0.240	0.344	0.000***	0.237	0.221	0.333
CEO International Experience	0.770	0.574	0.000***	0.734	0.743	0.567
Carbon Trading	0.132	0.041	0.000***	0.114	0.117	0.809
ISO14001	0.366	0.281	0.000***	0.353	0.344	0.655
Green Innovation	2.063	0.894	0.000***	1.783	1.789	0.920
Production Efficiency	14.38	13.92	0.000***	14.32	14.32	0.965
ESG Performance	4.972	4.147	0.000***	4.837	4.809	0.549

Panel B: Regression result

Variable	Pool Regression	Regression of PSM-matched firms
Disclose	0.616***	0.345***
	(7.20)	(4.66)
Firm Size	-0.381***	-0.138***
	(-14.99)	(-3.49)
ROA	1.752***	8.906***
	(8.24)	(8.20)
Leverage	0.070	-0.103
	(0.69)	(-0.39)
Sales Growth	0.333***	0.200***
	(10.25)	(2.87)
Firm Age	0.098*	-0.236**
	(1.81)	(-2.29)
CEO Duality	0.033	0.140*
	(1.03)	(1.75)
CEO International Experience	0.158***	0.175***
	(5.85)	(2.65)
Carbon Trading	-0.049	-0.178*
	(-0.76)	(-1.66)
ISO14001	-0.105***	-0.163**
	(-3.88)	(-2.53)
Green Innovation	0.027**	-0.083***
	(1.97)	(-3.30)
Production Efficiency	0.012	-0.094*
	(0.47)	(-1.72)
ESG Performance	-0.028***	0.015
	(-2.78)	(0.51)
Constant	9.985***	7.170
	(17.58)	(7.25)
Industry F.E.	YES	YES
Year F.E.	YES	YES

Province F.E.	YES	YES
N	18,124	2,662
Adj R^2	0.258	0.463

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$ in two-tailed tests. *t* statistics in parentheses.

3.5 Conclusion and Discussion

3.5.1 Summary and Principal Findings

Climate change is increasingly recognized as a grand challenge of the 21st century, with carbon emissions identified as a primary driver of this global environmental crisis (Zhang *et al*., 2024). Consequently, carbon-related issues have gained both theoretical significance and practical relevance in recent years. While the relationship between carbon risk and financial performance has been widely studied, the findings are often mixed and typically focused on firms in developed economies, such as the U.S. and the EU (e.g., Busch *et al*., 2022; Delmas *et al*., 2015). This study addresses this gap by examining the impact of carbon risk on long-term, market-based financial performance, as measured by Tobin's *q*, using a more recent large-scale panel dataset of Chinese listed firms. The findings consistently reveal a negative association between carbon risk and firm value, a relationship that is further supported by a set of robustness checks. Notably, we find that operational strategies such as enhanced production efficiency and increased green innovation can mitigate the adverse financial effects of high carbon risk. Furthermore, while ESG performance does not demonstrate a significant moderating effect across the full sample, it does significantly reduce the adverse impact of carbon risk in firms adopting less greenwashing practices. In addition, firms that voluntarily disclose emissions information experience a less pronounced value decline than those that do not disclose. Below, we discuss the implications of these findings for research and practice.

3.5.2 Implications for Research

This study extends the sustainable OM literature in general and the financial implications of carbon risk in emerging markets in particular. Although a number of studies have explored the emissions-financial performance relationship, the findings remain inconclusive (Busch *et al*., 2022; Delmas *et al*., 2015; Jacobs, 2014; Lee *et al*., 2015; Matsumura *et al*., 2014). For example, Delmas *et al*. (2015) find that high emissions positively correlate with short-term financial performance, i.e., ROA, but negatively correlate with long-term financial performance, i.e., Tobin's *q*, among U.S. firms. Busch *et al*. (2022) expand upon this by including European firms and extending the study period, find instead a positive link between carbon emissions and both ROA and Tobin's *q*, thus highlighting the sensitivity of this relationship to contextual factors like region and research design. This study shifts the attention to China's unique market environment, characterized by distinct institutional frameworks, capital market development, and regulatory pressures. Our findings reveal a negative link between carbon risk and long-term financial performance, suggesting that Chinese investors increasingly consider carbon risk in their valuations, aligning more closely with Delmas *et al*. (2015) than with Busch *et al*. (2022). This underscores the role of emerging regulatory pressures and growing environmental awareness among investors, indicating that carbon emissions are more likely perceived as liabilities in the Chinese context. In doing so, our study offers new empirical evidence that contextual factors, such as country-specific regulatory dynamics and investor expectations, can shape how carbon emissions affect firm value, thereby enhancing the robustness and sensitivity of prior findings (Wickert *et al*., 2024).

Our focus on operational strategies that mitigate the negative effects of carbon risk on firm value is well aligned with the principles of NRBV. Hart (1995) argues that firms should build capabilities in pollution prevention, product stewardship, and sustainable development to derive competitive advantage from environmental initiatives. Consistent with NRBV, our findings suggest that enhancing production efficiency and green innovation—aligned with pollution prevention and sustainable development strategies—could mitigate the negative financial impact of carbon risk. Although the moderating effect of ESG performance is only significant for firms with low levels of greenwashing, this underscores the strategic importance of authenticity in environmental practices, resonating with NRBV's emphasis on long-term adaptability and ecological balance. In response to Lam *et al*. (2022), who call for OM researchers to explore the role of OM-related factors in mitigating internal and external negative shocks, and George *et al*. (2016), who urge management research to contribute to understanding and tackling societal grand challenges, this study demonstrates that NRBV-aligned operational strategies provide effective responses to carbon-related risks, contributing novel insights to the sustainable OM scholarship.

Finally, our study enriches the environmental disclosure literature by providing insights into how investors interpret and respond to carbon-related disclosures in an emerging market context. The literature on environmental disclosure remains divided on whether such disclosures exert a real impact (Song *et al*., 2024). By examining ESG performance's moderating effect on the carbon risk–firm value relationship, we find this effect is significant only for firms with lower levels of greenwashing, highlighting the critical role of authenticity in environmental initiatives. This finding suggests that investors are increasingly discerning regarding the credibility of ESG claims, shedding light on how transparency and substantive environmental actions influence firm valuation. Moreover, our study reveals that while the market, in general, penalizes all the firms for their carbon emissions, firms that voluntarily disclose emissions information experience a less pronounced value decline than their non-disclosing counterparts. This evidence enriches the literature on disclosure incentives, indicating that voluntary transparency may mitigate the financial penalties associated with emissions while addressing information asymmetry. By analyzing investor responses within China's unique institutional context, our study contributes a regionally nuanced perspective to the environmental disclosure literature.

3.5.3 Implications for Practices

This study offers several actionable insights for practitioners. First, the findings highlight a clear financial incentive for firms to engage in proactive emissions reduction, as these actions enhance long-term firm value. Managers should consider implementing strategies that improve production efficiency, foster green innovation, and rigorously develop ESG initiatives, given the efficacy of these approaches in mitigating the negative financial impact of carbon risk. By investing in green technologies and embedding sustainable practices across operational processes, firms not only meet regulatory requirements but also differentiate themselves in the marketplace. In addition, our findings stress the strategic value of authentic ESG practices over superficial greenwashing. For managers, this reinforces the importance of rigor and transparency in ESG efforts, which are increasingly scrutinized by investors and contribute more reliably to firm value.

For investors, the study underscores the importance of assessing the authenticity of firms' ESG practices and emissions disclosures. Firms that engage in substantive emissions reduction and other sustainable initiatives demonstrate stronger resilience in market value, highlighting the potential long-term benefits of responsible environmental practices. Moreover, voluntary emissions disclosures appear linked to more favorable valuations, suggesting that investors can benefit from incorporating scrutiny on firms' transparency in sustainability reporting. Firms with consistent, credible disclosures not only signal a commitment to managing carbon risks but also align with the growing trend of responsible investing, offering stability in returns and supporting sustainable investment goals.

Policymakers also stand to benefit from these findings, particularly as they design regulations and develop standards promoting sustainable business practices in emerging markets. The study suggests that voluntary emissions disclosures can mitigate the financial penalties associated with high emissions, indicating that policies encouraging transparency may lead to improved economic and environmental outcomes. By incentivizing firms to provide transparent environmental data and invest in genuine ESG practices, policymakers can reduce information asymmetry and empower investors to make informed decisions. Furthermore, our findings demonstrate that authentic ESG efforts correlate with higher firm value, lending support to stricter regulations that discourage greenwashing and ensure that firms' environmental claims are credible. Such policies could foster an environment where sustainable practices align with financial stability and market resilience, encouraging firms to integrate sustainability into their core strategies and contribute to broader environmental goals.

3.5.4 Limitations and Future Research Directions

Along with the above contributions, this study also has several limitations that suggest directions for future research. First, our analysis relies exclusively on data from publicly listed firms, as these firms face more stringent disclosure requirements and scrutiny than private companies. Consequently, there may be a selection bias toward firms that are under greater external pressures to engage in emissions reduction and transparency. Although our Heckman selection model analysis indicates that this bias does not significantly affect our results, the sample composition may limit the generalizability of our findings to the broader business landscape, particularly to privately held firms. Future research could extend this work by incorporating private firms when data become available (e.g., Hoopes *et al*., 2024), thereby providing a more comprehensive perspective on emissions-related financial outcomes across different firm types.

In addition, this study is centered on firm-level financial performance metrics, particularly firm value, while emissions are frequently the result of activities across a firm's supply chain. Focusing solely on internal firm performance may not fully capture the broader carbon impact that firms generate through their suppliers and supply networks. Future studies could investigate emissions effects at the supply chain or supply network level, examining how emissions from different stages in the supply chain influence both firm-level and supply chain-wide performance (e.g., Song *et al*., 2024). Such research would offer insights into interdependencies within supply chains, uncovering ways firms could mitigate carbon-related risks more effectively by addressing emissions throughout their value networks (Feng *et al*., 2022).

Finally, this study examines the moderating effects of three specific operational strategies on the carbon risk-firm value relationship, guided by our theoretical framework and consideration of page constraints. While production efficiency, green innovation, and ESG performance provide meaningful insights into emissions management, focusing on these three strategies limits the study's scope regarding other potentially influential operational strategies. Future research could explore a broader range of operational tactics, such as energy efficiency initiatives, waste reduction practices, and carbon offset investments, to assess their effectiveness in mitigating the impact of carbon risk. Examining a broader array of operational strategies would enrich understanding of how diverse approaches contribute to sustainable management, firm value resilience, and competitive advantage.

Chapter 4 Study Three: The Bright Side of Being Uncertain: The Impact of Economic Policy Uncertainty on Corporate Innovation

4.1 Introduction

In recent years, the economic and regulatory landscapes around the globe have undergone significant upheavals. Many events, such as Brexit (Steinberg, 2019), the Sino-US trade war (Benguria *et al*., 2022), the Russia-Ukraine war (Shen & Hong, 2023), and frequent extreme weather shocks (Zhang *et al*., 2023), make it necessary for governments in many countries to frequently adjust economic policies and regulations. In particular, the COVID-19 pandemic provided a real-life example of how uncertain economic policies significantly distorted the vision for the economy and affected many market participants and the global economy's interconnections (Al-Thaqeb *et al*., 2022; Mokni *et al*., 2022; Sharif *et al*., 2020). For instance, Baker *et al*. (2020) offer empirical evidence by employing three indicators to document and quantify the dramatic increase in economic uncertainty and suggest that the COVID-induced uncertainty levels are much higher than those during the 2008 global financial crisis. Indeed, frequent economic policy changes are bound to be accompanied by a rise in economic policy uncertainty (EPU), which means that firms may find it hard to form reasonable expectations of future economic outlooks and operating environments (Gulen & Ion, 2016). EPU thus has profound impacts on diverse corporate decision-makings, spanning operations, finance, accounting, and strategy, making it difficult for firms to assess the risks and opportunities of their investments (Marcus, 1981).

A number of studies have well documented the negative impacts of EPU on firms' financial consequences, such as corporate investment (Gulen & Ion, 2016), foreign direct investment (Choi *et al*., 2021; Nguyen *et al*., 2018), management disclosure (Nagar *et al*., 2019;

Wang *et al*., 2022), mergers and acquisitions (Bonaime *et al*., 2018; Nguyen & Phan, 2017), cash holding (Goodell *et al*., 2021; Phan *et al*., 2019), as well as trade credit (D'Mello & Toscano, 2020; Jory *et al*., 2020). In the operations management (OM) field, while prior studies have long investigated many common uncertainties that firms might face in the production and operations processes, such as supply uncertainty (Li *et al*., 2017), demand uncertainty (Biçer *et al*., 2018), and price uncertainty (Mandl & Minner, 2023), very limited knowledge has been developed about EPU's operational implications to date. Similar to the findings in the finance and accounting literature, several recent empirical OM studies show that EPU has adverse effects on some firm-level operating indicators, such as increasing various types of inventories, raising the level of working capital, enhancing vertical integration and product diversification, and lowering firm value (Darby *et al*., 2020; Dbouk *et al*., 2020; Fan & Xiao, 2023; Leung & Sun, 2021).

Yet, some anecdotal and emerging empirical evidence suggests that firms' innovation activities, as one of the key drivers of competitive advantage, are not necessarily negatively affected by EPU. Within a certain EPU range, i.e., moderate EPU, firms might be incentivized to pursue innovation more actively. This effect can be explained by several interrelated mechanisms. First, moderate uncertainty can act as a strategic pressure that prompts firms to explore new technologies and adapt to a fluid business environment (Chen & Tian, 2022). Second, EPU may alter the regulatory and competitive landscape, creating both risks and opportunities for early movers. For example, the Chinese government has promulgated a series of anti-trust regulations targeting technology giants such as Alibaba. While these measures have disrupted established business models, they have also encouraged firms to pivot toward deep-tech innovation in areas such as artificial intelligence, cloud computing, and semiconductor manufacturing. This adaptive response illustrates how policy-induced uncertainty can act as a catalyst for innovation when the level of risk remains manageable. In fact, the law enforcement actions that started with the initial public offering failure of Ant Group have finally triggered substantial innovation-oriented investments in order to navigate an increasingly uncertain environment[4].

Considering the above conflicting views, we hypothesize a non-linear relationship between EPU and innovation. By acknowledging the role of cognitive and emotional biases in decision-making, prospect theory provides a more realistic model of human behavior, which has had a profound influence on the study of behavioral economics and the development of decision-making models (Barberis, 2013; Kahneman & Tversky, 1979). For instance, the prospect theory argues that people's choices can change depending on how a decision is framed (i.e., reflection effect). When presented with a decision as a potential gain, individuals tend to be risk-averse. However, when the same decision is framed as avoiding a potential loss, they tend to become more risk-seeking. We therefore leverage the prospect theory as the theoretical lens and postulate that EPU may benefit innovation performance up to a certain threshold, beyond which there is a negative effect, leading to an inverted-U relationship. In addition, a number of examples show that it is not easy for innovative companies to benefit from innovation. Teece (1986) proposed the complementary assets view to explain this phenomenon and suggested that the successful development and commercialization of innovative achievements are inseparable from the support of complementary assets or organizational capabilities such as manufacturing, operations, marketing, distribution, logistics, and after-sales service (Hess & Rothaermel, 2011; Rothaermel & Hill, 2005; Swink & Nair, 2007; Taylor & Helfat, 2009). We therefore argue that firms with higher organizational capabilities, i.e., operational capability and marketing capability, are likely to obtain extra benefits from a moderate level of EPU for their innovation activities. The existence of these complementary

[4] https://www.cigionline.org/articles/how-antitrust-facilitates-chinas-goal-to-achieve-technological-self-sufficiency/

capabilities enables firms to create value more efficiently from their core technologies, allowing firms to benefit more from their innovation efforts (Lampert *et al*., 2020; Taylor & Helfat, 2009).

We collect and combine longitudinal secondary data from multiple reliable sources and construct our sample to examine the above postulates. Our result documents an inverted-U shape relationship between EPU and firms' innovation performance. Further moderating effect analysis indicates that firms' operational and marketing capabilities could make the inverted-U curve steeper, highlighting the importance of organizational capabilities at a moderate level of EPU. Moreover, we also find that the simultaneous possession of high operational and marketing capabilities at a moderate level of EPU leads to an extra positive impact, suggesting a positive three-way interactive effect on corporate innovation. These findings are consistent across a battery of robustness tests such as alternative measures, the instrumental variable (IV) approach, and subsample analysis. Our study contributes to the literature in the in the following three ways. First, it advances operational risk management literature by expanding the applicability of the prospect theory in the firm-level innovation decision-making context and showing that there is an inverted-U relationship between EPU and firms' innovation performance, which challenges traditional view and highlights the importance of psychological factors in affecting firms' strategic responses to policy uncertainty. Moreover, our investigation enriches the complementary assets literature by demonstrating the crucial roles of complementary assets (i.e., operational capability and marketing capability) in helping firms yield more innovative benefits when faced with moderate EPU. Finally, our research responds to the recent calls (e.g., Fan & Xiao, 2023; Tokar & Swink, 2019) which encourage to bring policy-related risk into the scope of operations and supply chain risk management by theoretically hypothesizing and empirically examining the non-liner impact of EPU on firms' innovativeness.

4.2 Literature Review and Hypothesis Development

4.2.1 EPU and Firm Behavior

The great economist Frank Knight (1921) creates the modern definition of uncertainty and defines it as people's inability to predict the occurrence of future events. Since then, scholars have discussed a lot on the outcomes of uncertainty. Subsequent studies employ various measures such as selected national elections, government official turnover, and unexpected departures of national leaders to serve as proxies for different sources of uncertainty (An et al., 2016; Julio & Yook, 2012; Pertuze et al., 2019). Among the various sources of uncertainty in the literature, one critical uncertainty source for organizations is economic policy uncertainty (EPU) which refers to the frequently changing decisions made by politicians and regulatory institutions that alter the environment where a firm operates (Bhattacharya et al., 2017; Gulen & Ion, 2016). Federal Open Market Committee (FOMC) and International Monetary Fund (2012) both point out that the intensified uncertain policies in the United States and Europe contribute to a sharp economic decrease in 2008-2009 and sluggish recoveries afterward. In addition to its effects on a country's real economy, the increases in EPU could also influence firm value and behavior in several ways, raising widespread attention from researchers, practitioners as well as policymakers.

The existing research on the consequences of EPU predominantly focuses on two aspects. First, there is a growing literature exploring the effects of uncertainty on firms' investment and financing decisions from the real options perspective. Bernanke (1983) and Bloom et al. (2007) model the association between uncertainty and corporate investment behavior. In their models, firms in the face of uncertainty are cautious to make irreversible investments and prefer a "wait and see" strategy until the uncertainty is resolved. Consistent with this view, a series of subsequent studies suggest that EPU leads to a significant decrease in corporate capital expenditures while causes growth in derivatives use and FDI level for risk management purposes (Gulen & Ion, 2016; Nguyen et al, 2018). Furthermore, Nguyen & Phan (2017) and Bonaime et al. (2018) find that EPU is negatively associated with mergers and acquisition activities. While some studies have shown investment is a monotonically decreasing function of uncertainty, other scholars document a positive, ambiguous, or non-monotonic relationship, both theoretically and empirically. Sarkar (2021) modifies the traditional real-option model into a new one, where both timing and size of investment are endogenous and chosen optimally by the firm. With this modification, the extreme uncertainty in both directions could hinder corporate investment, implying that investment is an inverted-U shaped function of uncertainty. Similarly, Bo & Lensin (2005) and Lensink & Murinde (2006) provide strong empirical evidence for an inverted-U relationship on this issue. In short, no consensus is reached in neither theoretical predictions nor empirical evidence on the uncertainty-investment association. In addition to the potential impacts of uncertainty on investment strategy, related literature also finds that EPU may increase the cost of external financing and accordingly exacerbate firms' financial constraints (Nguyen & Phan, 2017; Pástor & Veronesi, 2013). Likewise, subsequent studies indicate that the increase in the cost of borrowing brought by high uncertainty will urge firms to strategically adjust their behaviors, such as providing less trade credit and holding more cash (D'Mello & Toscano, 2020; Phan et al., 2019).

Some recent studies also pay attention to the operational implications of EPU. For instance, Darby et al. (2020) employ resource dependence theory and argue that firms are inclined to accumulate inventory to buffer against their exposure to potential policy risks since the government could indirectly promote or limit the flow of key resources among firms through changes in policies. The working capital that firms tied to their operation may also increase accordingly during periods of high policy uncertainty (Dbouk et al., 2020). In addition, firms have stronger incentives to diversify their customer bases to obtain greater bargaining power within the supply chain when anticipating unstable economic policies (Leung & Sun, 2021).

4.2.2 Corporate Innovation Performance

As Porter (1992) highlights the strategic importance of innovation in his work: "To compete effectively in international markets, a nation's businesses must continuously innovate and upgrade their competitive advantages." Technological innovation, defined as the extent to which a firm introduces and establishes new products, processes, or services together with its supply chain partners (Cao & Zhang, 2011), not only has a far-reaching influence on a firm's competitive advantage over its rivals (Porter, 1992), but also has long been the driver of a country's economic growth (Schumpeter & Backhaus, 2003). Moreover, similar to many other operational tasks, innovation and new product development are considered an important part of project management within the operational process (Mishra & Browning, 2020). Following He & Tian (2018), we review previous studies on the antecedents of corporate innovation from three analysis levels (i.e., firm-level characteristics, market characteristics, and institutional features).

We first review the literature that examines the micro-level firm characteristics influencing corporate innovation, such as factors controllable by shareholders like corporate governance and incentive schemes, and those external forces that are not under the direct control of shareholders, such as financial analysts, institutional investors, and other stakeholders. Scholars first pay their attention to CEO's personal traits and skill sets and argue that firms managed by overconfident CEOs, CEOs with flying airplanes hobbies, and generalist CEOs with general managerial skills are more willing to take a risk and pursue risky and uncertain innovative projects (Custódio et al., 2019; Galasso & Simcoe, 2011; Hirshleifer et al., 2012; Sunder et al, 2017). Moreover, the appointment of better-connected CEOs in the social network has also been proved to bring more invention knowledge to corporations and promote innovative capacity since such CEOs have easier access to innovation-related information via personal network connections (Faleye et al., 2014). In terms of CEO incentive schemes, those "innovation-friendly" compensation contracts that allow managers to endure early failures and reward for long-term success are the most effective in encouraging exploratory innovative projects and outcomes (Baranchuk et al., 2014; Ederer & Manso, 2013; Mao & Zhang, 2018). Given the critical roles played by employees in innovative process, several papers then explore the effect of employee innovative-related incentives, and employee welfare on innovation outcomes (Chang et al., 2015; Wei et al., 2020). These results indicate that the active engagement of employees in exploratory activities can stimulate corporate innovative vitality to a large extent. Another group of studies investigates available resources within the organization and tests the effect of slack resources on innovation activities. However, the conclusions tend to be mixed and are contingent on firms' operating environment and some organizational characteristics (Duan et al., 2020; Huang & Li, 2012; Lee, 2015). Except for the aforementioned internal determinants of innovation behavior, we eventually take those external features beyond the direct control of shareholders into account. The participation of institutional investors and foreign ownership is expected to foster investments in innovation by actively forcing managers out of their "quiet life" and bringing knowledge spillovers from high-innovation countries (Aghion et al., 2013; Guadalupe et al., 2012; Luong et al., 2017). Besides, it is also interesting to understand how the relationship with stakeholders affects innovation outputs. Such studies have found that a concentrated customer base, customer knowledge spillover, and higher levels of accessibility and interconnectedness in supply network will motivate suppliers to become more innovative (Bellamy et al., 2014; Chu et al., 2019; Krolikowski & Yuan, 2017).

Next, we turn our attention to the impact of market-wide forces on firms' incentives to engage in innovation projects. There have been extensive studies attempting to investigate whether product market dynamics encourage or impede innovation performance since one of the major purposes of innovation is to gain a competitive edge in the product market (He & Tian, 2018). Aghion et al. (2005) develop a model where competition hinders laggard firms from initiating innovative projects but encourages neck-and-neck firms to innovate, and they also empirically discover an inverted-U relationship between product market competition and innovation. Spulber (2013) points out that competition among producers creates incentives to innovate as long as there are protections for intellectual property rights. Likewise, Bloom et al. (2013) also prove that the product market rivalry will lead to more innovative investments and outputs. Instead, recent research finds that competition from foreign countries, unlike domestic competitive pressures, results in a decline in domestic innovation (Dorn et al., 2020).

Finally, we assess how legal policies, financial market development, and other institutional aspects affect the incentives to innovate. While intellectual property (IP) rights protection is considered to facilitate innovative investment by a few studies (Fang et al., 2017; Kafouros et al., 2015), other relevant articles argue that the effect of IP protection on subsequent scientific research and product development outcomes might be exaggerated or even adverse (Lerner, 2009; Williams, 2013). Moreover, Acharya et al. (2014) explore the effect of labor laws and find that the promulgation of wrongful discharge laws can motivate employees and stimulate their enthusiasm to innovate by mitigating the hold-up risk faced by employees. Apart from the protection rules concerning innovators and employees, the bankruptcy code is also assumed to affect new product introductions. Acharya & Subramanian (2009) argue that a credit-friendly bankruptcy code may discourage innovative firms to pursue innovative investments for fear of excessive liquidations. However, Cerqueiro et al. (2017) reach an opposite conclusion in a closely related work by suggesting that the most plausible reason is the stronger debtor protection which can largely reduce the supply of external debt financing. Other than laws, a few articles analyze how a nation’s market and political environment affect innovative project investments. Song et al. (2015) find that the anti-corruption actions urge firms to abandon their behavior of seeking political connection and tend to spend more on innovation. In terms of market environment, a more transparent information environment is found to bring greater firm innovation through reducing information asymmetries and lowering the cost of equity financing (Brown & Martinsson, 2019). As for the implication of social traits for innovation, Bénabou et al. (2015) identify a significantly negative connection between religiosity and generated patents per capita. A follow-up paper by Ucar (2018) explores the role of local culture and concludes that a firm located in areas with strong creative culture can generate more patents and citations via the firm's interaction with its location and local culture.

4.2.3 Prospect Theory and Inverted-U Relationship Between EPU and Innovation

Previous studies usually assume a linear monotonic decreasing relationship between uncertainty and investment through the real options channel, while largely ignoring the varied managerial risk preferences under different scenarios. In this study we adopt prospect theory to theorize and develop our hypothesis. The conventional viewpoint holds that individuals and economic agents typically make rational decisions by calculating expected utility based on the risks and rewards associated with a range of available choices. However, Kahneman & Tversky (1979) as well as Tversky & Kahneman (1981, 1992) provide compelling evidence suggesting that individuals' actual decision-making processes may not conform to the principles of rational calculations. Consequently, prospect theory has attracted considerable attention from practitioners and has been employed as a fundamental theoretical framework in disciplines such as economics, psychology, finance, and management (Shimizu, 2007). Based on the assumption of bounded rationality, prospect theory argues that economic agents will demonstrate distinct risk preferences in various situations. They may exhibit a tendency toward risk aversion when facing gains, and toward risk seeking when facing losses (Kahneman &

Tversky, 1979; Zona, 2012). Since an agent's utility typically depends on relative gains or losses rather than absolute income states in the real world, when the potential losses caused by exogenous shock can be controlled within a certain threshold, there will be risk-seeking behaviors, which indirectly provides a theoretical explanation for our hypothesized inverted U-shaped relationship between EPU and firm innovation (Bo & Lensin, 2005). In other words, managers tend not to worry about losses smaller than a threshold value arising from increased uncertainty. Instead, they prefer to undertake risky but promising projects such as innovation activities to achieve target performance (Greve, 2003). Specifically, when the business environment is stable and easily predictable, firms will simply respond to the incidents that have already happened rather than undertake innovative projects. In contrast, the unpredictability of future business conditions encourages firms to pursue more proactive strategies to know what is happening outside and take preventive actions towards upcoming changes (Aragón-Correa & Sharma, 2003; Jahanshahi & Brem, 2020). For example, entrepreneurs could provide a wider variety of products and services and build new capabilities to enrich market information and better deal with the perceived uncertainty (Miller & Shamsie, 1999). Obviously, an uncertain environment requires entrepreneurs to put forward novel and creative ideas to respond to the challenges as long as the risk-seeking behavior is within the domain of small losses. Moreover, investment in innovation is an active behavior that helps a firm gain a larger market share, consolidate its strategic position, and discourage entrants of potential competitors, especially in a turbulent environment (Kulatilaka & Perotti, 1998; Voss *et al*., 2008). Accordingly, a moderate level of EPU may encourage firms to improve innovation performance.

However, firms' risk tolerance relies on whether the decision-maker views the negative performance as a repairable gap or a threat to survival (Audia & Greve, 2006). When the uncertain environment implies a loss of control over operating decisions and even a threat to firm survival, managers will shift their strategy from seeking risk to avoiding risk to ensure firms' survival (Dutton & Duncan, 1987). If a firm no longer expects to recover performance from a deteriorating environment, the incentive to conduct the problematic search by undertaking risk-taking activities (e.g., innovation projects) will decline as well (Gao *et al.*, 2021). Therefore, firms confronted with threatening surroundings are expected to reduce investment in innovative competencies to limit the potential losses (Voss *et al.*, 2008). When EPU becomes too high and is even regarded as an extremely adverse condition, its negative effect becomes more salient, so the tendency to make a risky attempt becomes diminished because the chances of benefiting from newly introduced innovations are slim, leading to a decline in innovation performance.

The above discussion indicates that when EPU is at lower levels and less disruptive, firms make strategic investments through innovation to achieve target performance and stay ahead of competitors. However, as EPU further increases to levels where the likelihood of bankruptcy surges, firms will turn toward rigidity and reduce the deployment of long-term strategic initiatives. By integrating the two mechanisms simultaneously, a moderate level of EPU is anticipated to contribute more to developing creative products within a company, implying that the relation between EPU and innovation performance would not necessarily be a simple linear one. We assume that as EPU increases, its marginal benefits will gradually decrease because the incentive and profitability of problematic search may be more pronounced within a certain range of threats (Kahneman & Tversky, 1979; Shimizu, 2007). However, when threatened by a high level of EPU, a firm would enact strict retrenchment responses and exhibit threat-rigidity, resulting in reduced deployment of long-term strategic initiatives and increased reliance on more conservative short-term alternatives (Shi *et al.*, 2018). Accordingly, the dramatically increased costs of maintaining innovation will outweigh its marginal benefits, leading to a decline in innovation performance. In conclusion, a moderate level of EPU will be optimal for firms to innovate, so the impact of EPU on firm innovativeness might be positive up to a certain threshold, beyond which it becomes negative. We therefore hypothesize that:

H1: There is an inverted-U relationship between EPU and innovation performance.

4.2.4 Moderating effects of complementary capabilities

So far, we have illustrated why there is an inverted-U relationship between EPU and corporate innovation performance. Next, we explain how complementary assets, i.e., operational capability and marketing capability, might moderate the inverted-U link postulated above. We select organizational capabilities as the moderators for two main reasons. On the one hand, a wealth of literature has emphasized that a firm's capabilities play a key role in allocating multiple resources, unlocking resources value, and obtaining sustainable competitive advantage (Teece *et al*., 1997). There is a consensus that it is the proficiency in the use of resources, rather than the stock of resources *per se*, that makes a firm perform better than its competitors (Krasnikov & Jayachandran, 2008; Kwon *et al*., 2022). On the other hand, the prior literature has long acknowledged the importance of relevant organizational capabilities in coping with uncertainty (Tatikonda & Montoya-Weiss, 2001). Although some *ad hoc* measures could help firms temporarily overcome the difficulties caused by uncertainties (Winter, 2003), OM scholars believe that organizational capabilities, especially operational capability, is one of the fundamental means for firms to flexibly cope with uncertainty (Raddats *et al*., 2017). Unlike other short-term, local uncertainties, EPU tends to be regarded as a long-term, systemic uncertainty (Baker *et al*., 2016). In this case, firms need to develop the corresponding capabilities to avoid substantial negative impacts in the face of EPU and even to seize the potential opportunity to achieve growth. Among the various capabilities, we focus on operational and marketing capabilities because they represent a firm's ability to handle complicated internal production processes and respond to the demands of external stakeholders, respectively, and they also encompass the core business processes in a firm (Hirunyawipada & Xiong, 2018; Mishra *et al*., 2022; Rahmandad, 2012).

Operational capability is a relative efficiency indicator, which refers to a firm's ability to generate value-added outcomes from transforming constrained resources, and the extant OM studies often use operational efficiency or operational productivity as its alternative expression (Li *et al*., 2021; Yiu *et al*., 2020). The prior literature suggests that firms with superior operational capabilities are able to perform production and operations activities more efficiently, with lower costs and greater flexibility, as well as to adapt to the dynamic market conditions (Kortmann *et al*., 2014; Krasnikov & Jayachandran, 2008). A number of studies have shown the direct negative impacts of EPU on firms in terms of exacerbation of firms' financial constraints and increasing the operating and external financing costs (D'Mello & Toscano, 2020; Nguyen & Phan, 2017). Innovation activities require significant investment of capital and resources. Although a moderate level of EPU could incentivize firms to engage in more innovative activities, increased financial constraints and higher costs can discourage firms from doing so. High operational capability means that firms could use the limited resources more efficiently even in the face of resource constraints and rising costs. In other words, firms with high operational capability are more likely to achieve better innovation performance when faced with limited resources resulted from EPU.

In addition, OM scholars contend that the central idea of operational capability is that managers need to be competent in deploying the existing resource base for better performance outcomes, which is obtained via benchmarking practices and incremental improvement (Kwon *et al*., 2022). Therefore, operational capability has significant impacts on the enhancement of firms' managerial competency in maximizing short-run profits (Jacobs *et al*., 2016; Saunila *et al*., 2020). When faced with EPU, the improvement of short-term profits caused by operational capability may enable firms to have a more sufficient capital base for innovation activities, enhancing innovation performance and generating long-term innovation returns. Also, firms with efficient, reliable processes and procedures are more likely to maintain a stable environment for idea search and discovery, which is beneficial for firms to conduct R&D activities (Yiu *et al*., 2020; Zollo & Winter, 2002). We therefore hypothesize that:

H2: The inverted-U relationship between EPU and innovation performance is stronger (steeper) when firms' operational capability is high.

Marketing capability refers to a firm's efficiency in converting available marketing-related resources into outputs or marketing performance (Mishra & Modi, 2016; Xiong & Bharadwaj, 2013). The existing marketing literature highlights the significance of marketing capability in a firm. First, firms with high marketing competence are believed to have more ability to manage communication. Better communication could enable firms to have greater awareness of the innovation efforts among various stakeholders such as consumers, suppliers, employees, and the community. In many cases, stakeholders may not have a clear and timely understanding of firms' innovation initiatives. Thus, good communication is important to help firms uncover the potential stakeholder-based resources created by corporate innovation. Also, good communication could reduce stakeholders' perceived risks associated with corporate innovation, which may increase the likelihood of purchasing and adopting innovative products.

In addition, marketing capability also reflects a firm's ability to manage and utilize market information. Firms with high marketing capability do well in identifying customer needs and the factors influencing consumer behavior, which results in excellence in targeting, positioning, and advertising (Vorhies & Morgan, 2005). The significance of the marketing department is that it can make firms perceive and respond to markets and align organizational resources to meet the complex and personalized needs of customers. The existing literature has pointed out that EPU will make firms face more fierce market competition (Jory *et al*., 2020). In this case, to avoid falling into a price war, corporate innovation (e.g., new product development) is naturally an effective way to differentiate a firm from its competitors, but this arrangement is only possible with accurate perceptions of customer needs and preferences (Jansen *et al*., 2006). High marketing capability enables firms to understand the latent demand and to be able to better segment the market and to form well-constructed customer profiles (Hirunyawipada & Xiong, 2018; Xiong & Bharadwaj, 2013). Taken together, marketing capability could help firms increase the benefits of innovation activities when facing EPU, so we propose the following hypothesis:

H3: The inverted-U relationship between EPU and innovation performance is stronger (steeper) when firms' marketing capability is high.

The conceptual model of this study is summarized in Figure 4.1.

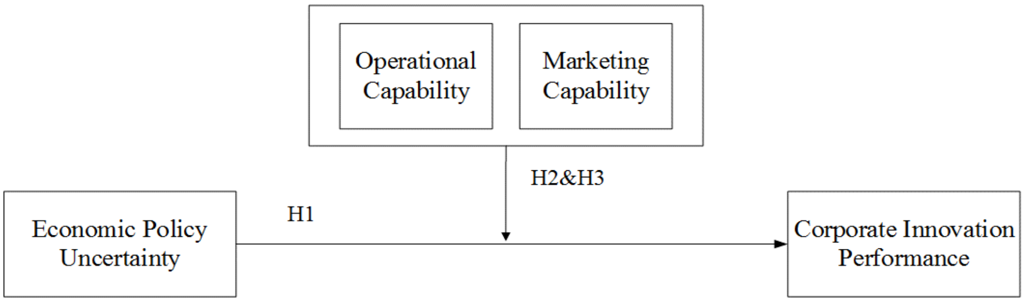

Figure 4.1 Conceptual model.

4.3 Methodology

4.3.1 Data and Sample

We obtain and combine longitudinal secondary panel data of Chinese A-share listed companies from multiple sources to perform our empirical analysis. First, the accounting data of public firms are collected from China Stock Market & Accounting Research (CSMAR) database. The financial information provided by CSMAR is reliable and commonly used by previous empirical studies on Chinese-related issues (e.g., Li *et al*., 2021; Zhu *et al*., 2021). Next, we obtain firms' patent information from Chinese Innovation Research Database (CIRD) as it distinguishes the patent applied by a company on its own and those jointly with other entities and provides complete patent applications of listed companies over a longer time horizon. To measure the degree of uncertainty in economic policies, we employ the EPU index developed by Baker, Bloom & Davis (BBD hereafter, 2016), which has been commonly used in prior relevant studies (e.g., Bhattacharya *et al*., 2017; Gulen & Ion, 2016; Nguyen & Phan, 2017). Our initial sample includes all Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2000 to 2020. Following prior literature, we exclude firms in financial industries due to their distinct regulatory policies, and observations with missing data on key variables (D'Mello & Toscano, 2020; Zhu *et al*., 2021). Moreover, all independent variables are lagged one year behind to mitigate potential endogeneity risks. Our sample finally consists of 11,769 firm-year observations of 1,392 unique firms between 2000 and 2019. The data set constitutes an unbalanced panel structure due to a lack of observation.

Table 4.1 Descriptive statistics of sample firms

Panel A: Distribution of sample firms across industries

CSRC industry code	Industry	Frequency	Percentage (%)
A	Agriculture, forestry, animal husbandry and fishery	673	5.72
B	Mining	773	6.57
C	Manufacturing	7,464	63.42
D	Utilities	129	1.10
E	Construction	629	5.34
G	Transportation, warehousing, and postal services	842	7.15
H	Accommodation and catering	33	0.28
I	Information transmission, software, and IT services	209	1.78
M	Scientific research and technical services	244	2.07
N	Water conservancy, environment, and public facilities management	370	3.14
O	Residential service, repair and other services	40	0.34
P	Education	15	0.13
R	Culture, sports and entertainment	348	2.96
Total sample size		11,769	100.00

Panel B: Distribution of sample firms across years

Year	Frequency	Percentage (%)
2000	280	2.38
2001	302	2.57
2002	319	2.71
2003	345	2.93
2004	372	3.16
2005	364	3.09
2006	382	3.25
2007	434	3.69
2008	470	3.99
2009	491	4.17
2010	568	4.83
2011	642	5.46
2012	698	5.93

2013	680	5.78
2014	684	5.81
2015	755	6.42
2016	830	7.05
2017	1,001	8.51
2018	1,065	9.05
2019	1,087	9.24
Total sample size	11,769	100.00

in certain years. Panels A and B of Table 4.1 present the sample distribution across industry and year, respectively.

4.3.2 Measures

Economic Policy Uncertainty. We rely on the Chinese BBD news index developed by Baker *et al*. (2016) to examine the impact of EPU on corporate innovation performance[5]. Specifically, Baker *et al*. (2016) first collect the articles in South China Morning Post about economic uncertainty pertaining to China by picking up all articles that contain at least one keyword from each of the following term sets: {China, Chinese} and {economy, economic} and {uncertain, uncertainty}. Subsequently, they identify the subset of the China economic uncertainty articles that also discuss policy issues. For this purpose, an article is required to satisfy the following text filter: {{policy OR spending OR budget OR political OR "interest rates" OR reform} AND {government OR Beijing OR authorities}} OR tax OR regulation OR regulatory OR "central bank" OR "People's Bank of China" OR PBOC OR deficit OR WTO. Finally, they compute the monthly EPU index by dividing the frequency count of these EPU-related articles by the total number of articles within the same month. The time series is then normalized to a mean value of 100 from 1995 to 2011. Since the index is published every month, we construct an annual index by taking the average of the monthly index in a given year. We compare the trend of the index with important historical events and find that the index jumps around major events (Figure 4.2), indicating that the index can generally reflect China's economic policy uncertainty. An alternative measure of EPU is the newspaper-based indices derived from two mainland Chinese newspapers: the Renmin Daily and the Guangming Daily, which are used in our robustness test.

[5] http://www.policyuncertainty.com/scmp_monthly.html

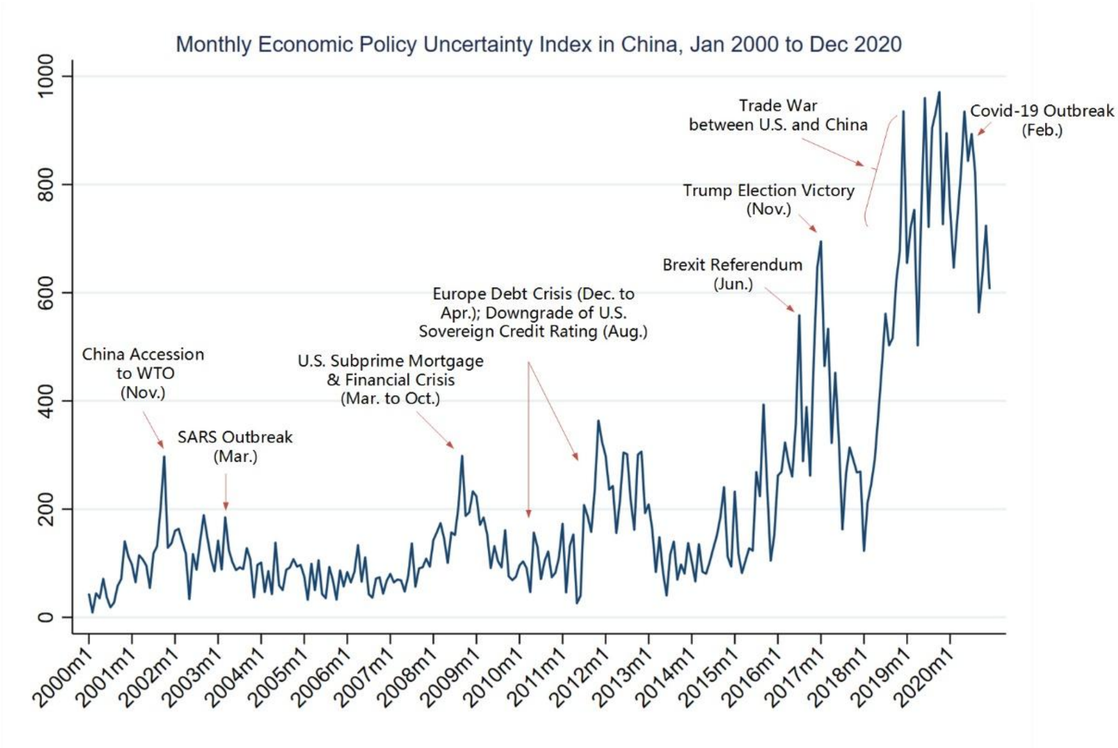

Figure 4.2 The monthly EPU index.

Corporate Innovation Performance. R&D expenditure and patent application are the two main proxies applied in prior research to capture innovation investment or productivity. Several studies have contended that patenting activities could better reflect firms' innovation quality and ability than R&D expenditures because the patent application represents innovative outputs and requires a consistent and rigorous examination process (Fang *et al*., 2014). Therefore, patent data is collected to reflect innovation activities. According to China's patent law, there are three basic types of patents: invention, utility model, and design. In this study, we concentrate on the overall patent applications and use filings of invention patents and utility model in our robustness test section.

We focus on the application year of the patents rather than the grant year as the former is closer to the time of actual innovation behavior (Fang *et al*., 2014). Specifically, the natural logarithm of one plus the number of patents is considered as representative of a firm's innovativeness (Liu & Ma, 2020; Wei *et al*., 2020; Xu, 2020; Yuan & Wen, 2018). We add one to the actual application values to retain the firm-year observations with zero patents (Fang *et al.*, 2014).

Moderating Variables. We adopt a stochastic frontier estimation approach to estimate operational and marketing capability. The stochastic production function reflects the efficiency of a firm relative to its peers in the same industry by calculating the level of output that can be transformed from a certain level of inputs (Li *et al.*, 2010). To measure operational capability, we empirically model a firm's operational efficiency in transforming its operational resources, i.e., number of employees, cost of goods sold, and capital expenditure, into outputs, i.e., operating income, in Equation 1 (Lam *et al.*, 2016; Yiu *et al.*, 2020). Regarding marketing capability, we use Equation 2 to estimate the transformation process that converts marketing-related input resources, i.e., number of employees, selling, general and administrative expenses, accounts receivable, and intangible assets, into outputs, i.e., sales (Li *et al.*, 2010; Mishra & Modi, 2016; Nath *et al.*, 2010).

$$In(Operating\ Income)_{ijt} = \beta_0 + \beta_1 In(Employees)_{ijt} + \beta_2 In(COGS)_{ijt} + \beta_3 In(CAEX)_{ijt} + \varepsilon_{ijt} - \gamma_{ijt} \quad (1)$$

$$In(Sales)_{ijt} = \beta_0 + \beta_1 In(Employees)_{ijt} + \beta_2 In(SGA\ expences)_{ijt} + \beta_3 In(account\ receivables)_{ijt} + \beta_4 In(intangible\ assets)_{ijt} + \varepsilon_{ijt} - \gamma_{ijt} \quad (2)$$

where ε_{ijt} is the stochastic random error term and γ_{ijt} reflects the relative inefficiency score of firm *i* in industry *j* (three-digit industry) compared to other firms within the same industry in year *t*. γ_{ijt} ranges from 0 to 1, where 0 means no technical inefficiency. The composite error term ($\varepsilon_{ijt} - \gamma_{ijt}$) is estimated based on the difference between the industry's highest realized operating income and the observed operating income, thereby yielding a consistent estimate of firm-specific operational inefficiency γ_{ijt}. We compute the efficiency term by subtracting the inefficiency score from 1 to capture a firm's operational and marketing capability respectively, with 0 indicating the lowest level of efficiency while 1 indicating the optimal boundary level performed by the "best practice" firm in the transformation process.

Control Variables. Consistent with prior studies, we control for several firm-specific variables that potentially affect firms' innovation outputs (Chang *et al*., 2015; Fang *et al*., 2014; Wei *et al*., 2020). We include return on assets (*ROA*, net income divided by total asset), *Tobin's q* (a firm's market value divided by its book value), *Leverage* (the ratio of the book value of debt to assets), *Firm Size* (the natural logarithm of total assets), *PPE* (net property, plant, and equipment scaled by total assets), *Financial Slack* (the ratio of cash reserves to the book value of total assets) into our estimation. We incorporate *Firm Size* and *PPE* because larger firms and those with higher capital intensity typically possess greater innovation resources and thus generate more patents (Chang *et al*., 2015). Moreover, the inclusion of *ROA* aims to capture operating profitability, while *Tobin's q* is included to delineate a firm's growth prospects, both anticipated to yield a positive impact on innovation performance. However, the impact of *Financial Slack* and *Leverage* on innovation performance remains contentious. While cash reserve is an indispensable resource for fostering innovation, firms with higher free cash flow might be susceptible to managerial resource abuse, potentially impeding firm innovation (Wei *et al*., 2020). The traditional viewpoint contends that debt may be unfavorable for innovation since innovation is inherently risky, and innovation endeavors are not easily deployable to alternative uses. In contrast, other studies have recognized that debt holders may exert a positive impact on innovation outputs by assuming a monitoring role (Choi *et al*., 2016). Further, following previous studies (Leung & Sun, 2021; Liu & Wang, 2022), two macro time-series variables accessed from Chinese National Bureau of Statistics, *CPI index* and *M2 growth*, are added into our model to allow for the influences of economic growth. Additionally, we perform firm fixed effects to remove the effect of unobservable factors that do not vary over time, which could help alleviate the endogeneity bias to a large extent. Haans *et al*. (2016) point out that fixed effects estimation with panel data can remedy the omitted variable bias, strengthen empirical identification, and thus is the best practice to test the quadratic relationship.

Similar to Gulen & Ion (2016), Nguyen & Phan (2017), and Phan *et al*. (2019), we do not control for year-fixed effects because the EPU index is the same for all of the firms in a given year. Adopting a year fixed effect will absorb the variation of the EPU.

4.3.3 Model Specification

We introduce the following panel data model as shown in Equation 3 to empirically test the above hypotheses. Hausman test is applied to determine whether fixed effects or random effects estimator is more efficient (Greene, 2012). The null hypothesis of Hausman tests, "no systematic difference in coefficients", is rejected at the 1% significance level, indicating that the fixed effects model is the preferred specification for our dataset. We lag our independent and moderating variables one year behind to alleviate the potential endogeneity concern due to reverse causality and estimate the models with robust standard errors clustered by firm for statistical inference. All continuous variables are winsorized at the 1% and 99% levels to mitigate the potential influence of outliers.

$$Innovation_{i,t+1} = \beta_0 + \beta_1 EPU_t + \beta_2 EPU_t^2 + \beta_3 Operational\ Capability_{i,t} * EPU_t + \beta_4 Operational\ Capability_{i,t} * EPU_t^2 + \beta_5 Marketing\ Capability_{i,t} * EPU_t + \beta_6 Marketing\ \ Capability_{i,t} * EPU_t^2 + \beta_7 Operational\ Capability_{i,t} + \beta_8 Marketing\ \ Capability_{i,t} + \beta_9 Controls_{i,t} + \beta_{10} Macro_t + \eta_i + \varepsilon_{i,t} \quad (3)$$

4.4 Results

4.4.1 Descriptive Statistics and Correlation

Table 4.2 documents the Pearson correlation matrix and descriptive statistics of the variables. The average variance inflation factor (VIF) score across all the variables is 2.47, which suggests that multicollinearity is not a major concern. Starting at 55.7 in 2000 and reaching a peak in 2019 of 791.9, EPU index shows an upward trend in our sample period although a quick decline appears in particular years. The large dispersion of the data set helps us find the correlations among variables in the follow-up research. There are 3,555 observations with zero number of patent applications, indicating the absence of patent filings in the respective years. It shows a significant positive correlation between the EPU index and innovation performance without considering the impact of other factors, which preliminarily confirms our hypothesis on prospect theory. Among the control variables, *ROA*, *Leverage*, *Firm Size*, *Financial Slack*, and *CPI index* have positive correlations with innovation outcomes. These findings suggest that firms with a larger scale, better profitability, more cash holdings, and higher levels of leverage are much more likely to achieve better innovation performance.

Table 4.2 Correlation matrix and descriptive statistics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
F. Patent Applications	1.000											
EPU Index	0.241***	1.000										
ROA	0.117***	-0.036***	1.000									
Tobin's q	-0.082***	-0.035***	0.058***	1.000								
Leverage	0.100***	-0.059***	-0.351***	-0.194***	1.000							
Firm Size	0.458***	0.211***	0.039***	-0.356***	0.376***	1.000						
PPE	-0.202***	-0.181***	-0.034***	-0.105***	0.040***	0.042***	1.000					
Financial Slack	0.009	-0.040***	0.244***	0.076***	-0.347***	-0.151***	-0.334***	1.000				
Operational Capability	0.259***	0.108***	0.342***	-0.066***	-0.101***	0.073***	-0.127***	0.121***	1.000			
Marketing Capability	0.097***	0.032***	0.135***	-0.121***	0.086***	0.093***	-0.018**	0.031***	0.402***	1.000		
CPI Index	0.030***	0.053***	0.044***	-0.080***	0.019**	0.028***	-0.006	0.052***	-0.014	-0.016*	1.000	
M2 growth	-0.270***	-0.648***	0.015	0.036***	0.087***	-0.194***	0.187***	0.051***	-0.098***	-0.012	-0.131***	1.000
Mean	2.155	259.1	0.034	1.805	0.445	21.93	0.257	0.173	0.708	0.606	102.4	13.65
Standard deviation	1.813	209.6	0.059	1.066	0.200	1.299	0.163	0.127	0.289	0.285	1.550	4.735
Minimum	0.000	55.69	-0.277	0.883	0.053	19.40	0.002	0.009	0.000	0.000	99.20	8.100
Maximum	8.779	791.9	0.191	8.379	0.908	25.85	0.730	0.671	1.000	1.000	105.9	28.50

4.4.2 Baseline Results

Table 4.3 reports the results of fixed effects analysis, where the overall patent application (collaborative innovation and solitary innovation) is the dependent variable. Model 1 only contains the control variables. We then gradually add the variable of our interest into the estimation model step by step. Model 2 puts EPU and its squared term into the equation to examine the inverted U-shape relationship between EPU and innovation performance. Model 3 and Model 4 introduce the interaction terms involving operational and marketing capability respectively to investigate their moderating effects. Model 5 is the full model.

The result of Model 2 shows a positive coefficient for EPU and a negative coefficient for its squared term, both significant at the 1% level, demonstrating the existence of an inverted U-shaped relationship between EPU and corporate innovation performance after including all the predictors but without the interactions. According to the research of Haans *et al*. (2016), the turning point is 412.58 (calculated as -$\beta_1/2\beta_2$) where the curve attains its maximum. The 95% confidence interval of the turning point is (397.92, 427.24), suggesting that the turning point lies well within the data range and removing the doubts that the data only reveal one-half of the curve. We also note that the slope at the lower bound of the EPU data range is 0.00406 ($\beta_1 + 2\beta_2 * EPU_{min}$), yet the upper bound of the data range is -0.00431 ($\beta_1 + 2\beta_2 * EPU_{max}$). The slopes at both ends of the data range are significant at the 1% level, once again showing the existence of an inverted U-shaped relationship. These findings are consistent with Hypothesis 1 that firms are more likely to engage in innovative activities when EPU is neither too high nor too low.

Models 3 and 4 introduce the interaction terms that include operational and marketing capability respectively to examine their moderating effects. The result in Model 3 reveals that the coefficient for the interaction term of EPU and operational capability is positive and significant. In contrast, the interaction term of squared EPU and operational capability has a significantly negative coefficient, implying that a steepening occurs for the inverted U-shaped relationship (Haans *et al.*, 2016). To formally test whether a shift in the turning point occurs, we examine the sign of the Equation 2 and its significance using the *nlcom* command in STATA (Ben-Jebara & Modi, 2021; Haans *et al.*, 2016). The average level of the operational capacity in our sample, that is 0.708, is assigned to perform the test. The results show that the sign of the numerator is negative ($\beta_1\beta_4 - \beta_2\beta_3 < 0$). However, it is critical to note that Equation 4 itself is not significantly different from zero (p value = 0.408), providing less support for the actual shift of the turning point.

$$\frac{\delta(EPU)}{\delta(OP\ Cap)} = \frac{\beta_1\beta_4 - \beta_2\beta_3}{2(\beta_2 + \beta_4 OP\ Cap)^2} \quad (4)$$

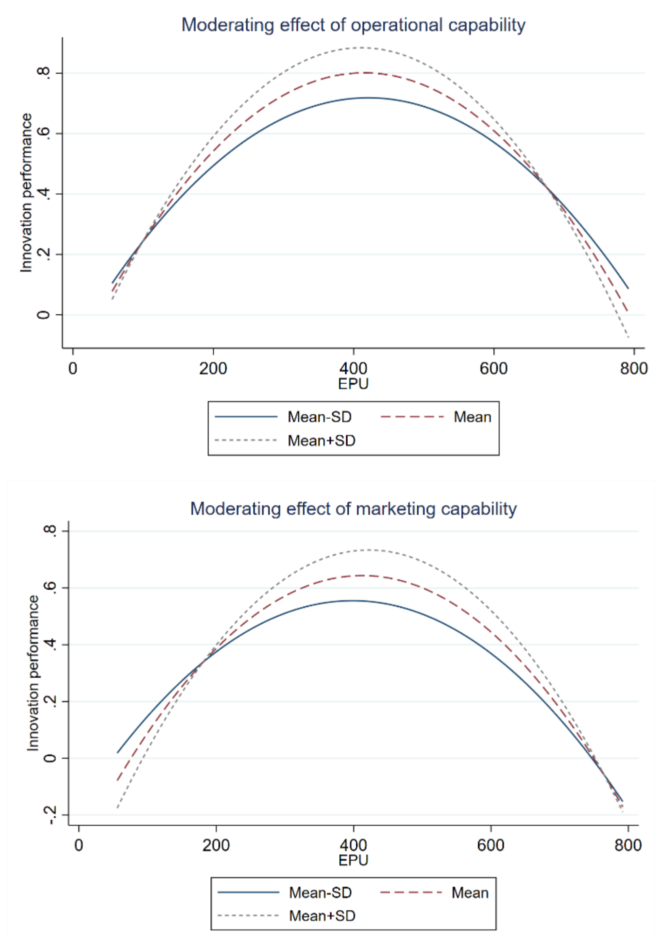

Figure 4.3 The moderating effects of operational capability and marketing capability.

The result in Model 4 indicates that the interaction term of EPU and marketing capability has a positive and significant coefficient, whereas the coefficient for the interaction term of the squared EPU and marketing capability is negative and statistically significant. This implies that the captured inverse U-shaped relationship between EPU and innovation performance is steeper. The sign of the numerator in Equation 5 is positive ($\beta_1\beta_6 - \beta_2\beta_5 > 0$). More importantly, Equation 3 as a whole significantly differs from zero, indicating strong support for a right shift occurrence when the marketing capability is strengthened (p value = 0.065). Figure 4.3 graphically illustrates that the inverted U-shaped curve becomes steeper for firms with higher operational and marketing efficiency, which is consistent with H2 and H3.

$$\frac{\delta(EPU)}{\delta(MK\ Cap)} = \frac{\beta_1\beta_6 - \beta_2\beta_5}{2(\beta_2 + \beta_6 MK\ Cap)^2} \quad (5)$$

Table 4.3 Results of fixed-effects regression analysis

Variables	Model1	Model2	Model3	Model4	Model5
*EPU Index * Marketing Capability*				0.00363***	0.00301***
				(4.82)	(3.75)
*EPU Index^2 * Marketing Capability*				-3.84e-06***	-2.86e-06***
				(-4.93)	(-3.38)
*EPU Index * Operational Capability*			0.00269***		0.00151*
			(3.68)		(1.94)
*EPU Index^2 * Operational Capability*			-3.47e-06***		-2.36e-06***
			(-4.38)		(-2.72)
EPU Index		0.00469***	0.00275***	0.00248***	0.00175***
		(19.17)	(4.65)	(4.62)	(2.62)
EPU Index^2		-0.00001***	-3.15e-06***	-3.34e-06***	-2.20e-06***
		(-24.78)	(-4.91)	(-6.06)	(-3.12)
Operational Capability	0.09637	0.07159	-0.23083**	0.07170	-0.06893
	(1.56)	(1.20)	(-2.14)	(1.20)	(-0.60)
Marketing Capability	-0.12601	-0.05513	-0.05494	-0.53045***	-0.47359***
	(-1.64)	(-0.73)	(-0.73)	(-4.13)	(-3.54)
ROA	1.00206***	0.97738***	0.96472***	0.99072***	1.00846***
	(3.63)	(3.69)	(3.64)	(3.76)	(3.82)
Tobin's q	0.15225***	0.13048***	0.13206***	0.13044***	0.13073***
	(10.29)	(9.01)	(9.10)	(9.05)	(9.05)
Leverage	-0.19644	-0.07921	-0.07764	-0.06606	-0.06491
	(-1.19)	(-0.49)	(-0.48)	(-0.41)	(-0.40)
Firm Size	0.93284***	0.85463***	0.85455***	0.84934***	0.85124***
	(21.44)	(18.50)	(18.48)	(18.49)	(18.48)
PPE	-0.22389	-0.13587	-0.13020	-0.12431	-0.11785
	(-1.19)	(-0.74)	(-0.71)	(-0.68)	(-0.65)
Financial Slack	-0.02391	-0.10616	-0.09010	-0.08995	-0.09242
	(-0.15)	(-0.66)	(-0.56)	(-0.56)	(-0.57)
CPI Index	-0.00646	0.01386**	0.01477**	0.01357**	0.01409**
	(-0.93)	(2.00)	(2.13)	(1.97)	(2.03)
M2 growth	-0.01640***	-0.00428	-0.00400	-0.00432	-0.00405
	(-4.20)	(-1.15)	(-1.08)	(-1.16)	(-1.09)
Constant	-17.572***	-18.732***	-18.621***	-18.308***	-18.342***
	(-12.93)	(-13.67)	(-13.60)	(-13.39)	(-13.41)
Firm Fixed Effect	YES	YES	YES	YES	YES
N	11,769	11,769	11,769	11,769	11,769
Within R^2	0.3143	0.3630	0.3645	0.3653	0.3661

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

4.4.3 Robustness Checks and Endogeneity Issues

We consolidate our findings through a series of robustness tests. First, we exclude the patent applications that are filed jointly with other entities during the year and retain those filed by the company independently. Solitary patent applications can better reflect a firm's own innovation capability. The results in Table 4.4 based on the alternative measure are consistent with previous findings.

Table 4.4 Robustness test-Alternative measure of dependent variable

Variables	Model1	Model2	Model3	Model4	Model5
*EPU Index * Marketing Capability*				0.00350***	0.00275***
				(4.54)	(3.33)
*EPU Index^2 * Marketing Capability*				-3.59e-06***	-2.47e-06***
				(-4.47)	(-2.84)
*EPU Index * Operational Capability*			0.00287***		0.00182**
			(3.87)		(2.28)
*EPU Index^2 * Operational Capability*			-3.62e-06***		-2.69e-06***
			(-4.45)		(-3.03)
EPU Index		0.00432***	0.00225***	0.00219***	0.00132**
		(16.65)	(3.81)	(4.10)	(2.00)
EPU Index^2		-0.00001***	-2.72e-06***	-3.18e-06***	-1.89e-06***
		(-21.94)	(-4.20)	(-5.72)	(-2.65)
Operational Capability	0.08998	0.07016	-0.26000**	0.07047	-0.10886
	(1.50)	(1.20)	(-2.41)	(1.21)	(-0.94)
Marketing Capability	-0.11440	-0.04258	-0.04264	-0.50965***	-0.43631***
	(-1.47)	(-0.55)	(-0.55)	(-3.89)	(-3.19)
ROA	0.86009***	0.78401***	0.76356***	0.79552***	0.80674***
	(3.09)	(2.93)	(2.85)	(2.98)	(3.01)
Tobin's q	0.14843***	0.12814***	0.12992***	0.12803***	0.12857***
	(10.32)	(9.11)	(9.23)	(9.16)	(9.17)
Leverage	-0.26261	-0.16434	-0.16286	-0.15109	-0.15034
	(-1.58)	(-1.01)	(-1.00)	(-0.93)	(-0.93)
Firm Size	0.88661***	0.82323***	0.82262***	0.81768***	0.81940***
	(20.36)	(17.73)	(17.72)	(17.73)	(17.73)
PPE	-0.18383	-0.10788	-0.10267	-0.09625	-0.09012
	(-0.94)	(-0.56)	(-0.53)	(-0.50)	(-0.47)
Financial Slack	0.05711	-0.02934	-0.01088	-0.01480	-0.01522
	(0.34)	(-0.18)	(-0.07)	(-0.09)	(-0.09)
CPI Index	-0.00792	0.01134*	0.01231*	0.01104	0.01167*
	(-1.15)	(1.66)	(1.80)	(1.62)	(1.71)
M2 growth	-0.01642***	-0.00661*	-0.00634*	-0.00665*	-0.00636*
	(-4.23)	(-1.80)	(-1.73)	(-1.81)	(-1.73)
Constant	-16.520***	-17.797***	-17.662***	-17.371***	-17.396***
	(-12.27)	(-13.06)	(-12.97)	(-12.78)	(-12.79)
Firm Fixed Effect	YES	YES	YES	YES	YES
N	11,769	11,769	11,769	11,769	11,769
Within R^2	0.2825	0.3283	0.3299	0.3305	0.3314

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. All the *p*-values are two-tailed. *t* statistics in parentheses.

Second, we perform the IV approach to mitigate the omitted variable bias concern. Although we have controlled for a wide range of firm-specific, time-invariant, and macroeconomic predictors in the estimation model, both EPU and innovation activities may be jointly related to unobservable variables, such as investment opportunities, resulting in a potential biased and inconsistent coefficient estimate (Nguyen & Phan, 2017). Specifically, we employ a two-stage least square (2SLS) estimation to address this endogeneity issue. Following Yuan *et al*. (2022), we choose the natural logarithm of the number of proposals submitted to the National People's Congress (NPC hereafter) in each year as our IV. The NPC exercises its power to formulate and amend the Constitution and the Basic Law of the state. In addition, it has the power to examine and approve the plans for national economic, social development, and state budget, and to monitor their actual implementation. In the context of China, the proposals submitted to the NPC should be a valid IV because they closely correlate with China's EPU and can only influence corporate investment decisions through the independent variable of our interest. Table 4.5 reports the two-stage results of the IV regression. The dependent variables in the second-stage regression are the overall patent applications, invention patents, and utility model, respectively. The Kleibergen-Paap Wald F statistic is significantly larger than the threshold of the Stock-Yogo weak identification critical values, and LM statistic is also significant at the 1% level, indicating that our selected IV is relevant and can be fully identified. The results in the second stage are similar to those in Table 4.3, indicating that the previous quadratic relationship between EPU and innovation performance remains valid after accounting for the omitted variable bias.

Table 4.5 Robustness test-Instrumental Variable (IV) approach

Variables	First stage		Second stage		
	EPU	EPU^2	Patent	Invention Patent	Utility Model
BILL	1302.6^{***}	1732995^{***}			
	(9.79)	(13.35)			
$BILL^2$	-104.5^{***}	-132287^{***}			
	(-10.13)	(-13.14)			
Instrumented EPU			0.01371^{***}	0.00905^{***}	0.01289^{***}
			(20.39)	(16.90)	(22.90)
Instrumented EPU^2			-0.00001^{***}	-0.00001^{***}	-0.00001^{***}
			(-17.51)	(-12.36)	(-22.56)
Operational Capability	40.80^{***}	30586.2^{***}	-0.10697^{*}	-0.11721^{**}	-0.04162
	(5.71)	(4.38)	(-1.85)	(-2.52)	(-0.85)
Marketing Capability	51.74^{***}	54851.5^{***}	-0.20114^{***}	-0.19439^{***}	-0.08734
	(6.67)	(7.25)	(-3.01)	(-3.51)	(-1.51)

ROA	-497.2***	-451396.8***	3.24934***	2.42688***	2.22473***
	(-15.46)	(-14.38)	(8.26)	(7.75)	(6.84)
Tobin's q	-6.468***	-6602.4***	0.09847***	0.08310***	0.08333***
	(-3.58)	(-3.74)	(7.62)	(7.82)	(7.29)
Leverage	-103.1***	-76510.5***	0.57155***	0.40517***	0.45991***
	(-6.99)	(-5.31)	(4.35)	(3.59)	(3.91)
Firm Size	77.89***	66371.3***	0.32572***	0.32459***	0.31649***
	(23.77)	(20.76)	(5.21)	(6.42)	(6.06)
PPE	-50.79***	-43433.0**	0.25849*	0.12859	0.08144
	(-2.94)	(-2.57)	(1.89)	(1.16)	(0.69)
Financial Slack	-89.84***	-93529.0***	0.19879	0.19151*	0.08494
	(-5.39)	(-5.75)	(1.44)	(1.75)	(0.72)
CPI Index	-2.680***	2676.8***	0.02977***	0.00996*	0.01428**
	(-2.82)	(2.89)	(4.06)	(1.78)	(2.31)
M2 growth	-16.95***	-12016.4***	0.07818***	0.05220***	0.05013***
	(-42.12)	(-30.61)	(8.10)	(7.15)	(6.53)
Constant	-4943.7***	-7072131***	-11.87***	-9.35***	-9.84***
	(-11.92)	(-17.48)	(-8.36)	(-7.94)	(-7.94)
Firm Fixed Effect	YES	YES	YES	YES	YES
N	11,693	11,693	11,693	11,693	11,693
Kleibergen-Paap rk LM statistic			208.711***	208.711***	208.711***
Kleibergen-Paap rk Wald F statistic			115.132	115.132	115.132
Cragg-Donald Wald F statistic			69.173	69.173	69.173
Stock-Yogo 10% critical value			7.03	7.03	7.03
Sargan statistic			0.000	0.000	0.000

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

Third, as suggested by Haans *et al*. (2016) and Qian *et al*. (2010), we split the observations into two subsamples based on the median value of EPU index (179.0) to validate the quadratic relationship again. Panel A of Table 4.6 identify a significant and positive association between EPU and corporate innovation in the lower samples but a significantly negative one in the upper samples. The opposite slopes are in line with the predicted shape of the curve in H1. Furthermore, we explore the impact of innovation output on firms' financial performance in the following year in both subsamples. The dependent variables in Panels B, C, and D of Table 4.6 are *Sales Growth*, *ROA*, and *Tobin's q* respectively. We find that the positive correlation between innovation outputs and financial outcome is more pronounced in the lower range of EPU, partially suggesting that innovation efforts could restore firm performance when EPU is not extremely high.

Table 4.6 Regression results in subsamples

Panel A: Two subsamples of observations split according to the median value of EPU index

Variables	Low EPU	High EPU
EPU Index	0.00266***	-0.00182***

	(6.47)	(-17.95)
Operational Capability	0.11598*	0.13577
	(1.76)	(1.50)
Marketing Capability	-0.07866	0.00830
	(-0.81)	(0.09)
ROA	0.36874	1.36682***
	(1.04)	(4.58)
Tobin's q	0.16249***	0.04251**
	(7.62)	(2.25)
Leverage	-0.26243	-0.24735
	(-1.16)	(-1.47)
Firm Size	1.02316***	0.45210***
	(17.36)	(8.80)
PPE	0.09218	0.03600
	(0.43)	(0.15)
Financial Slack	-0.21933	-0.11116
	(-1.08)	(-0.57)
CPI Index	0.02579***	0.00379
	(3.18)	(0.17)
M2 growth	0.00758*	-0.15209***
	(1.85)	(-17.35)
Constant	-23.802***	-5.456***
	(-15.05)	(-1.93)
Firm Fixed Effect	YES	YES
N	5,863	5,906
Within R^2	0.3355	0.2582

Panel B: The impact of innovation output on firms' sales growth in two subsamples

	F.Sales Growth			
	Low EPU	High EPU	Low EPU	High EPU
Patent	0.05761**	0.05491		
	(2.13)	(1.38)		
Invention Patent			0.07556*	0.09069
			(1.86)	(1.61)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
N	5,856	5,906	5,856	5,906
Within R^2	0.0053	0.0180	0.0053	0.0188

Panel C: The impact of innovation output on firms' ROA in two subsamples

	F.ROA			
	Low EPU	High EPU	Low EPU	High EPU
Patent	0.00253**	0.00079		
	(2.36)	(0.74)		
Invention Patent			0.00295**	0.00020
			(2.26)	(0.17)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
N	5,863	5,906	5,863	5,906
Within R^2	0.0655	0.0638	0.0652	0.0637

Panel D: The impact of innovation output on firms' *Tobin's q* in two subsamples

	F.*Tobin's q*			
	Low EPU	High EPU	Low EPU	High EPU
Patent	0.10609***	0.01446		
	(6.27)	(0.94)		
Invention Patent			0.14651***	0.01446
			(6.46)	(0.94)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
N	5,863	5,906	5,863	5,906
Within R^2	0.0234	0.0939	0.0251	0.0939

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

Next, we check the robustness of the results by replacing the key variables and estimation strategies. Model 1 in Table 4.7 replaces the previous EPU index with the newspaper-based indices derived from two major Chinese newspapers: the Renmin Daily and the Guangming Daily. Model 2 in Table 4.7 uses the natural logarithm of one plus the number of invention patents as a substitute for the dependent variable because invention patents are subject to stricter examination than utility model and design patents (Liu & Ma, 2020). Our findings persist based on these alternative measures. Since the initial innovation application is a count-based variable, we also re-estimate our baseline regression employing a count-based model. The variance of patent counts is much larger than its mean, indicating that the negative binomial model is more suitable than the Poisson model. The empirical results remain robust after we change the estimation strategy (Model 3 in Table 4.7).

In another robustness check, we dispel the doubts about the measurement errors of the BBD index. Previous research has raised the concern that the BBD index might pick up some other macro-level uncertainties that are unrelated to public policy, leading to potential bias in our estimation results. Thus, related studies in the U.S. context remove the common parts of EPU between the U.S. and Canada and extract the residuals as an alternative regressor (D'Mello & Toscano, 2020; Gulen & Ion, 2016; Leung & Sun, 2021; Nguyen & Phan 2017; Phan *et al*., 2019). Following their approaches, we first regress the Chinese BBD index on the global BBD index and other macroeconomic variables, and then pick up the residual as a proxy for EPU in the baseline model estimation. The reason is that China has established close economic ties with other countries through extensive trade and investment since joining the World Trade Organization (WTO) in 2001. Thus, the worldwide economic shocks will also affect the economic fluctuations in China. Our findings still hold after eliminating the possible confounding factors (Model 4 in Table 4.7).

Since our benchmark model does not control for time-fixed effects, if the negative shock caused by the global financial crisis results in a surge in EPU and influences firm investment decisions simultaneously, the previous results could be induced by insufficient control for the neglected negative shock (Leung & Sun, 2021). To ensure the robustness of our results, we first follow Bekaert *et al*. (2014) in setting the years 2008 and 2009 as crisis years and show that our findings still hold when we exclude observations during these two years, which indicates this is not a concern in this study (Model 5 in Table 4.7). Second, although we cannot include time fixed effects in our specifications, we add a linear time trend variable to the regression to disentangle the temporal effect and EPU itself (Yuan *et al*. 2022). Model 6 in Table 4.7 shows the inverted-U relationship remains significant after accounting for the time trend that potentially affects innovation performance. Moreover, to mitigate potential cyclical variations in annually averaged EPU, we adopt the rolling approach proposed by Fama & French (1992) to calculate each firm's exposure to EPU as such:

$$R_{i\tau} - R_{f\tau} = \beta_0 + \beta_{i\tau}^{EPU} EPU_\tau + \beta_{i\tau}^{MKT} MKT_\tau + \beta_{i\tau}^{SMB} SMB_\tau + \beta_{i\tau}^{HML} HML_\tau + \varepsilon_{i\tau} \quad (6)$$

where $R_{i\tau}$ is the monthly stock return of firm *i* in month τ and $R_{f\tau}$ represents the monthly risk-free rate. EPU_τ is the EPU index in month τ. MKT_τ, SMB_τ, and HML_τ refer to the Fama-French three factors in month τ. We use the absolute value of $\beta_{i\tau}^{EPU}$ in December of each year to measure firm i's exposure to EPU (Francis *et al*., 2014). The past 6 months (τ-5, τ), 36 months (τ-35, τ), 48 months (τ-47, τ) and 60 months (τ-59, τ) are set as the rolling windows, representing short-term and long-term exposure respectively. The quadratic relationship between firms' exposure to EPU and innovation performance still holds after adopting the rolling regression (Model 7 in Table 4.7).

Finally, we conduct an ad hoc analysis to examine whether possessing both a high level of operational capability and marketing capability would lead to better innovation performance than just having a single capability. This test may help us further understand the synergy effect of diverse organizational capabilities in dealing with EPU. For each of the two capabilities, a dummy variable is created and assigned 1 if a firm's efficiency is more than the median level of the industry in a given year, and 0 otherwise. *Two Cap* is the product of two dummy variables, which is then included in the regression model to perform a two-way interaction among EPU, operational capability, and marketing capability. The result shows that firms with both higher levels of two capabilities will have a significantly steeper inverted-U curve than those with only one capability or neither (Model 8 in Table 4.7). Furthermore, we investigate the heterogeneity effect of EPU on innovation performance across different industries and find the inverted-U relationship is more pronounced for manufacturing firms, indicating that manufacturing firms may realize better innovation performance from medium levels of EPU. Figure 4.4 presents the heterogeneity effect across different industries.

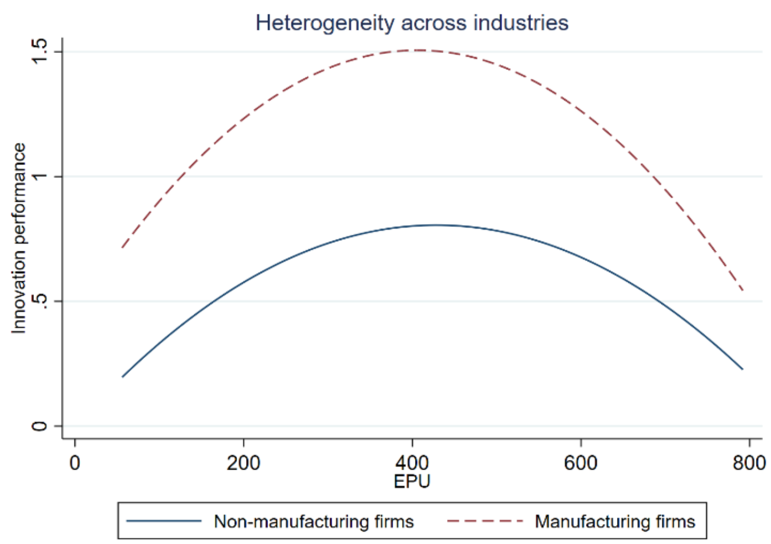

Figure 4.4 The heterogeneity effect across industries.

Table 4.7 Robustness test

	Alternative newspaper	Invention patents	Negative binomial model	U.S. EPU	Deletion of 2008 & 2009	Time trend	Rolling regression: 6 months	Rolling regression: 36 months	Rolling regression: 48 months	Rolling regression: 60 months	Two capabilities
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7				Model 8
EPU Index	0.01623***	0.00284***	0.0042***	0.00212***	0.00413***	0.00244***					0.00249***
	(22.61)	(14.11)	(19.29)	(7.82)	(16.30)	(10.80)					(4.76)
EPU Index^2	-0.00004***	-3.16e-06***	-3.84e-06***	-0.00001***	-0.00001***	-4.05e-06***					-1.70e-06*
	(-25.48)	(-16.54)	(-17.94)	(-16.24)	(-22.27)	(-19.74)					(-1.79)
*EPU Index * Two Cap*											0.00196**
											(2.11)
EPU Index^2 ** Two Cap*											-3.33e-06**
											(-1.96)
EPU Exposure							21.60***	63.52*	262.96***	439.32***	
							(4.02)	(1.81)	(4.05)	(4.06)	
EPU Exposure^2							-1224.1***	-2512.7*	-65516.2**	-161255.5*	
							(-5.56)	(-1.82)	(-2.17)	(-1.85)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time trend	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	NO
N	11,769	11,769	12,369	11,769	10,808	11,769	11,244	9,931	9,931	9,931	9,855
Log likelihood	No	No	-36866.0	No	No	No	No	No	No	No	No
Within R^2	0.3810	0.3459	No	0.3452	0.3835	0.3909	0.3395	0.3371	0.3387	0.3402	0.3891

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

4.5 Summary, Discussion, and Future Research

4.5.1 Summary and Principal Findings

Based on a longitudinal dataset of publicly listed firms from 2000 to 2019, we empirically examine the impact of uncertainty caused by government economic policy changes (EPU) on firms' innovativeness and document an inverted U-shaped relationship in the Chinese context. We conduct a range of additional tests to validate the sensitivity of our results (e.g., alternative measures, IV approach, sub-sample grouping tests) and ultimately reach consistent findings. In addition, our moderating effect analysis shows that firms' operational capability and marketing capability will make the discovered inverted-U relationship steeper. This study provides a new perspective on understanding the EPU-innovation performance link and reconciles the inconsistent findings reported in the prior literature (e.g., Bhattacharya *et al*., 2017; Gulen & Ion, 2016; Pertuze *et al*., 2019; Sarkar, 2021). The research and practical implications of our findings are discussed below.

4.5.2 Implications for Research

Our study makes multiple contributions to the literature, challenging conventional wisdom and enriching our understanding of how EPU influences firms' innovation strategies. First, our study extends the application of the prospect theory in the context of firm-level innovation. Kahneman & Tversky (1979) proposed the prospect theory to explain individual decision-making under risk and uncertainty, which finds resonance in the corporate world through its insights into risk attitudes. By hypothesizing an inverted-U relationship between EPU and firms' innovation performance, we align with prospect theory's premise that individuals, and by extension, firms, exhibit nonlinear responses to risk. Our findings suggest that moderate levels of EPU may trigger firms to adopt more risk-seeking behaviors, akin to the "prospect effect", which denotes increased willingness to take risks in the pursuit of gains.

This extension of the prospect theory to the corporate domain highlights the relevance of psychological factors in shaping firm-level innovation strategies.

Moreover, the study emphasizes the role of complementary assets in shaping the impact of EPU on innovation performance. The complementary assets view posits that the value and effectiveness of a core asset or innovation are contingent on the presence and alignment of supportive complementary resources (Teece, 1986; Wu *et al*., 2014). Our results corroborate this view by demonstrating that firms' operational and marketing capabilities act as crucial complementary assets, enhancing the relationship between EPU and innovation performance. In addition, when firms possess both operational and marketing capabilities at a higher level, the inverted U-shaped curve becomes even steeper compared to having individual moderating impact of each capability alone. In essence, these capabilities serve as mechanisms to navigate and harness the potential benefits of economic uncertainty (Lampert *et al*., 2020). This finding underscores the importance of considering the interplay between core assets and their complementary counterparts in the OM literature.

Furthermore, our study offers theoretical extensions that warrant exploration in future research. For instance, it prompts a deeper investigation into the underlying mechanisms through which operational and marketing capabilities interact with EPU to promote innovation. This might involve delving into the specific strategies and practices that firms employ when facing moderate EPU levels, such as agile product development, dynamic marketing campaigns, or adaptive supply chain management. These insights could lead to the development of more nuanced theoretical frameworks regarding the interplay between core assets, complementary assets, and external environmental factors.

In short, our study contributes to the theoretical understanding of the relationship between EPU and innovation performance, expanding the applicability of the prospect theory in the corporate context and shedding light on the vital role of complementary assets in navigating

EPU. These theoretical insights offer new perspectives on how firms can harness the moderated economic uncertainty to drive innovation, paving the way for a more comprehensive understanding of strategic decision-making in an ever-changing business landscape.

4.5.3 Implications for Practices

This study also provides several practical implications for managers and regulators. First, our findings reveal that different degrees of EPU may lead to diametrically opposite innovative outcomes. A moderate level of EPU implies desirable growth opportunities and may encourage firms to embrace innovation, whereas excessive EPU will hinder innovative and risky behavior. This finding is particularly important for corporate managers since the awareness of this tendency could help organizations predict competitors' actions against EPU and make proper allocation of organizational resources in advance. For instance, managers may preempt their opponents' moves and take the lead in grabbing market share as soon as policies change. Instead, when EPU is extremely high, managers need to be vigilant because its negative impact on firm operations may far outweigh its potential benefits and, under the circumstances, a conservative strategy may be more appropriate. In short, managers should realize the pros and cons of EPU and strategically adjust the operational strategy when facing different levels of EPU.

Second, managers should also be aware of the importance of operational capability and marketing capability in the relationship between EPU and innovation performance. While there is no one-size-fits-all approach to dealing with EPU, a firm is better able to react to customer needs and discover new market opportunities in an uncertain environment by building stronger operational and marketing capabilities. If conditions permit, firms should possess a high level of both capabilities, as this will allow them to achieve better innovation performance.

Finally, policymakers in developing countries might maintain the policy-related uncertainty at a moderate level to avoid unilaterally impeding corporate innovation. Neither invariable nor excessively changing EPU is beneficial for firms to engage in innovation activities. Our findings suggest that policymakers not only consider the impact of the policy itself when exercising power, but also take the uncertainty induced by policy changes into account. Understanding this mechanism will be more helpful for governments to develop scientific and accurate policies.

4.5.4 Limitations and Future Research Directions

Like other secondary data-based OM research, this study is not without limitations, which also provide several avenues for future research. First, our sample is only limited to publicly listed firms in China. Although it is acceptable to select Chinese firms when focusing on emerging economies, subsequent research scenarios can be shifted to other developing countries (e.g., Brazil, India, Russia, and South Africa) to test the generalizability of our results. We believe that policy-related studies in emerging market economies will be a promising direction for future empirical OM research. Besides, future studies can also investigate whether our findings are applicable to non-public firms, which face more challenges and are more vulnerable to EPU.

Second, our sample period begins in 2000 and ends in 2019 due to data availability. Another noticeable issue is that the BBD index and innovation data are both captured on an annual basis, which largely reduces the overall sample size. Therefore, more data from other countries and longer time horizons could be supplemented in future research. Such investigations can better reveal the EPU-strategic firm behavior linkage and help verify the conclusions drawn in our research.

Finally, in terms of the theoretical lens, despite that prospect theory fits our research purpose, we suggest that other theoretical perspectives be deployed in future related studies.

For instance, signaling theory could be used to interpret how the macro-level signals related to policy variation and industry-level signals correlated with resource availability are perceived by the firms (Connelly *et al*., 2011). Complementary or competing theories can provide diverse insights and shed additional light on this issue. Accordingly, other contingent factors could also be explored to enhance our understanding of the boundary conditions of the impacts of EPU in the future.

Chapter 5 Conclusion

5.1. Summary of the Findings

This thesis examines the impact of three emerging exogenous risks on firm performance and the corresponding strategies for mitigation. Compared to endogenous risks within firms and supply chains, exogenous disruptions have been less explored in prior research. This thesis contributes to a deeper understanding of how exogenous disruptions affect firm financial, operational, and innovation performance, while also proposing targeted strategies to mitigate their adverse effects. Specifically, the main findings of these three studies are summarized as follows:

Study 1 investigates the direct impact of extreme weather events on firm operational performance and evaluates the moderating effects of three buffering or bridging strategies. Specifically, extreme weather is proxied by six types of natural hazards (i.e., droughts, extreme temperatures, wildfires, landslides, floods, and storms). A staggered difference-in-differences (DID) method is used to infer the causal relationship between weather shocks and labor productivity. The results reveal a significant negative impact of extreme weather events on firm labor productivity. Moreover, strategies such as operational slack, cash hedging, and digital technology deployment are found to effectively mitigate such adverse effects. The findings remain robust across a range of robustness checks including parallel trend analysis, alternative measures, Mahalanobis distance matching approach, placebo test, and adjustment of estimation window.

In Study 2, we evaluate the effect of carbon risk on firm financial performance measured by Tobin' q and identify a negative association between carbon risk and firm performance. The causal link is further consolidated through various methods, including alternative measures, the instrumental variable (IV) approach, the treatment effect model, system generalized method of moments (GMM) estimation, and a quasi-natural experiment. Additionally, we find that strategies such as production efficiency and green innovation help mitigate the negative effects of carbon risk. Although ESG performance did not show a significant moderating effect across the entire sample, further analysis indicates that only companies with lower levels of greenwashing benefit from its protective effect. Lastly, we observe that the market generally penalizes carbon emissions across all firms. However, firms that voluntarily disclose their emission information experience a smaller decline in value compared to those that do not disclose such information, shedding light on the underlying causes behind carbon emission disclosures.

Study 3 explores the influence of EPU on firm innovation performance and the moderating effects of complementary organizational capabilities. The results indicate an inverted U-shaped relationship between EPU and innovation incentives. Further analysis of the moderating effects reveals that this inverted U-curve becomes steeper with higher levels of firm operational and marketing capabilities. These findings remain robust across various tests, including the inverted U-shape relationship test, alternative measures, the instrumental variable (IV) approach, and subsample analysis.

5.2 Implications for Research

This thesis contributes to the relevant research in several ways. Study 1 enriches the literature on extreme weather by providing direct evidence of its impact on firm-level operations in emerging markets, contrasting with prior research that primarily focuses on developed markets or financial outcomes. Furthermore, it contributes to disaster management research by demonstrating the effectiveness of leveraging operational slack, digital technology, and cash hedging in mitigating the adverse effects of extreme weather events. While prior research mainly focuses on the use of slack and hedging to manage endogenous disruptions, this study illustrates their applicability in addressing exogenous shocks such as extreme weather. By integrating operational flow, financial flow, and information flow, this study emphasizes the importance of an integrated approach to managing exogenous risks, suggesting that both buffering and bridging strategies are essential for minimizing disruptions caused by extreme weather shocks. These contributions enhance our understanding of how firms can navigate extreme weather challenges and pave the way for further research on their operational and supply chain responses in similar disruptive contexts.

Study 2 makes valuable theoretical contributions to the fields of sustainable operations management (OM) and environmental disclosure. By providing empirical evidence from China, it deepens our understanding of the financial implications of carbon risk in emerging markets and highlights the critical role of local institutional contexts in shaping the relationship between emissions and financial performance. While existing literature has explored the consequences of carbon risk, it has offered limited insights into mitigation strategies. This study contributes theoretically by demonstrating that operational strategies aligned with the Natural Resource-Based View (NRBV) can mitigate the negative financial impacts of carbon risk. Furthermore, Study 2 enriches the environmental disclosure literature by emphasizing the importance of authenticity in ESG practices. Investors respond more favorably to firms with transparent, substantive environmental actions, suggesting that voluntary disclosure can mitigate the financial penalties associated with carbon emissions, particularly in China's market context.

Study 3 adopts prospect theory as a novel theoretical lens to explore how economic policy uncertainty (EPU) influences corporate innovation strategies, bridging the gap between existing literature and real-world cases. Unlike the conventional real options theory, which suggests a monotonic negative impact of EPU on firm investment, this study finds an inverted U-shaped relationship between EPU and firm innovation performance. Specifically, moderate levels of EPU can encourage risk-seeking behavior among firms, thus enriching existing perspectives on decision-making under uncertainty. Furthermore, the study emphasizes the critical role of complementary assets, particularly operational and marketing capabilities, in moderating the relationship between EPU and innovation performance. The findings indicate that both capabilities serve as mechanisms to help firms navigate and capitalize on the potential benefits of EPU. As the levels of these capabilities increase, the inverted U-shaped relationship becomes more pronounced. These insights contribute to the theoretical perspective on the impact of EPU on innovation performance and offer a more nuanced understanding of strategic decision-making in turbulent environments.

5.3 Implications for Practices

This thesis offers several managerial implications. First, it suggests that companies are encouraged to integrate climate-related risks into their daily strategic planning. To this end, establishing a dedicated committee to oversee climate-related policies can help firms better manage weather-related disruptions. Furthermore, taking proactive steps to enhance infrastructure resilience is essential. Regular evaluations and reinforcement of both physical and digital infrastructure are necessary to protect critical assets, such as data centers. Firms should also prepare contingency plans, ensuring they are ready to migrate critical data ahead of potential crises. The study also underscores the value of operational slack, digital tools, and financial hedging strategies in countering productivity losses from extreme weather. In regions susceptible to such risks, it is vital for firms to avoid overemphasizing operational efficiency at the expense of slack, as this could prove counterproductive. Instead, a balanced approach that incorporates both efficiency and operational flexibility is recommended. Leveraging digital technologies, such as cloud-based recovery systems, can facilitate faster recovery processes and maintain the stability of material and information flows. Weather derivatives can be also used to hedge financial risks. Lastly, fostering resilience through effective risk management, transparent stakeholder communication, and financial preparedness is essential to protecting investor confidence and ensuring long-term value. These strategies are crucial for mitigating the negative impacts of extreme weather on market valuation and overall business prospects.

Second, managers are strongly incentivized to proactively reduce emissions, as such actions can significantly enhance long-term firm value. Strategies that focus on improving production efficiency, fostering green innovation, and robustly advancing ESG initiatives are particularly encouraged, as these approaches effectively mitigate the financial risks associated with carbon emissions. By investing in green technologies and integrating sustainable practices throughout their operations, firms can not only comply with regulatory standards but also differentiate themselves in the competitive marketplace. Moreover, managers should prioritize transparency and credibility in their ESG efforts, as these practices are increasingly scrutinized by investors and are more likely to contribute reliably to firm value. For investors, assessing the authenticity of ESG practices and emissions disclosures is essential. Firms that genuinely reduce emissions and adopt sustainable initiatives are more likely to demonstrate greater market resilience and provide long-term benefits. Additionally, voluntary emissions disclosures appear to be correlated with higher firm valuations, suggesting that investors should take this voluntary disclosure behavior into account when evaluating a firm’s sustainability efforts. Finally, policymakers can leverage these insights to develop regulations and standards that promote sustainable business practices, especially in emerging markets. By incentivizing transparent emissions reporting, policymakers can help mitigate the financial penalties associated with high emissions, while promoting both economic and environmental benefits. Furthermore, stricter regulations against greenwashing would ensure the credibility of firms’ environmental claims, aligning sustainable practices with firm value and contributing to broader societal goals.

Third, the innovation performance of firms may vary depending on the level of EPU they face. A moderate level of EPU can stimulate innovation by presenting growth prospects, whereas high EPU typically dampens risk-taking behavior. This insight holds value for corporate managers, as it allows them to anticipate competitors' responses to EPU fluctuations and allocate resources more strategically. For instance, managers may capitalize on emerging market opportunities promptly when policy changes occur. In contrast, during periods of high EPU, a more cautious strategy may be necessary to protect the firm from potential operational disruptions. Thus, it is crucial for managers to understand the dual nature of EPU and adjust their strategies based on its intensity. Thus, it is crucial for managers to recognize the dual nature of EPU and adjust their strategies accordingly based on its intensity. Moreover, firms with robust operational and marketing capabilities are better equipped to respond to market demands and capitalize on opportunities in uncertain environments. The impact is further enhanced when both capabilities are developed in tandem. Finally, policymakers, especially in developing countries, should strive for balanced policy changes that are neither too rigid nor overly volatile. They should consider both the direct effects of their policies and the uncertainty they generate, thereby fostering a more stable environment conducive to innovation.

5.4 Limitations and Future Research Directions

As with any empirical study based on secondary data, this thesis has several limitations, which also presents avenues for future research. First, our sample is limited to publicly listed companies in China, which constrains the generalizability of the findings. Given that institutional environments, market characteristics, and cultural contexts differ significantly across countries, the results may not be directly applicable to other regions or types of firms. Future research could expand the sample to include firms from various countries, thereby testing the global applicability of these conclusions. Furthermore, cross-national comparative studies would help uncover how responses to exogenous risks are contingent on institutional environments, providing deeper insights into the diverse strategies firms adopt in managing such risks.

Second, due to data limitations, our study is unable to capture certain finer variables. For instance, the lack of detailed location data for each subsidiary and factory means that this thesis only considers the impact of extreme weather on the headquarters of publicly listed firms. This limitation may have led to an underestimation of the negative effects of extreme weather on firm performance. Moreover, extreme weather is measured using a binary variable that indicates whether an event occurred. While this approach allows for objective recording of extreme weather events and facilitates effective causal inference, it does not offer a more detailed understanding of the specific characteristics of these events, such as wind speed, precipitation, maximum temperature, and other related dimensions. Future research could incorporate more granular data over longer time horizons, thereby generating more nuanced insights

Third, from a theoretical perspective, future research in risk management would benefit from incorporating a wider range of theoretical approaches, with a particular focus on exploring additional contingent factors. A deeper investigation into a wider variety of operational strategies will greatly enhance our understanding of how to improve firm resilience and competitive advantage, while also contributing to a more nuanced understanding of potential causal relationships, ultimately offering more practical insights.

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