Essays on Corporate Performance under Technological Competition

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Abstract

This thesis presents three studies related to the innovation competition. Chapter 1 acts as the outline and introduction for the thesis.

Chapter 2 investigates relationship between technological peer pressure (TPP) and corporate sustainability performance. We uncover strong and robust evidence that TPP decreases corporates' environmental and social performance. Our empirical findings support the view that resource constraints and agency problems serve as channels in establishing this relationship. Additional analyses reveal an industry heterogeneity for this relation, with stronger negative impacts observed in firms with characteristics of high research and development (R&D) intensity, in high-tech industries, non-customer-facing sectors, and "green" industries. In summary, our results highlight the importance of technological competition in the product market in the knowledge-based economy, as well as firms' sustainability strategies in competitive industries.

Chapter 3 explores the relationship between TPP and firms' mergers and acquisitions (M&As) activities. We provide compelling evidence that TPP serves as a significant motivator for firms to pursue acquisitions. Facing heightened technological pressure from peers, firms exhibit an increased propensity for diversifying acquisitions and targeting innovative companies. Furthermore, our findings demonstrate a positive correlation between acquisitions driven by TPP and improved firm performance, measured by cumulative abnormal returns. Cross-sectional analyses reveal that TPP-driven acquisitions in high-tech industries and single-segment firms lead to superior postmerger performance for the acquirers. Additionally, TPP-induced acquisitions take less time to complete. In conclusion, this research highlights the critical role of technological competition in the product market, particularly within the knowledge-based economy.

In Chapter 4, we present convincing evidence that green technological peer pressure positively correlates with stock returns. This relationship holds across different portfolio sorting techniques and is unaffected by common market factors. Additionally, we observe that this positive impact is pronounced during times of heightened public concern about climate change. Specifically, the influence of green technological peer pressure on stock returns is salient only in periods of increased climate change awareness. Overall, our findings deepen the understanding of the important role of green innovation and its valuation in the stock market.

Chapter 5 concludes this thesis by highlighting significant remarks, limitations, and avenues for future research.

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Declaration

Chapter 2 of this thesis is based on the paper "Technological Peer Pressure and Corporate Sustainability" coauthored by myself, Cheng Yan, Yuqian Zhao. This paper was published in *Energy Economics* in 2024, with me serving as the primary author.

I hereby declare that all information in this thesis has been obtained and presented in accordance with academic rules and ethical conduct. Furthermore, all material and results that are not original to this work have been properly cited and referenced. This thesis is an original work and has not been submitted elsewhere for a degree. No part of this thesis may be quoted or disseminated in any form without the express written consent of the author.

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Chapter 1

Introduction

1.1 Background and motivation

Innovation is widely regarded as a driving force behind competitive advantage at both the national and firm levels (Solow, 1956, 1957), particularly in the U.S., where technology has been the primary driver of economic growth (Solow, 1956; Zingales, 2000; Eisdorfer and Hsu, 2011). The capacity for innovation is crucial for firms to maintain competitiveness, ensure their success, and even secure their survival (Cao et al., 2018). Given the important role of innovation, it is interesting to explore how firms adjust their financing decisions, investment decisions, and corporate governance in response to intense innovation competition. Therefore, this thesis aims to answer this question through three interlinked essays that examine the relationships between innovation competition and corporate sustainability performance, acquisition decisions, and stock market reactions.

The seminal study on technological competition originates from Joseph Schumpeter's work Schumpeter (1942). Schumpeter introduces the concept of "creative destruction," which describes the process by which innovation transforms or replaces old industries. According to him, firms compete by developing new products, technologies, or processes, rather than merely lowering prices or increasing output. He argues that the possibility of gaining market power incentivizes firms to pursue innovation. Based on this idea, Futia (1980) provides a theoretical framework for understanding how technological innovation drives market dynamics, particularly in industries where firms continually strive to disrupt their competitors through the development of new products or processes. Specifically, Futia (1980) constructs a dynamic, stochastic model based on Schumpeterian competition, demonstrating that the competitive advantages and economic rents obtained by firms through innovation are temporary. Over time, these advantages are eroded by imitation, the entry of new firms into the market, and further innovations by rivals. Building on the concept of Schumpeterian competition, a substantial body of literature explores various aspects of technological competition (e.g., Wersching, 2010; Weeds, 2002; Winter, 1984).

Despite the extensive theoretical literature on technological competition, there is scant empirical research on its effects. A large literature explores how product market competition shape firms' behavior (e.g., Srinivasan, 2020; Hoberg and Phillips, 2010; Li and Zhan, 2019; Alimov, 2014). Some recent studies investigate the relationship between technology competition and skill specificity of job postings (Cao et al., 2023), product disclosure (Cao et al., 2018), auditors' going-concern assessment (Xu et al., 2022), and corporate bankruptcy (Eisdorfer and Hsu, 2011). Glaeser and Landsman (2021) find technological competition causes firms to delay the disclosure of patent information to prevent releasing proprietary information to their rivals. Kamepalli et al. (2021) argue that firms may acquire their innovative peers to halt the target's ongoing projects and preempt future competition. In this thesis, we aim to extend our understanding of the consequences of technological competition on corporate decision-making.

1.2 Finding and contribution

In Chapter 2, by using the panel data of publicly traded firms in the U.S. from 2002 to 2021, we find technological peer pressure is negatively associated with firms' environmental and social engagement. Our main finding is unaffected when conducting a battery of robustness tests. Specifically, we use (1) the MSCI ESG KLD database as alternative data source to ensure our finding is not biased from the disparity of ESG rating methodology, (2) additional controls for other aspects of competition and fixed effects (such as state fixed effect) to account for omitted variables, (3) different model specification, (4) control the effect of corporate social responsibility reports disclosure, and (5) a regulatory event—the introduction of state-level R&D tax credits as an instrumental variable to address potential endogeneity concerns.

To explore plausible underlying mechanisms that could explain the observed negative relationship, we attribute the inferior E&S performance under technological threats to resource constraints and agency problems. First, our results suggest that the effect of intensifying technological competition on E&S performance is less pronounced for firms with greater financial slack. This is consistent with the findings of Xu and Kim (2022) that financial constraints are negatively associated with corporate social responsibility engagement. Additionally, we examine firms' strategies of becoming either E&S specialists, who invest in a narrow range of E&S activities, or generalists, who distribute their investments equally across all E&S categories. We find that, , under technological peer pressure, firms tend to specialize in E&S factors rather than adopting a generalist approach. This aligns with the idea that undertaking a wide range of sustainability activities introduces barriers for firms by requiring multidimensional knowledge (Fu et al., 2020). Under intense competition, firms prefer to be involved in a narrow range of E&S activities due to limited resources. Finally, we investigate the resource constraint channel by examining whether innovation efficiency alters our main results. We find that the impact is weaker for firms with high innovation efficiency, indicating that these firms can achieve innovation success even with limited resources. Our findings also support the view that managers engage in E&S policies for their private interests (e.g. Ho et al., 2023).Using proxies from both the CEO and board perspectives, we observe that the negative relationship is more pronounced in firms with potential agency problems, aligning with the notion of product market competition's disciplinary role (e.g., Chen et al., 2023a).

We further explore cross-sectional heterogeneity from various perspectives. First, we investigate whether our results vary based on R&D investment intensity. We divide our sample into R&D-intensive industries and non-R&D-intensive industries by firm's R&D expenditures over its total assets and the classification proposed by Loughran and Ritter (2004). We find that the negative effects of TPP on E&S performance are stronger among the firms operating in the R&D-intensive-industries. One possible explanation is that, due to the cumulative and path-dependent nature of innovation activities, firms in R&D-intensive industries may prioritize R&D and respond significantly to technological threats. Second, we document that this negative relationship is less pronounced for firms in the business-to-consumer (B2C) sectors, where customers are more sensitive to firms' sustainability efforts. Third, we demonstrate a weaker relation between TPP on E&S performance for firms in heavily polluting industries, due to their larger fixed inputs compared with firms operating in "green" industries.

We contribute to the existing literature in three-fold. First, we contribute to the limited but growing body of literature on the corporate consequences of technological peer pressure. We provide robust evidence of a causal relationship between technological peer pressure and corporate sustainability, which is new to the literature. Second, by proposing a new determinant of technological peer pressure, we contribute to the extensive literature on the determinants of corporate sustainability (e.g., Flammer, 2015; Lins et al., 2017). Third, to the best of our knowledge, we are the first to explore the unexpected corporate consequence resulting from the peers' R&D.

In Chapter 3, we investigate how acquisition activity shifts in response to changes in the technological competition landscape. We use a sample of publicly listed firms in the United States (U.S.) over the period 1983-2022 to empirically examine the propensity of making acquisitions. Our findings provide strong evidence that technological peer pressure increases the likelihood of corporate acquisition decisions. The results indicate that the probability of a firm's acquisition probability increases by 0.9%, corresponding to an approximately 8.04% increase from the average probability of the sample of 11.2%. Our main finding remains qualitatively unchanged after conducting a series of robustness tests. Specifically, we employ (1) alternative specifications using linear probability model (LPM) and probit models, (2) patent-based TPP measure, and (3) subsamples by excluding industries with the largest representations. Our findings are unchanged after addressing potential sources of endogeneity by using the matching approaches proposed by Bena and Li (2014) and instrumental variable of introduction of state-level R&D tax credit.

Additionally, we examine the types of M&As undertaken under technological peer pressure, particularly in terms of target selection. We find that firms tend to pursue targets in different industries, suggesting that acquirers are likely to adopt a diversifying strategy to confront threats from technology competition. Furthermore, we observe that acquirers are more inclined to select innovative targets when facing heightened technological competition, which aligns with the findings of Phillips and Zhdanov (2013) and Bena and Li (2014).

To further investigate the positive association between acquisition likelihood and technological peer pressure, we examine the impact of firms' responses to technology competition on shareholder wealth. We run cross-sectional regressions of acquirers' cumulative abnormal returns (CAR) centered on the deal announcement day to capture the short-term effect of technological peer pressure on acquirer shareholder value. Additionally, we use buy-and-hold abnormal returns (BHAR) to evaluate the quality of M&As over the long term. The evidence indicates that firms acquiring in response to intense technological competition create positive shareholder wealth. Furthermore, we find acquirers do not overpay in M&A deals motivated by TPP. Taken together, our findings provide robust evidence that mergers and acquisitions are an optimal response to technological peer pressure.

Lastly, we explore the cross-sectional heterogeneity of our findings and the relationship between TPP and deal characteristics. First, we examine whether M&A quality varies by industry characteristics. We find that post-merger performance is more pronounced among high-tech industries, confirming the importance of innovation in technologically competitive sectors. Firms operating in a single segment also experiences higher long-term announcement returns. Second, we discover that acquisitions driven by TPP have a shorter time of deal completion. Additionally, firms prefer cash financing over equity financing as the M&A payment method.

We make three key contributions to the existing literature. First, we deepen the understanding of the determinants of firms' motives to engage in acquisitions. Second, We provide new evidence that firms engage in M&As to maintain competitive advantages and explore potential growth opportunities. (e.g., Hitt et al., 1996; Cassiman et al., 2005). Third, we contribute to the limited but growing body of literature on the corporate consequences arising from technological peer pressure.

Chapter 4 aims to enhance the understanding of green innovation by examining the stock market's reactions to a firm's green innovation preparedness in comparison to its product market competitors. Prior research has predominantly focused on the pricing of carbon transition risk by exploring the relationship between carbon emissions or toxic pollution and cross-sectional stock returns (e.g., Hsu et al., 2023; Bolton and Kacperczyk, 2021; Zhang, 2024; Bolton and Kacperczyk, 2023; Pástor et al., 2021). Recently, a growing body of literature has begun to investigate whether financial markets consider green patents, which indicate a firm's ability to address environmental issues (e.g., Hege et al., 2023, 2024; Andriosopoulos et al., 2022). While these studies have pioneered the investigation into market perceptions of green innovation, there remains a limited understanding of its impact on firms' competition in green innovation. To address this gap, we offer a new perspective by analyzing green innovation competition in the product market and the corresponding reactions of financial markets. We find compelling evidence indicating that green technological peer pressure has a positive relationship with stock returns. Our findings remain robust across various portfolio sorting methods and are unaffected by common factors. Furthermore, we discuss the positive effects observed during periods of increasing public concern about climate change. Specifically, we find that the effect of green technological peer pressure on stock returns is significant only during periods of heightened concern about climate change.

The contribution of this paper is threefold. First, we contribute to the burgeoning research on green innovation by examining the relationship between green technological peer pressure and stock returns. To the best of our knowledge, we are the first to explore financial market reactions to green innovation competition. Second, our paper speaks to the broader literature research regarding climate-related asset pricing. Finally, we contribute to the emerging literature investigating the impact of innovation competition on firms.

1.3 Thesis structure

This thesis is composed of three interlinked essays, presented in Chapters 2, 3, and 4. Each chapter presents original, self-contained research. All references are consolidated at the end of the thesis. Footnotes are numbered from the beginning of each empirical chapter, while page numbers follow a sequential order throughout the thesis. Since these three empirical chapters are presented as working papers co-authored with my supervisors, I use the third person ("we" and "our") instead of the first person ("I" and "my") throughout this thesis.

The remainder of this thesis is organized as follows. In Chapter 2, the research focuses on the impact of technological peer pressure on corporate sustainability performance. In Chapter 3, we investigate whether firms catch up with their competitors' pace of innovation by making external acquisitions. Chapter 4 focuses on the stock market reactions to firms' green technological peer pressure. Chapter 5 provides a summary of the three essays and outlines the conclusions of this thesis. Additionally, we provide suggestions that could guide future research directions based on the limitations of this thesis.

CHAPTER 2

Technological Peer Pressure and Corporate Sustainability

2.1 Introduction

The famous argument by Friedman (1970) is that the primary goal of a firm is to maximize returns to its shareholders. Corporate sustainability is usually considered unnecessary and inconsistent with the goal of profit maximization, potentially harming shareholders' interests. Nonetheless, an increasing number of companies are actively involved in ESG (Environmental, Social and Governance)–related activities. For example, as documented by KPMG in 2020, 96% of the world's largest 250 firms report their engagements and commitments to corporate sustainability, which has increased substantially from 35% in 1999.[1] Many countries and associations also set rules about ESG information disclosure.

Meanwhile, innovation competition has gained increasing attention in today's knowledge-based economy. Both investments in R&D and corporate sustainability are crucial for

[1] See details on: https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2020/11/the-time-has-come.pdf.

satisfying a diverse range of stakeholders. Therefore, firms usually need to strike a balance between investing in R&D and corporate sustainability, given the limited resources (Hull and Rothenberg, 2008; Mithani, 2017). For example, in the pharmaceutical industry, some firms prioritize R&D to compete with their rivals, often at the expense of reducing investments in sustainability activities (IFPMA; Upton, 2017). In this paper, we focus on the aforementioned two fields and aim to answer the question of whether and how technological competition shapes corporate sustainability strategy.

Specifically, the relationship between the technological dimension of product market competition and firm-level sustainable practice is investigated. We focus on technological competition instead of other dimensions of competition, such as price, customer service, and distribution, amongst others, for two reasons. First, it is vital for firms to maintain profitability or even survive in today's knowledge-based economy, especially for firms in the U.S., where technology has been the primary driver of economic growth (Solow, 1956; Zingales, 2000; Eisdorfer and Hsu, 2011). Second, both investments in R&D and sustainability engagement are time-consuming processes. Innovation activities require accumulative investment, and engaging in sustainability, such as investing in workforce health and safety to build loyalty, may pay off in the long term. Thus, under intense technological peer pressure, firms should balance the prioritization of investing in R&D and social responsibility due to internal competition for scarce resources.

We use the panel data of publicly traded firms in the U.S. from 2002 to 2021 for our study. Following Cao et al. (2018), we construct the technological peer pressure (TPP) to measure technological competition. TPP captures the firm-level technological threats by comparing the R&D stocks of all competitors in an industry to the focal firm's R&D stock. The R&D stock is calculated by the focal firm's cumulative R&D expenditure in most recent years with a 15% decay rate. In other words, TPP measures rivals' technological advances relative to the firm's technological preparedness. Concerning the fact that TPP only measures the competition from an input perspective, we also construct the patent-based TPP for robustness to capture the competitive dynamics on the output side. To measure corporate social responsibility, we mainly use two pillar scores, Environmental and social (E&S), provided by the Thomson Reuters ESG database. We expand our analysis on the heterogeneity across different sustainability dimensions. In additional robustness checks, we use an alternative ESG ranking score as the dependent variable collected from the MSCI ESG KLD database to ensure that our findings are not driven by a particular ESG rating methodology.

Controlling for firm-level determinants of social responsibility identified in the existing literature, we uncover robust evidence that technological peer pressure is negatively associated with firms' environmental and social engagement. Our main finding is unaffected when conducting a battery of robustness tests. To be specific, we use (1) the MSCI ESG KLD database to ensure our finding is not biased from the disparity of ESG rating methodology, (2) additional controls for other aspects of competition and fixed effects (such as state fixed effect) to account for omitted variables, (3) different model specification, (4) control the effect of corporate social responsibility reports disclosure, and (5) a regulatory event—the introduction of state-level R&D tax credits as an instrumental variable to address potential endogeneity concerns.

To shed light on plausible underlying mechanisms that may explain the revealed negative relationship, we attribute the inferior E&S performance under technological threats to resource constraints and agency problems. First, our results indicate that the impact of intensifying technological competition on E&S performance is smaller for firms with more financial slack. This is consistent with the findings of Xu and Kim (2022) that financial constraints are negatively associated with corporate social responsibility engagement. Besides, we investigate firms' strategies of becoming either E&S specialists, who invest in a narrow scope of E&S activities, or generalists, who equally invest in all E&S categories. We find that firms tend to be E&S specialists rather than generalists under technological peer pressure. This aligns with the idea that undertaking a wide range of sustainability activities introduces barriers for firms by requiring multidimensional knowledge (Fu et al., 2020). Under intense competition, firms prefer to be involved in a narrow range of E&S activities due to limited resources. Finally, we investigate the resource constraint channel by examining whether innovation efficiency alters our main results. We find a weaker impact on high innovation efficiency firms, indicating these firms can achieve innovation success using limited resources. Our findings also support the view that managers engage in E&S policies for their private interests (e.g. Ho et al., 2023). Using proxies from the CEO perspective and board perspective, we observe that the negative relationship is more pronounced in firms with potential agency problems, which is in line with the notion of the disciplinary role of product market competition (e.g., Chen et al., 2023a).

We further explore the cross-sectional heterogeneity from different perspectives. First, we investigate whether there is variation in our results based on R&D investment intensity. We divide our sample into R&D intensive industries and non-R&D intensive industries by firm's R&D expenditures over its total assets and the classification, proposed by Loughran and Ritter (2004). We find that the negative effects of TPP on E&S performance are stronger among the firms operating in the R&D-intensive industries. The possible explanation is that, given the cumulative and path-dependent nature of innovation activities, firms in R&D-intensive industries may prioritize R&D and pronouncedly respond to technological threats. Second, we document that this negative relationship is less pronounced for firms in the business-to-consumer (B2C) sectors where customers are more sensitive to firms' sustainability engagement. Third, we demonstrate a weaker relation between TPP on E&S performance for firms in heavily polluting industries because of their larger fixed inputs compared with firms operating in "green" industries.

Our paper contributes to the existing literature in three-fold. First, we make a contribution to the limited but growing strand of literature on corporate consequences from technological peer pressure. We provide robust evidence of a causal relationship between technological peer pressure and corporate sustainability, which is new to the literature. Previous literature in related fields document the effects of technological peer pressure on product disclosure (Cao et al., 2018), job postings (Cao et al., 2023), auditors' decision-making (Xu et al., 2022) and corporate financial policies (Qiu and Wan, 2015). In this paper, we complement this strand of literature, and our findings shed new light on how technological peer pressure affects corporate social responsibility initiatives and commitments.

Second, by proposing a new determinant of technological peer pressure, we contribute to the large literature on the determinants of corporate sustainability (e.g., Flammer, 2015; Lins et al., 2017). Several studies have documented how the general product market competition influences the corporate social responsibility engagement (e.g., Dupire and M'Zali, 2018; Flammer, 2015; Ding et al., 2022). However, there is no evidence showing whether and how the technology dimension of competition affects firms' social responsibility performance. Our paper complements this strand of literature by empirically evidencing the negative relationship between technological competition and sustainability practice.

Third, to the best of our knowledge, we are the first to explore the unexpected corporate consequence from the peers' R&D. It is not uncommon to conjecture that the peers' R&D will increase the R&D investment of the focal firm, but the potential cost of this R&D herding phenomenon is unclear. Our findings show that technological threats lead to a decrease in sustainability performance, and this relation can be explained by the resource constraints inside the firm and potential agency concerns.

The remainder of this paper proceeds as follows. Section 2.2 reviews related literature and proposes our hypothesis. Section 2.3 presents our variable construction, data, and sample. Section 2.4 reports our baseline results as well as results from a series of robustness tests. Section 2.5 discusses the cross-sectional heterogeneity and we conclude in Section 2.6.

2.2 Literature review and hypothesis development

2.2.1 Literature review

The motivations and consequences for firms' engagement in ESG have been discussed in recent research (e.g., Bénabou and Tirole, 2010; Aguinis and Glavas, 2012), although no consensus has been reached. In general, the motivations and consequences of striving for ESG performance can be categorized into three main groups: the first category is commonly referred to as "doing well by doing good", suggesting that if a firm acts as a responsible corporate citizen, its firm value, profitability, and competitiveness can be enhanced (Deng et al., 2013; Flammer, 2015). The second perspective considers ESG as a response to stakeholders' demands for corporations to deal with market failures and offers public goods, especially for state-owned enterprises (Hsu et al., 2021). The third category regards ESG as a sign of agency problem that raises corporate governance issues, such as insiders enhancing their reputation with charities (Barnea and Rubin, 2010) or political causes (Di Giuli and Kostovetsky, 2014) by investing in ESG.

There is a growing body of research investigating the determinants of corporate sustainability at both the macro and micro levels. Some of these studies explore how social norms, characteristics of the economies, and regulations affect firms' social responsible engagements (Di Giuli and Kostovetsky, 2014; Liang and Renneboog, 2017; Ding et al., 2022; Peng et al., 2023). There is a stream of literature focusing on whether and how a firm's financial status, such as profitability, credit constraints, and ownership, influences corporate sustainability (Hong et al., 2012; Dyck et al., 2019; Xu and Kim, 2022; Hsu et al., 2021). From an insider horizon, the characteristics of firms' leadership and corporate governance structures also play crucial roles in firms' engagement in socially responsible activities (Ferrell et al., 2016; O'Sullivan et al., 2021; Benlemlih et al., 2022). Additionally, some research works document that the peer effect plays an important role in firms' corporate sustainability decisions (Li and Wang, 2022).

The existing research on corporate sustainability determinants presents diverse perspectives on the impact of competition on corporate sustainability. Some researchers suggest that the firms would look for a product differentiation strategy to enhance market power or establish a stronger connection with their customers by prompting better social performance (Flammer, 2015; Dupire and M'Zali, 2018; Leong and Yang, 2020; Fernández-Kranz and Santaló, 2010; Du et al., 2011; Ding et al., 2022). The product differentiation strategy can help them keep profitability or at least survive in the intense competition environment. For instance, employing a difference-in-differences methodology, Flammer (2015) finds that importing tariff reductions (exogenous increase in competition) increases firms' corporate social responsibility performance. Besides, engaging in socially responsible practices can be regarded as a strategy to compete, as good social responsibility performance leads to lower cost of capital (El Ghoul et al., 2011; Cheng et al., 2014). To sum up, the existing studies indicate the strategic nature of social initiatives.

Another vein of literature demonstrates competitive product market environment can reduce investment in corporate sustainability. These studies are in line with the resource constraints view (Hong et al., 2012; Xu and Kim, 2022), and agency concerns view (Ferrell et al., 2016; Krüger, 2015; Hsu et al., 2021) on corporate sustainability. Hong et al. (2012) consider corporate sustainability as a luxurious good so only well-performed firms can afford it, which also refers to "doing good by doing well". In the context of competition, with the squeezed profit margin, firms are forced to focus on survival, leading to an abandonment of long-term investment, such as corporate sustainability. What is more, prior literature shows the disciplinary role of the product market competition in curbing insiders' behaviour to pursue private interests, such as political career, positive image to the public, or just personal preference (Di Giuli and Kostovetsky, 2014; Masulis and Reza, 2015). Hence, firms tend to reduce their sustainability investment under intensifying competition.

Nonetheless, the existing studies mainly use the Hirschman-Herfindahl Index (HHI) or 10-K-based Product Market Fluidity (introduced by Hoberg et al. (2014)) as proxies of product market competition. There are few works of literature that directly discuss the relationship between technological competition and corporate sustainability. Therefore, further empirical analyses and discussions on this specific relationship are needed. Our paper aims to fill this research gap.

2.2.2 Hypothesis development

To explore the relationship between technological competition and corporate sustainability, we draw upon arguments related to resource constraints and agency problems. First, intensifying product market competition can diminish corporate sustainability activities due to resource constraints. Firms facing resource constraints tend to forgo long-term investment, such as corporate sustainability, which has been well documented in previous studies (e.g., Hong et al., 2012). In the context of technological competition, firms are concerned about losing market power and growth opportunities, and may even face survival challenges if they cannot maintain a competitive advantage in the innovation competition (Cao et al., 2018). In a knowledge-based economy, succeeding firms in technological competition gain market power by reducing production costs, developing new products or product lines, and adding new features to their product. Thus, innovation capability is critical to firms. At the same time, R&D activities require significantly fixed assets investing, while corporate sustainability demands lower investments in fixed assets, making it comparatively easier to reverse. Hence, when facing threats from rivals' technological advances, a firm may cut its expenditure on corporate social responsibility practices with constrained resources.

Second, according to the agency model, product market competition can reduce corporate sustainability by restraining firm insiders' pursuits of personal interests through socially responsible activities. Jensen (1986) and Jensen and Meckling (1976) point out that managers have the incentives to overinvest for their own interests. Insiders may pursue their personal interests due to the severe information asymmetry problem in a less competitive market. Besides, because the majority of corporate sustainability activities require long-term investment and only yield results over the long term, their actions might not be immediately recognized. By investing in socially responsible activities, insiders may benefit from obtaining positive reputations, establishing social visibility after retiring from the company, and satisfying personal altruistic preferences. Furthermore, shareholders are willing to sacrifice for corporate sustainability when they are satisfied with the firm's profitability (Fernández-Kranz and Santaló, 2010). Thus, in an intensifying market competition industry, the squeezed profit margin compels insiders to focus on firm survival, and as a result, firms can behave worse in social responsibility performance. Consequently, a firm's corporate sustainability efforts may be caused by the agency concern. Based on the aforementioned literature and discussion, we propose the following:

Hypothesis: Technological peer pressure has a negative effect on firms' corporate sustainability performance.

2.3 Measures, data and sample

In this section, we introduce the data sources and discuss the construction of the main variables that will be used in the empirical analyses. We also present the distribution and descriptive statistics of our sample.

2.3.1 Measures

Corporate sustainability performance

To evaluate the firm-level social responsibility performance, we obtain data from the Refinitiv ESG database (also known as Thomson Reuters ASSET 4), which has been extensively adopted by researchers in corporate social responsibility related studies (e.g., Amiraslani et al., 2023; Asimakopoulos et al., 2023). Based on verifiable reported data in the public domain, such as annual reports, company websites, NGO websites, stock exchange filings, media outlets, and sustainability or ESG reports in the public domain, Refinitiv ESG ratings consist of over 450 ESG measures (including both ESG compliance and ESG initiatives) with a history dating back to 2002. We focus on the Environmental and Social pillar scores as the primary proxies of firms' social responsibility performance.[2]

Refinitiv rates firms' environmental performance in three categories[3]: product innovation, resource reduction, and emission reduction. Social performance is evaluated in four categories: product responsibility, community, human rights, and workforce. Each subcategory contains several E&S performance themes. For example, the emission reduction category contains four themes: carbon dioxide emission, waste, biodiversity, and environmental management systems. The product responsibility category covers themes of responsible marketing, product quality, and data privacy. The environmental and social scores are the relative sum of the category weights, which can vary across

[2]The Governance pillar score is excluded in our analysis because we are interested in the effect of technological peer pressure on environmental and social activities. It is common in the literature on corporate social responsibility that researchers always focus on environmental and social performance and exclude the financial and governance factors in the analysis (e.g., Dyck et al., 2019; Albuquerque et al., 2020; Naughton et al., 2019). However, when we investigate firms' engagement in governance issues by using the corporate governance pillar score, the explored negative relationship still holds.

[3]The Refinitiv ESG score structure is shown in Figure 2.1. The definitions of each Environmental and Social categories and sub-categories are presented in Table A1.

industries. The pillar weights are normalized to percentages ranging between 0 and 100 (also in letter grades from D- to A+) and provided annually.

In our paper, we consider firms with at least two years of historical data available, and most of the firms (approximately 95.3% of observations) are covered from 2005 onward.[4] For robustness checks in Section 4.2, we also obtain E&S performance data from the MSCI ESG KLD database (KLD), which is another major ESG data provider, to avoid potential bias with respect to the choice of data vendors.

Technological peer pressure

One important part of this paper is to calculate the technological competition in the product market, which will be the key independent variable in our analysis. Although there are some technological competition measures proposed in recent studies, those measures mainly capture the technological competition in the technology space (Qiu and Wan, 2015; Bloom et al., 2013; Glaeser and Landsman, 2021). The measure of technological peer pressure (TPP) is inspired by the product market rivalry variable proposed in Bloom et al. (2013). Cao et al. (2018) modify it and construct the TPP variable, which gauges a firm's technological threat that comes from its peers' technological advances proxied by R&D investments. The logic behind this is that a sample firm i's technological threat comes from a peer firm j's R&D stock $G_{j,t}$ at the end of year t weighted by the closeness ω_{ij} between these two firms in the product market. Considering the R&D investment benefits a firm in an extended period, Bloom et al. (2013) apply a depreciation rate of 15% when calculating $G_{j,t}$, following Jaffe (1986): $G_{j,t} = R\&D_{j,t} + (1 - 15\%) * G_{j,t-1}$, where $R\&D_{j.t}$ is the R&D expenditure in year t.

[4]We also conduct a subsample analysis by dropping the firms with observations of less than 5 consecutive years. The coefficients of TPP are still significant at the 1% level.

The closeness between two firms, ω_{ij}, is calculated in the product market space using firm i's and j's sales in every four-digit Standard Industrial Classification (SIC) industries according to the Compustat Historical Segment database.[5] We denote V_i a K-dimensional vector for firm i's share of sales in every four-digit industry k. In our sample, each firm reports sales in 2.66 different four-digit industries on average, spanning 224 industries. Then, ω_{ij} can be defined as the cosine of vectors V_i and V_j in the product market space:

$$\omega_{ij} \equiv cos(\theta_{ij}) = \left\langle \frac{V_i}{\|V_i\|} \cdot \frac{V_j}{\|V_j\|} \right\rangle = \frac{\sum_{k=1}^{K} v_{ik} v_{jk}}{\sqrt{\sum_{k=1}^{K} v_{ik}^2}\sqrt{\sum_{k=1}^{K} v_{jk}^2}}. \tag{2.1}$$

Cao et al. (2018) formally calculate $TPP_{i,t}$ in Equation (2.2).[6]

$$TPPi,t = ln\left[1 + \frac{1}{Gi,t}\sum^{i\neq j} \omega_{ij\times Gj,t}\right]. \tag{2.2}$$

The ratio inside the square brackets captures the relative threat posed by rivals' technological advancements compared to firm i's own level of technological preparedness. Firms with lower investment in technology face greater competitive pressure than those that have invested heavily. A higher value of TPP indicates that a firm is experiencing more intense technological competition, both in terms of its own preparedness and the R&D efforts of its peers.[7] For instance, a TPP value of 5 implies that a firm's peers spend five times more on R&D than the firm itself. In our sample, the mean of TPP is 4.41, which suggests that, on average, peers invest \$81.27 ($e^{4.41} - 1$) in R&D for every

[5]Following Bloom et al. (2013), we use sales from the entire sample span to calculate the proportions of each firm's segment sales crossing our analyses. Our results still hold when using the sales from the previous two years to calculate the proportions of each firm's segment sales following Cao et al. (2018).

[6]The advantages of using TPP are discussed in Cao et al. (2018).

[7]To alleviate the concern that TPP is correlated with other omitted variables, in the untabulated results, we further control whether focal firm lacks R&D investment relative to its rivals. Our main findings are not affected when we conduct the same specification as the baseline regression.

dollar of R&D investment by the focal firm.

Control variables

Following the literature on other explanatory of E&S performance (Chen et al., 2020b; Dyck et al., 2019), we control for a series of firm-level covariates commonly used in most corporate finance research. Based on the accounting data from Compustat, we include the following control variables: firm size (*Size*), *Tobin's Q*, *Leverage*, and *Tangibility*. In particular, *Tobin's Q* and *Tangibility* are assumed positively related to firms' E&S performance. *Leverage* is positively related to firms' E&S performance. In this paper, firm size (*Size*) is measured by the natural log of firms' total assets plus one; *Tobin's Q* is calculated by the total assets minus the book value of equity plus the market value of equity over total assets; *Leverage* is measured as the sum of long-term and current debt deflated over total assets; *Tangibility* is defined as the net property, plants and equipment deflated by total assets. All control variables have been winsorized at the 1% level in each tail, and all price-related variables have been adjusted by CPI. The details about the definitions of all variables used in this study are provided in Appendix Table A1.

2.3.2 Data and sample

Our sample covers public companies listed on the NYSE and NASDAQ. The accounting data are obtained from the Compustat and are used to construct control variables and calculate the TPP. To calculate the closeness of any two firms in the product market, we use the Compustat Historical Segment Dataset on each firm's sales, which is broken down into four-digit SIC codes. The E&S performance data is from the Refinitiv ESG database. The full sample period ranges from 2002 to 2021 fiscal year. The sample starts in 2002 since it is the first year of firm-level ESG ranks available from Refinitiv.

We start with a total of 118,973 firm-year observations, and we then exclude 12,074 observations from the finance industry (SIC 6000-6999) and utility industry (SIC 4900-4999) because these industries have different competition landscapes and unique nature of their business operations (Li and Zhan, 2019). Second, we drop 71,914 firm-year observations that do not have R&D stock information and sales information in the sample year following Cao et al. (2018). Third, we exclude 131 observations without sustainability data. Finally, we eliminate 22,792 observations without the control variables and singleton observations. After these data clean processes, we get an unbalanced panel dataset of 12,062 observations in 1,536 unique firms from 2002 to 2021.[8] Table 2.1 reports our sample by two-digit industry and year. We find that most of firms from our sample are operating in R&D-intensive industries, and the Refinitiv ESG database covers more firms in recent years. Table 2.2 shows descriptive statistics for all variables used for primary results. One can refer to Table A1 in the Appendix for the definition of the variables.

[Insert Table 2.1 and Table 2.2 here.]

We use the lagged TPP as our key independent variable. The mean and standard deviation of TPP_{t-1} are 4.41 and 2.33, respectively, consistent with Cao et al. (2018). The maximum value and mean values of TPP_{t-1} at the enterprise level are 14.23 and 4.41, respectively, and the standard deviation is greater than 1, indicating that there are large gaps between the firms included in the study. The dependent variables in our paper are

[8] According to the methodology of the Refinitiv ESG database, the ESG scores will be marked as "definitive" for all historical years excluding the five most recent. Specifically, in our sample, the years before 2017 are unchanged even if there are changes to the underlying data due to company restatements or data corrections. To alleviate the concern that the changed ESG score may affect our results, we repeat our baseline model using the subsample from 2002 to 2016. The results are quantitatively similar to our baseline results.

Environmental and *Soacial* pillar scores. A larger value of these variables indicates better E&S performance. The standard deviation of *Environmental* and *Soacial* are 31.76 and 23.75, respectively. This shows that there exist big divergences between firms, which is in line with previous studies that firms' social responsibility engagement and compliance are influenced by many factors such as the ownership structure, regions, laws, social forms and industries (Hsu et al., 2021; Cohen et al., 2020; Di Giuli and Kostovetsky, 2014; Liang and Renneboog, 2017; Ding et al., 2022).

Table 2.3 lists the Pearson correlation coefficients for the key variables. Consistent with our conjectures, we observe a significant negative correlation between E&S performance and 1-year lagged TPP, with coefficients of approximately -0.551 and -0.411, respectively. None of the control variables exhibits considerable correlations with the dependent variable $Environmental$ and $Social$, or the explanatory variable TPP to mitigate concern of multicollinearity. Note that the correlations between Refinitiv E&S performance scores and KLD E&S performance scores are lower than 0.4, which is in line with the previous studies about the disparities of E&S performance scores for the same firm crossing different rating agencies (Berg et al., 2022; Chatterji et al., 2016).

[Insert Table 2.3 here.]

2.4 Empirical results

In this section, we empirically verify our main hypothesis by examining whether the technological competition in the product market affects firm-level E&S performance. We subsequently discuss the empirical results. In Section 2.4.1, we introduce the baseline model and report the baseline empirical results. Section 2.4.2 conducts a set of robustness checks by using alternative measures of E&S performance, different fixed effect combinations, and subsample analysis, adding additional control for product market competition. Lastly, to alleviate the endogeneity concerns, we adopt the instrumental variables approach in Section 2.4.3.

2.4.1 Baseline

Let us first concentrate on the following baseline model,

$$Sustainability\ performance_{i,t} = \alpha + \beta TPP_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FEs + \varepsilon_{i,t}. \tag{2.3}$$

where i denotes a firm, and t denotes a year. The dependent variable Sustainability performance can be chosen as either the $Environmental$ or $Social$ rating score for firm i in year t, and the key independent variable $TPP_{i,t-1}$ is the technological peer pressure for firm i in year $t-1$.[9] The coefficient β is what we are interested in, which represents the effect of technological competition on firms' sustainability performance.

$\mathbf{X}_{i,t-1}$ is a vector of the firm-level control variables described in Section 2.3 including *Size*, *Tobin's Q*, *Leverage* and *Tangibility*. FEs are fixed effects. Given the variability of E&S performance across industries and its evolution over time, we add the industry and year fixed effects to further control the time-invariant industry-level characteristics and the variation across years to avoid omitted variables.[10] Throughout empirical analysis, standard errors are clustered at the firm level to correct for cross-section correlation.

As shown in Table 2.4 Column (1) and (4), we first estimate the baseline model without any controls. The coefficients of TPP on $Environmental$ and $Social$ pillars

[9] Our main results are unaffected when we use the log scores of E&S performance instead of raw scores. Besides, we replicate our baseline estimation by using TPP_t as the main independent variable. The coefficients are -1.809 and -1.469 respectively, and they are significant at the 1% significance level.

[10] We use the three-digit SIC code to define industries. Our main results are robust to the Fama-French 48-industry classification for industries.

are, -7.518 and -4.188, respectively, and they both are significant at the 1% significance level. After taking account for the firm-level controls, as well as year- and industry-fixed effects, we find the negative relation between the technological competition in the product market and firm-level E&S performance remains significant both statistically and economically. Specifically, in Column (3), the coefficient of the key dependent variable TPP is -1.883, which implies that a one-standard-deviation increase in TPP is associated with approximately a 4.39 (-1.883*2.33) units decrease in the firm's environmental performance. It accounts for 13.1% (4.39/33.57) of the sample mean of $Environmental$. The magnitude for $Social$, in Column (6), is about 7.3% (-1.528*2.33/48.99).

Moreover, the coefficients of firm-level controls echo the findings in previous research on the determinants of E&S performance. The coefficient of $Size$ and *Tobin's Q* are significantly positive, which indicates bigger firms and better performance firms also do well in E&S activities, which is in line with the view "doing good by doing well" (Hong et al., 2012). The negative association between $Leverage$ and E&S performance is consistent with the findings that financial slack also predicts E&S engagement (Xu and Kim, 2022). Firms with a higher proportion of tangible assets tend to perform better in E&S aspects.

[Insert Table 2.4 here.]

The cost and materiality of corporate sustainability engagement vary among firms (e.g., Khan et al., 2016). To further explore the heterogeneity across different sustainability dimensions, we substitute the dependent variables $Environmental$ and $Social$ with their subcategory scores. This allows us to investigate whether or not our results on the negative relationship are driven by any specific factor. According to the Refinitiv ESG rating methodology, each pillar score is calculated based on the weighted value of its subcategory scores. The Environmental pillar includes subcategory scores of environmental innovation, resource reduction and emission reduction. Social performance is rated in four categories: product responsibility, community, human rights and workforce.[11] As shown in Table 2.5, the coefficients of TPP remain negative significantly across all Environmental and Social subcategory scores. In terms of economic significance, on average, a one-standard-deviation increase in TPP is associated with a decrease of 15.5% in the environmental innovation score and 13.2% in the resource reduction score. Notably, we find that TPP has a big influence on a firm's emission category score. A one-standard-deviation increase in TPP is associated with approximately 5.63 (-2.415*2.33) units decrease in the firm's emission reduction, which accounts for 16.0% of the sample mean of emission reduction score. Consistent with the baseline findings, the economic significance on social category scores, while appearing smaller, still indicates a 3.4% and 6.6% decrease in the community and product responsibility categories, respectively. A potential explanation is that the cost of investment in environment-related activities is relatively higher than those associated with social issues. Thus, firms might be less inclined to engage in these costly activities in conditions of intense technology competition. These findings suggest that TPP remains robust to worsen firms' sustainability, but the magnitude of the impact can vary across subcategories.

[Insert Table 2.5 here.]

[11] The definitions of each category score are shown in Appendix Table A2.

2.4.2 Robustness tests

Alternative measures of ESG

In the baseline regression, we use the Refinitiv ESG rating to proxy firms' sustainability performance. However, some studies find that different methodologies and data sources provided by various ESG rating vendors may result in different ESG scores for the same firm (Berg et al., 2022; Chatterji et al., 2016). Chatterji et al. (2016) suggest cross-validation of the results with alternative ESG data providers. To tackle this issue, we reperform the baseline model using ESG scores from another ESG rating vendor: MSCI ESG KLD database, which has been widely used in previous research (e.g., Cheng et al., 2022; Albuquerque et al., 2019). The KLD provides comprehensive data on firm-level social ratings across a number of criteria, including community, workforce diversity, employee relations, human rights, environment impact, product quality, corporate governance, and whether a firm's operations are related to tobacco, alcohol, gaming, firearms, military contracting, nuclear power. A firm receives one "Strengths" (or "Concerns") point for each socially positive (or poor) act it performs in each dimension. In this study, we only consider the KLD rating scores for environmental and social dimensions (including community, diversity, employee relations and product).[12]

Following previous studies (Deng et al., 2013), we first exclude the controversial business involvement rating, i.e., whether a firm's operations are related to "sin" sectors such as tobacco, and alcohol, because firms can not change their primary business operations, and these dimensions are mainly industry level and only score "Concerns". We calculate the annual Strength (Concern) score by summing up the total number of strengths (concerns) divided by the maximum number of strengths (concerns) for each di-

[12]We exclude the dimension of human rights because this category is only applied to a few companies so the variation of human rights is neligible (Chen et al., 2020b).

mension. Then, we subtract the concerns from the strengths to obtain the total corporate sustainability score: $Environmental\ KLD$ and $Social\ KLD$.

We re-analyse the baseline model using these two sustainability measures as the dependent variables.[13] As shown in Table 3.6 Column (1) and (4), the negative relationship between TPP and firm-level E&S performance remains unchanged. Thus, the association between firms' sustainability performance and TPP is not likely driven by the peculiarity of the Refinitiv data.

As discussed in Section 2.2, a firm that engages in ESG may result from agency problems. Due to the unique rating methodology of the KLD ESG score, i.e., the corporate social responsibility performance equals strengths minus concerns, we can further divide the $Environmental\ KLD$ and $Social\ KLD$ into two parts: Environmental (Social) strength and concern, and then we test if the negative relation between TPP and E&S performance results from agency problems. Indicated by the findings of Krüger (2015) that investors are sensitive to negative ESG events but not to positive ESG events, firms without agency concerns may spare no effort on mitigating the ESG concerns. On the contrary, if the goal of firm insiders is to pursue their own desires, engaging in philanthropy and personal interests, e.g., building a positive socially friendly image, rather than creating value for shareholders, they are more likely to invest more in strengths. Hence, we expect that, when facing intense competition in the product market, the negative relation will be more significant or only exist between TPP and the Strength. We rerun the regression with the dependent variables replaced by Strength and Concern of environmental and social score. Table 3.6 Column (2) and (5) show the negative relations are still significant. In contrast, Column (3) and (6) indicate there is no significant associa-

[13] The latest version of the KLD database has been updated to 2019. Thus, after merging with our main sample, there are fewer observations compared with the baseline regression.

tion between TPP and concerns. These results support the view that E&S engagement stems from agency problems. We will further test the agency view in Section 2.5.2.

Patents-based TPP measure

In our baseline regressions, we construct the TPP based on the firms' R&D investment, which captures the innovation competition on the input side. However, innovation competition is multidimensional as well, such as the race on patenting (e.g., Cappelli et al., 2023; Xu et al., 2023). Consequently, there is a concern that the negative relationship between technological peer pressure and corporate sustainability could be affected by a specific measure of technological peer pressure. To ensure our primary results are robust to alternative measures of TPP, we modify the Equation 2.2 discussed in Section 2.3.1 by replacing R&D stock $G_{j,t}$ with the number of patents filed and issued in a given year t, which are commonly used to measure outputs of innovation (Glaeser and Lang, 2024).[14] The new patent-based TPP captures the level of technology competition from the output perspective. The correlation between the patent-based TPP and our original R&D investment-based TPP is approximately 0.8, indicating a strong connection across different dimensions of technological competition. As presented in Table 2.6 Panel B, the coefficients of TPP are significant statistically and economically. For instance, a one-standard-deviation increase in $TPP\ patent\ filing$ is associated with a decrease of 8.3% and 5.4% to Environmental and Social performance, respectively. The negative relationship between technological peer pressure and firms' E&S performance remains unchanged by investigating the output-side competition of innovation.

[14] The number of observations are fewer than that used in the benchmark regressions due to the absence of patenting information for certain firms in the United States Patent and Trademark Office (USPTO) database. We conduct the baseline regression using the sample of firms with patent information. The primary findings still hold.

[Insert Table 2.6 here.]

Other robustness checks

We conduct a series of robustness tests to mitigate concerns that the negative relation between TPP and E&S performance is driven by omitted variables and sample selection.

Control other dimensions of competition. Our TPP captures the technological competition from one of the dimensions of the product market. There is a concern that this negative relationship between TPP and E&S performance is mainly driven by general product market competition instead of technological competition. Therefore, we add three different firm-specific competition measures in our baseline model separately in order to capture the product market competition in general terms. They are the product market concentration measure Herfindahl-Hirschman Index (HHI), the 10-K Text-based Network Industry Industry concentration ($TNIC - HHI$) and the 10-K based Product Market Fluidity ($Fluidity$). The HHI, calculated as the sum of the squared market share of all members in the focal firm's two-digit SIC industry, is widely used in previous research as the measure of product market competition (e.g., Cao et al., 2023). The $TNIC - HHI$, introduced by Hoberg et al. (2014) and Hoberg and Phillips (2016), are based on the Text-based Network Industry Classifications (TNIC), identifing competitors to each firm using business descriptions disclosed in their 10-Ks.[15] $Fluidity$ measures the similarity between a firm's products and the moves made by its competitors in the firm's product market. The more a firm's product lines overlap with its rivals' product lines, the greater the competitive threat the firm faces. Both of these text-based measures of product market competition have been employed in previous studies (e.g., Chen et al.,

[15] The data are available on the authors' website: https://hobergphillips.tuck.dartmouth.edu/.

2023a; Li and Zhan, 2019; Alimov, 2014). In Table 2.3, we show the correlation between TPP and these three competition measures. The correlations between TPP and HHI, $TNIC - HHI$ and $Fluidity$ are -0.230, -0.134 and 0.256, respectively, which are all significant at the 1% significance level. The low absolute values of the correlations suggest that these measures capture different dimensions of product market competition. Table 2.7 Panel A reports the results after controlling the different product market competition measures. The coefficients of TPP are all significantly negative, and the magnitude is compatible with our baseline results.

Alternative sets of fixed effects. In the baseline regression, we use industry and year level fixed effects to control the industry-level time-invariant factors and year-specific effects. In order to mitigate the concern that our findings are sensitive to the choices of fixed effects combinations, we rerun our baseline regression with other fixed effects. The results are documented in Table 2.7 Panel B. We first control the firm- and year-fixed effects as shown in Column (1) and (4). Then, we add the state fixed effect[16], in Column (2) and (5), since the previous study shows that the headquarter location of firms can influence their ESG engagements due to the political leaning (Di Giuli and Kostovetsky, 2014). Besides, according to Gormley and Matsa (2014)'s findings, it is vital to control industry-year fixed effects as the Refinitiv ESG score is industry-demeaned. We reanalyse the baseline regression with extra industry-year fixed effect to capture the variation from specific years in industries. The results are reported in Table 2.7 Panel B Column (3) and (6). We find that the negative relationship between TPP and firms' E&S performance is robust to different fixed effects combinations.

[16] In the Compustat database, the firms' headquarters state are the current records. Firms sometimes change headquarters. To alleviate this concern, we apply the Firm Historical Headquarter State datasets developed by Gao et al. (2021), who extract the header information from historical SEC filings. The data is shared on the author's personal website: https://mingze-gao.com/posts/firm-historical-headquarter-state-from-10k/#data-available-for-download. The Firm Historical Headquarter State datasets are merged with the dataset used in each chapter of my thesis.

Changes instead of levels. The environmental and social strategies may be stable for several years (Benlemlih et al., 2022). The TPP may influence the E&S strategies differently from these firms to the firms with flexible E&S strategies. To address this concern, we conduct a change model: estimating the association between changes in TPP and changes in E&S performance. As reported in Table 2.7 Panel C, the coefficients of ΔTPPs are still negatively significant at the 10% significance level, indicating that changes in TPP contribute to changes in E&S performance. This is in concordance with our main findings.

Control corporate social responsibility (CSR) reports disclosure. The CSR reporting is one of the main sources for the ESG rating agency to assess firm sustainability engagement. One may argue that the worsened sustainability performance may not driven by the TPP but by the stand-alone CSR reports disclosure. Ryou et al. (2022) find that the heightened product market competition from the reduction in import tariffs decreases the propensity and quality of voluntary corporate social responsibility reporting. To enhance the reliability of our baseline findings, we additionally control the impact of CSR report disclosure. The $CSR\ reports\ disclosure$ indicates whether a firm discloses a separate CSR report or a section on sustainability engagement in its annual report.

Panel D in Table 3.6 presents the results with the same specification as the baseline model, and the coefficients on TPP remain significantly negative. The economic significance of TPP to $Environemntal$ and $Social$ is 13.2% and 7.4%, respectively, which is close to the results obtained from the baseline regressions. These results suggest that this alternative explanation can largely be ruled out after controlling for potential confounding effects.

[Insert Table 2.7 here.]

2.4.3 Endogeneity concerns

The potential endogeneity problem can bias the OLS coefficients. The main concern is the omitted variable issues: some unobservable factors not included in the baseline regression model may affect firms' E&S performance. Furthermore, there is a reverse-causality concern: firms with poor E&S performance often face higher financing costs, which in turn hinders their ability to invest in R&D. Firms would get more technological peer pressure at this time. To address these problems, we adopt an instrumental variable (IV) approach to mitigate the endogeneity concerns.

We employ the introduction of state-level R&D tax credit to calculate the instrumental variable $Tax\ credit$. This event can lower the cost of R&D activities by firms headquartered in the affected states, which introduces exogenous increases to R&D (Wilson, 2009). Thus, $Tax\ credit$ satisfies the relevance requirement for an IV. Besides, the introduction of the state-level R&D tax credit is legislature support that can promote the overall R&D in an economy (Byun et al., 2023; Wilson, 2009), so it is unlikely related to firms' sustainability strategies. We, thereby, deem the state-level R&D tax credit can be regarded as exogenous to firms' E&S performance.

To better understand our IV, we decompose TPP into two components, see Equation (2.4). TPP can be divided by whether the state in which the peer firm is headquartered is the same state as the focal firm.

$$TPPi,t = ln\left\{1+\frac{1}{Gi,t}\left[\sum^{i\neq j}\omega_{ij}\times G_{j,t}\times I(S_{i,t}\neq S_{j,t})+\sum^{i\neq j}\omega_{ij}\times G_{j,t}\times I(S_{i,t}=S_{j,t})\right]\right\}, \tag{2.4}$$

where $I(\cdot)$ is an indicator function that represents if the focal firm and its peer firm are headquartered in the same state. $S_{i,t}$ is the state in which firm i headquarter located in year t.

Then, we can construct our instrumental variable $Tax\ credit$ as follows:

$$Tax\ credit_{i,t} = \sum^{i \neq j} \omega_{ij} \times I(Tax\ credit(S_{j,t})) \times I(S_{i,t} \neq S_{j,t}), \tag{2.5}$$

where $I(Tax\ credit(S_{j,t}))$ denotes if peer firm j is headquartered in the state that has introduced tax credit at year t. The $Tax\ credit$ captures the increases of R&D stocks for the peer firms as the consequence of exogenous regulatory changes. $Tax\ credit$ is highly correlated with TPP but it is unlikely to affect the focal firm's E&S performance.

In Table 2.8, we present the IV estimation results by using $Tax\ credit$ as the instrument variable.[17] We find that, in the first stage, the IV are significantly positively associated with the TPP, as we expected. In the second stage, the fitted values of TPP are negatively related to the $Environmental$ and $Social$ scores, which corroborate our primary findings in Section 2.4.1. The Kleibergen-Paap F statistic is extremely high, which indicates that the instrument is very strong. Thus, the negative relationship between technological peer pressure and firm-level E&S performance remains statistically significant after accounting for the potential endogeneity.

[Insert Table 2.8 here.]

2.5 Cross-sectional analysis

Having identified the negative relationship between technological peer pressure and firm-level E&S performance, we subsequently investigate the cross-sectional heterogene-

[17]We use a reduced sample because the introduction of state-level R&D tax credit only applied to firms headquartered in the U.S.. So the firms located outside the U.S. are excluded. We also repeat the OLS regression using this subsample. The findings in the 2.4.1 are unaffected.

ity of our main results. In this section, we employ multiple tests to explore the potential mechanisms between technological peer pressure and firm-level E&S performance.

2.5.1 Resource constraints

Previous studies have documented that more profitable firms perform better in social responsibility activities, implying that investing in corporate sustainability is luxurious (e.g., Hong et al., 2012). This is in line with the view of corporate sustainability that only well-performing firms can afford to invest in corporate sustainability activities, which is commonly referred to as "doing good by doing well". In this sub-section, we aim to investigate whether the uncovered negative relationship between TPP and E&S performance is driven by limited resources. We conduct several tests to check if this relation can be explained by the resource constraint assumption.

Financial constraints

We first examine if the negative relation between technological peer pressure and firm-level performance arises from financial constraints. Corporate sustainability requires a long-term investment and the benefits of engaging in corporate responsibility are likely to manifest over an extended time horizon (Ding et al., 2022). Several studies have shown that financial constraints are negatively associated with firm-level E&S performance (Di Giuli and Kostovetsky, 2014; Ding et al., 2022; Ma et al., 2023). Investment in E&S-related activities is costly, and only the profitable firms or those with good financial situations can afford such endeavors (Xu and Kim, 2022; Hong et al., 2012). When firms face constraints on financial resources, they are more likely to allocate these limited resources to what they consider as vital for their survival. Therefore, under technological peer pressure, we anticipate that firms are inclined to cut costs on E&S activities. Consequently, the negative relationship between TPP and E&S performance exists.

To test our hypothesis discussed in Section 2.2, we construct two financial constraint proxies to test it. The first is the financial slack, which is computed as the ratio of current assets to current liabilities, and it has been widely used in the literature (e.g., Fu et al., 2020). The second is the cash ratio, calculated as the ratio of cash holdings plus short-term investments over total assets. Firms with lower financial slack and cash holdings experience a weaker financial situation.

We divide our sample into high-constrained and low-constrained groups based on the median of the financial slack and cash ratio. We then rerun the baseline model with these subsamples. The results are presented in Table 2.9 Panel A. Consistent with our prediction and previous research (e.g., Xu and Kim, 2022), we find the negative association is more pronounced if the firms are financially constrained, such as shown in Columns (2) and (6). These results support the view that (a) technological peer pressure motivates firms to reallocate scarce resources between R&D and sustainability (Hull and Rothenberg, 2008; Mithani, 2017), and (b) financially constrained firms are more likely to reduce their ESG investment under intense product market competition (Ding et al., 2022).

ESG specialization

In addition to the financial constraints discussed above, we further investigate whether firms alter their corporate sustainability engagement strategy in response to increased technological competition. Fu et al. (2020) find that firms may specialize in one particular ESG dimension while neglecting others. Engaging in broader dimensions of corporate sustainability activities requires the integration of diverse fields of knowledge, which can be more expensive. Thus, firms may face a tradeoff between engaging in a broad range of corporate sustainability dimensions or concentrating on specific areas, conditioning on limited resources. Given our finding of a negative relation between technological peer pressure and E&S performance, we anticipate that firms may opt to specialize in specific aspects rather than corporate sustainability generalists.

$$Sustainability\ specialization = \frac{\left\{\left[\sum_{i=1}^{n}(Category\ score_i - Pillar\ score)^2\right]/n\right\}^{1/2}}{Pillar\ score}, \tag{2.6}$$

where $Pillar\ score$ is the environmental or social pillar scores; $Category\ score$ is the subdimension scores of each pillar score. To be specific, the environmental pillar comprises three categories: environmental innovation, resource reduction, and emission reduction. Social performance is evaluated in four categories: product responsibility, community, human rights, and workforce. The term n represents the number of categories for each pillar (three for the environmental pillar and four for the social pillar). An increasing corporate sustainability specialization reflects higher levels of firm specialization in corporate sustainability activities.

We report the results of the relation between $Environmental$, $Social\ specialization$ and TPP in Table 2.9 Panel B. The coefficient of TPP is significantly positive, which indicates firms would focus on specific E&S categories rather than stick to broader, generalized commitments to E&S. This finding supports the view that the relationship may be a result of resource constraints.

R&D efficiency

Next, we further investigate the resource constraint channel by investigating whether innovation efficiency influences our main results. As previously discussed, we observe the firms decrease their engagement in the E&S activities due to resource constraints. Firms prefer to allocate limited resources on R&D-related activities under intense technology competition. However, if firms are more efficient in innovation, they might not be eager to withdraw the effort on the corporate sustainability issues as they have the ability to achieve innovation success with limited resources. Therefore, we expect that firms with high innovation efficiency would decrease less in E&S performance. We measure the innovation efficiency by comparing the innovation output and input, the annual patents applied or granted over the R&D expenditure. After categorizing the sample based on innovation efficiency, we re-estimate the baseline model. The results are presented in Table 2.9 Panel C. As anticipated, we find a weaker impact on firms with high innovation efficiency.

[Insert Table 2.9 here.]

2.5.2 Agency problems

Corporate sustainability engagement can be considered as an agency problem (Masulis and Reza, 2015; Cai et al., 2021; Cheng et al., 2023). Firms investing in socially responsible issues may, in part, be driven by managers' pursuit of personal interests at the expense of shareholders' benefits. Jensen (1986) and Jensen and Meckling (1976) argue that managers have the incentive to overinvest because of their personal benefits. Bénabou and Tirole (2010) document that E&S investment is motivated by management's own desire to engage in philanthropy, i.e., "delegated philanthropy". Cheng et al. (2023)

refer to this as “do good with other people’s money”. Chen et al. (2023b) also find that CEOs’ career concerns during the early stages of their tenure motivate them to engage in voluntary CSR reporting as a means of signaling their ability to maximize long-term shareholder value.

In the context of product market competition, intense competition makes firms decide whether they should prioritize short-term survival or long-term profit-maximizing investment. Some studies have shown that a competitive environment can lead to poorer E&S performance by alleviating the inside agency concerns (Krüger, 2015; Masulis and Reza, 2015). In other words, product market competition can be viewed as playing a disciplinary role. In low-competitive industries, the agency problem becomes more pronounced. Managerial overinvestment in E&S activities to pursue personal interests is less likely to be detected. Besides, investing in E&S activities may not be identified as an overinvestment, given that E&S investment often involves long-term commitments. Therefore, managers are more inclined to invest E&S in a low-competitive environment. However, in highly competitive industries, the primary focus for firms is survival and gaining a competitive edge. The investment in E&S is less essential for the shareholders.

In this regard, we would like to examine whether the negative relationship between TPP and E&S performance is attributable to agency concern. To assess agency problems from an insider perspective, we utilize two proxies: (1) whether the CEO is close to retirement age; and (2) the tenure of the CEO in the firm.[18] First, if a CEO seeks personal interests, such as building a positive image to the public, and getting good political career prospects, they may invest more in ESG activities, revealing greater agency problems. Second, the longer the tenure of a CEO, the more likely are CEOs to be entrenched in

[18] CEO retirement age is identified as if the CEO of the firm is above 60 years old (Hsu et al., 2021).

the firm, indicating greater agency problems.

Table 2.10 Panel A presents the results. We find this negative relationship is particularly pronounced in the group where the effects are stronger when the CEO is close to retirement age, as shown in Column (1) and (5). Furthermore, as presented in Column (3) and (7), the effects are stronger in firms with longer-tenure CEOs. Our findings support the view that E&S engagement results from agency problems and the disciplinary role of product market competition.

Moreover, we text the agency problem from the board's perspective. The independence of the board denotes firm contexts with potential severity of agency problems (Aktas et al., 2019). The negative effect of TPP on corporate sustainability performance is more substantial for firms with low board independence. Following prior studies (e.g., Gu et al., 2021; Li et al., 2022), we use two common proxies for board independence. The first proxy $CEO\ duality$ is a binary variable that equals one if a sole individual acts as both CEO and chair of the board of a firm. The second proxy $Board\ independence$ is measured as the percentage of strictly independent board members on the board. Firms with CEO duality or lower board independence are more likely to suffer from agency problems. We perform the subsample tests with the same specification as the baseline model. As shown in Table 2.10 Panel B, the negative relationship between TPP and E&S performance is stronger for firms with severe agency concerns. The results offer empirical support for the perspective that engaging corporate sustainability is indicative of agency problems. Firms are prone to cut their investments in corporate sustainability when faced with intense technological competition.

[Insert Table 2.10 here.]

2.5.3 Industry heterogeneity

The materiality varies from industry due to ESG referring to multiple dimensions (Khan et al., 2016). Thus, a question arises if the negative TPP-$E\&S$ relationship also depends on the type of industry. In this section, we further perform industry-wise analyses in three-fold. First, we consider the heterogeneity between R&D-intensive industries and non-R&D-intensive industries, as our paper focuses on the technological competition in the product market. The high-tech and low-tech industries in terms of the R&D intensity can be calculated by using a firm's R&D expenditures over its total sales (Fu et al., 2020). In addition, we also use the classification defined by Loughran and Ritter (2004) to divide the sample into high-tech and low-tech groups.

As shown in Table 2.11 Panel A Column (1) and (2), we find that the negative relation is more pronounced for the firms with high R&D intensity. The potential explanations are as follows: on one hand, innovation activities are highly path-dependent and accumulative in nature (Nelson and Winter, 1985), so firms may set R&D activities as the primary task to ensure the success of R&D. Other activities, such as E&S, can be adjusted subject to R&D activities in firms with high R&D intensity or in R&D-intensive industries. On the other hand, in response to technological peer pressure, firms in R&D-intensive industries may be more sensitive and reactive. The results in Panel B, which show the heterogeneity between firms operating in high- and low-tech industries, also support our analysis above.

Second, we explore the consumer- and nonconsumer-facing industries. Previous study shows that firms increase their sustainability as a strategy to differentiate them from their rivals in the product market (Flammer, 2015). In addition, Lev et al. (2010) show that individual customers are more sensitive to firms' social responsibility engagement compared to industrial buyers. Thus, firms in consumer-facing industries invest more in E&S-related activities to maintain customer loyalty or build positive images to the public. Consequently, we observe that the negative relationship between TPP and E&S performance can be weaker in the consumer-facing industries than in the nonconsumer-facing industries. In order to examine this assumption, we divide the firms into two categories: operating in the B2C sector and non-B2C sectors, following Lev et al. (2010).[19] Then we rerun the baseline regression using these two subsamples. As is shown in Table 2.11 Panel C Column (1) and (3), the negative effect is significantly weaker for firms operating in the B2C industries, consistent with the differentiation view of firms' E&S engagement.

Third, we consider the "dirty" industries. Firms in pollution-intensive industries, such as chemicals, are always under great pressure from environmental regulations and get relatively low sustainability ranking (Liu and Zhang, 2023). It is harder for firms with bad performance on corporate social responsibility to get access to external financing (Cheng et al., 2014). To maintain their competitiveness, firms in pollution-intensive industries would have a greater motivation in E&S investment. Furthermore, heavily polluting firms may be less flexible in adjusting their E&S engagement due to their larger fixed inputs compared with firms operating in "green" industries (Liu et al., 2019). Thus, we expect that the negative relationship between TPP and E&S performance would be weaker for firms in "dirty" industries.

To this end, we divide our sample into two groups based on whether the firms are operating in the "dirty" industries. We obtain the "dirty" industries from Berrone et al.

[19]The firms are assigned in the B2C sector by their four-digit SIC codes: 0000-0999, 2000-2399, 2500-2599, 2700-2799, 2830-2869, 3000-3219, 3420-3429, 3523, 3600-3669, 3700-3719, 3751, 3850-3879, 3880-3999, 4813, 4830-4899, 5000-5079, 5090-5099, 5130-5159, 5220-5999, 7000-7299, 7400-9999.

(2013) and classify the "dirty" industries based on the total amount of toxic emissions.[20] Table 2.11 Panel D reports the results. Column (1) and (3) indicate firms in the "dirty" industries are less likely to reduce their E&S initiatives under technological peer pressure. Taking the Environmental Pillar as an example, TPP has a negative impact on firms' environmental performance. The estimated coefficient on TPP is less negative for firms operating in "dirty" industries (coeff. = –1.623), but more negative for those in "green" industries (coeff. = –3.152). These findings highlight the importance of corporate sustainability for "dirty" industries and imply the potential costs associated with sustainability engagement.

[Insert Table 2.11 here.]

2.6 Conclusion

With increasing attention to corporate sustainability, this paper sheds light on a less debated topic in relation to corporate sustainability, that is, the association between technological peer pressure and corporate sustainability. We use an extensive unbalanced panel dataset of 12062 firm-year observations from 1536 public list firms in the U.S. over 20 years to empirically explore the effect of technological competition on firm-level sustainability engagement. Different from previous studies exploring the relationship between product market competition and firms' corporate sustainability, we use a measure of technological peer pressure to capture the threats from the technology dimension in the product market. The rationale is that technological competition is crucial for firms

[20] Berrone et al. (2013) identify 20 most pollution industries according to the total amount of toxic emissions from U.S. Environmental Protection Agency's (EPA) TRI (Toxic Release Inventory) program data. The top 20 most polluting industries in the U.S. as defined by two-digit SIC code are 10, 50, 33, 49, 28, 36, 12, 13, 20, 32, 30, 51, 26, 34, 29, 31, 35, 37, 24, and 27. We also use this classification and get the same results. Following Dupire and M'Zali (2018), we also use another dirty industries classification, the firms operating in SIC 2000-3999, to reestimate and get similar results.

to succeed and possibly even survive in the knowledge-based economy.

We find compelling evidence indicating that technological peer pressure decreases corporate sustainability performance, as measured by the Refinitiv Environmental and Social pillar scores. Our findings remain robust across various measures of corporate sustainability measures, additional controls for other aspects of competition and fixed effects, different model specifications, alternative patent-based TPP measures, and IV approach to control for endogeneity. In the analyses, our findings support the argument that resource constraints and agency problems may explain the negative relationship between technological peer pressure and corporate sustainability. First, we highlight the significant role of financial slack in diminishing corporate social responsibility performance. Second, firms would focus on a narrow range of sustainability activities. Third, the impact is weaker for firms with high innovation efficiency. Fourth, from the CEO and board perspectives, we demonstrate the disciplinary role of innovation competition on corporate sustainability engagement by using information from CEOs. Moreover, we debate the industry's cross-sectional heterogeneity. We observe that the negative association is notably stronger for firms operating in R&D-intensive industries, high-tech industries, non-B2C industries, and "green" industries.

Overall, our collective evidence enhances our understanding of the consequences of technological competition and the determinants of corporate sustainability. In contrast to prior studies that primarily focus on general product market competition, (e.g., Ding et al., 2022; Flammer, 2015), this paper provides a new perspective on technological competition and investigates the unexpected corporate consequences from the peers' R&D advances. Additionally, we establish a connection between technological peer pressure and corporate sustainability, contributing to the growing literature on the determinants of firms' ESG engagements (e.g., Bénabou and Tirole, 2010).

Given the increasing importance of corporate social responsibility and innovation in the knowledge-based economy, our findings hold practical relevance and provide implications for firms, shareholders and related stakeholders. Regulators should encourage firms to play a more proactive role in promoting sustainability, rather than viewing ESG as a strategic tool for pursuing private interests. Additionally, our findings suggest that firms need to pursue an optimized resource allocation strategy to achieve synergies in integrating sustainability and R&D.

While our study has provided strong evidence regarding the impact of technological peer pressure on corporate sustainability performance, we admit a few limitations that could guide future research directions. First, in this paper, we focus on the technology competition in the product market. For future research, it would be interesting to examine the relationship between technological peer pressure and corporate sustainability within the technology sector. Second, due to the limitation of data availability, our paper utilizes the sample of publicly traded firms in the United States. Given the significant differences in competition landscapes and business environments across countries, future studies could expand our investigation to include global evidence.

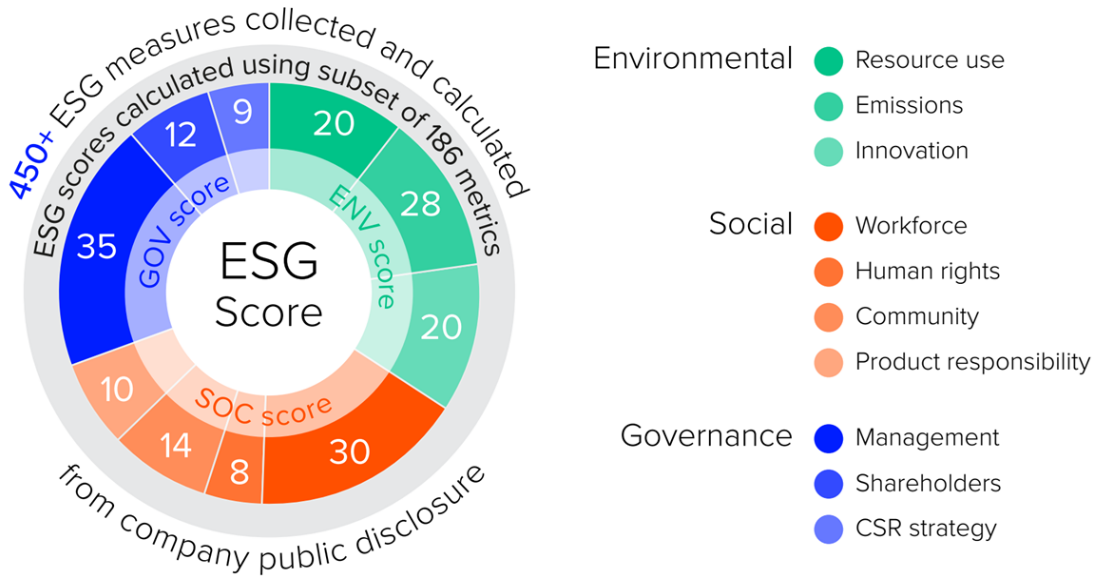

Figure 2.1: Refinitiv data methodology.

***Note*:** This figure shows the scores structure of Refinitiv ESG data. The source of this figure: https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores#methodology.

Table 2.1: Distribution of sample firm-year observations by industry and year

Panel A Distribution of sample firm-year observations by industry

2-Digit SIC	Industry Description	Frequency	Percentage (%)
28	Chemicals and allied products	2,737	22.69
73	Business services	1,584	13.13
36	Electronic and other electrical equipment	1,549	12.84
38	Instruments and related products	1,220	10.11
35	Industrial and commercial machinery and computer equipment	1,214	10.06
Others	-	3,758	31.16
Total		12,062	100.00

Panel B Distribution of sample firm-year observations by year

Year	Frequency	Percentage (%)
2002	152	1.26
2003	179	1.48
2004	232	1.92
2005	262	2.17
2006	269	2.23
2007	285	2.36
2008	333	2.76
2009	373	3.09
2010	390	3.23
2011	399	3.31
2012	410	3.40
2013	422	3.50
2014	457	3.79
2015	636	5.27
2016	849	7.04
2017	1,070	8.87
2018	1,189	9.86
2019	1,337	11.08
2020	1,459	12.10
2021	1,359	11.27
Total	12,062	100.00

***Note*:** This table reports the two-digit Standard Industrial Classification (SIC) codes industry (Panel A) and annual (Panel B) distribution of the sample. The sample is comprised of 12062 firm-year observations over the period 2002–2021.

Table 2.2: Summary statistics

VARIABLES	N	mean	sd	q1	median	q3
TPP	12,062	4.41	2.33	2.56	4.20	6.20
$Environmental$	12,062	33.57	31.76	0.00	27.41	62.52
$Social$	12,062	48.99	23.75	29.89	46.31	67.84
$Size$	12,062	7.73	2.20	6.16	7.85	9.38
$Tobin's\ Q$	12,062	2.19	1.64	1.20	1.65	2.51
$Leverage$	12,062	0.23	0.19	0.07	0.21	0.34
$Tangibility$	12,062	0.40	0.35	0.15	0.30	0.56
$TNIC-HHI$	8,700	0.31	0.26	0.11	0.21	0.42
HHI	12,062	0.09	0.11	0.04	0.06	0.08
$Fluidity$	9,024	6.54	3.87	3.67	5.52	8.38
$Environmental\ specialization$	11,555	0.43	0.51	0.00	0.25	0.69
$Social\ specialization$	12,022	0.56	0.36	0.27	0.55	0.76
$Environmental\ KLD$	9,242	0.03	0.11	0.00	0.00	0.00
$Environmental\ strength$	9,242	0.05	0.12	0.00	0.00	0.00
$Environmental\ concern$	9,242	0.02	0.07	0.00	0.00	0.00
$Social\ KLD$	9,242	0.13	0.46	0.00	0.00	0.22
$Social\ strength$	9,242	0.27	0.47	0.00	0.00	0.50
$Social\ concern$	9,242	0.14	0.30	0.00	0.00	0.17
$TPP\ patents\ filing$	5,654	3.59	2.01	2.01	3.47	5.04
$TPP\ patents\ issue$	5,905	3.68	2.05	2.06	3.63	5.18
$CSR\ reports\ disclosure$	11,997	0.56	2.02	0.00	0.00	1.00
$Tax\ credit$	8,823	10.55	2.09	9.49	10.90	12.08

***Note*:** This table presents the summary statistics (number of observations, mean, standard deviation, first quartile, median, and third quartile) for the key variables used in our regressions, including the technological peer pressure, corporate environmental and social performance, and other firm-level control variables. TPP is the measure of technological peer pressure on firms following Cao et al. (2018). The $Environmental$ and $Social$ are corporate sustainability performance collected from the Refinitiv ESG database. *Size* is measured by the natural log of firms' total assets plus one. *Tobin's Q* is calculated by the total assets minus the book value of equity plus the market value of equity over total assets. *Leverage* is measured as the sum of long-term and current debt deflated over total assets. *Tangibility* is defined as the net property, plants, and equipment deflated by total assets. The sample consists of 12,062 firm-year observations from 2002 to 2021. Firm size (*Size*), *Tobin's Q*, *Leverage* and *Tangibility* are winsorized at the 1% and 99% levels. The Appendix Table A1 provides the definition for the variables.

Table 2.3: Correlation coefficients

Variables	*TPP*	*Environmental*	*Social*	*Size*	*Tobin's Q*	*Leverage*	*Tangibility*	*TNIC – HHI*	*HHI*	*Fluidity*
TPP	1.000									
Environmental	-0.551 ***	1.000								
Social	-0.411 ***	0.748 ***	1.000							
Size	-0.681 ***	0.713 ***	0.567 ***	1.000						
Tobin's Q	0.244 ***	-0.258 ***	-0.124 ***	-0.345 ***	1.000					
Leverage	-0.142 ***	0.164 ***	0.127 ***	0.224 ***	-0.102 ***	1.000				
Tangibility	-0.287 ***	0.356 ***	0.178 ***	0.333 ***	-0.263 ***	0.160 ***	1.000			
TNIC – HHI	-0.134 ***	0.063 ***	-0.038 ***	0.033 ***	-0.122 ***	0.065 ***	0.189 ***	1.000		
HHI	-0.230 ***	0.089 ***	0.021 **	0.165 ***	-0.108 ***	0.043 ***	0.164 ***	0.159 ***	1.000	
Fluidity	0.256 ***	-0.316 ***	-0.086 ***	-0.330 ***	0.231 ***	-0.165 ***	-0.343 ***	-0.504 ***	-0.196 ***	1.000
Environmental specialization	0.000	-0.116 ***	-0.090 ***	0.036 ***	-0.048 ***	0.025 ***	0.049 ***	0.109 ***	0.075 ***	-0.247 ***
Social specialization	0.289 ***	-0.612 ***	-0.821 ***	-0.412 ***	0.101 ***	-0.131 ***	-0.112 ***	0.011	-0.002	0.127 ***
Environmental KLD	-0.168 ***	0.247 ***	0.224 ***	0.152 ***	-0.018 *	0.034 ***	-0.018 *	-0.003	-0.042 ***	-0.056 ***
Environmental strength	-0.271 ***	0.306 ***	0.251 ***	0.265 ***	-0.065 ***	0.077 ***	0.038 ***	0.022 *	-0.006	-0.101 ***
Environmental concern	-0.192 ***	0.125 ***	0.067 ***	0.207 ***	-0.082 ***	0.077 ***	0.093 ***	0.042 ***	0.057 ***	-0.079 ***
Social KLD	-0.091 ***	0.274 ***	0.344 ***	0.144 ***	0.113 ***	-0.000	-0.100 ***	-0.090 ***	-0.125 ***	0.095 ***
Social strength	-0.171 ***	0.198 ***	0.264 ***	0.195 ***	0.094 ***	0.030 ***	-0.092 ***	-0.080 ***	-0.033 ***	0.038 ***
Social concern	-0.184 ***	0.077 ***	0.054 ***	0.196 ***	-0.024 **	0.042 ***	0.036 ***	0.001	0.080 ***	-0.057 ***
Tax credit	0.621 ***	-0.113 ***	0.040 ***	-0.093 ***	0.176 ***	-0.067 ***	-0.257 ***	-0.397 ***	-0.191 ***	0.236 ***

Variables	*Environmental specialization*	*Social specialization*	*Environmental KLD*	*Environmental strength*	*Environmental concern*	*Social KLD*	*Social strength*	*Social concern*	*Tax credit*
TPP									
Environmental									
Social									
Size									
Tobin's Q									
Leverage									
Tangibility									
TNIC – HHI									
HHI									
Fluidity									
Environmental specialization	1.000								
Social specialization	0.057 ***	1.000							
Environmental KLD	-0.022 **	-0.196 ***	1.000						
Environmental strength	-0.018 *	-0.183 ***	0.820 ***	1.000					
Environmental concern	0.004	0.003	-0.212 ***	0.386 ***	1.000				
Social KLD	-0.086 ***	-0.285 ***	0.312 ***	0.229 ***	-0.120 ***	1.000			
Social strength	-0.033 ***	-0.202 ***	0.432 ***	0.557 ***	0.255 ***	0.786 ***	1.000		
Social concern	0.044 ***	0.011	0.163 ***	0.451 ***	0.508 ***	-0.292 ***	0.362 ***	1.000	
Tax credit	-0.051 ***	-0.041 ***	0.000	-0.083 ***	-0.138 ***	0.158 ***	0.097 ***	-0.096 ***	1.000

***Note*:** This table shows the pairwise correlation coefficients of key variables used in our analysis. The sample used in the main regression comprises 12,062 frim-year observations covering the period 2002-2021. TPP is the measure of technological peer pressure on firms following Cao et al. (2018). The $Environmental$ and $Social$ are corporate sustainability performance collected from the Refinitiv ESG database. *Size* is measured by the natural log of firms' total assets plus one. *Tobin's Q* is calculated by the total assets minus the book value of equity plus the market value of equity over total assets. *Leverage* is measured as the sum of long-term and current debt deflated over total assets. *Tangibility* is defined as the net property, plants, and equipment deflated by total assets. The Appendix Table A1 provides the definition of variables. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Table 2.4: Baseline regression: TPP and corporate sustainability performance

VARIABLES	Environmental			Social		
	(1)	(2)	(3)	(4)	(5)	(6)
TPP_{t-1}	-7.518***	-1.470***	-1.883***	-4.188***	-0.480**	-1.528***
	(0.261)	(0.266)	(0.264)	(0.204)	(0.230)	(0.246)
$Size_{t-1}$		8.670***	9.865***		6.073***	7.452***
		(0.295)	(0.315)		(0.262)	(0.269)
$Tobin's\ Q_{t-1}$		0.181	0.974***		1.181***	0.976***
		(0.226)	(0.219)		(0.201)	(0.182)
$Leverage_{t-1}$		-0.932	-7.823***		0.345	-4.463**
		(2.382)	(2.068)		(2.095)	(1.863)
$Tangibility_{t-1}$		11.637***	13.270***		-0.137	7.299***
		(1.772)	(2.113)		(1.619)	(1.765)
N of Obs.	12,062	12,062	12,062	12,062	12,062	12,062
Adj. R^2	0.304	0.531	0.653	0.169	0.328	0.521
Industry FE	NO	NO	YES	NO	NO	YES
Year FE	NO	NO	YES	NO	NO	YES

***Note*:** This table reports the baseline results from examining the effects of *TPP* on firms' environmental and social performance using OLS regression. The sample is comprised of 12062 firm-year observations over the 2002–2021 period. The dependent variables are $Environmental$ and $Social$, which are collected from the Refinitiv ESG database. The main variable of interest is TPP_{t-1}, technological peer pressure, which indicates the technological threats from rivals in the product market space. Column (1) and (4) include no control variables, and fixed effects; Column (2) and (5) include firm-level controls; Column (3) and (6) include firm-level controls and industry and year fixed effects. Industries are defined based on the three-digit Standard Industrial Classification (SIC) codes. The Appendix Table A1 provides the definition of variables. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity and clustered by firm.

Table 2.5: Relationship between TPP and different corporate sustainability subcategories

	Environmental			Social			
VARIABLES	Innovation	Resource use	Emission	Product responsibility	Community	Human rights	Workforce
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TPP_{t-1}	-1.665***	-2.185***	-2.415***	-1.350***	-0.909***	-1.145***	-2.175***
	(0.309)	(0.309)	(0.301)	(0.368)	(0.293)	(0.322)	(0.311)
N of Obs.	12,060	11,557	12,062	12,062	12,062	12,022	12,062
Adj. R^2	0.478	0.614	0.602	0.300	0.359	0.497	0.483
Controls	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

***Note*:** This table presents results of OLS regressions of *TPP* on firms' *Environmental* and *Social* subcategories using the control variables and fixed effects from the baseline model. The definitions of these category scores are shown in the Appendix Table A2. Industries are defined based on the three-digit Standard Industrial Classification (SIC) codes. The Appendix Table A1 provides the definition of variables. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity.

Table 2.6: Robustness tests: Alternative corporate sustainability and TPP measures

Panel A: Alternative corporate sustainability measures

VARIABLES	Environment KLD	Environmental strength	Environmental concern	Social KLD	Social strength	Social concern
	(1)	(2)	(3)	(4)	(5)	(6)
TPP_{t-1}	-0.007***	-0.007***	-0.000	-0.021***	-0.023***	-0.002
	(0.001)	(0.002)	(0.001)	(0.006)	(0.006)	(0.004)
N of Obs.	9,242	9,242	9,242	9,242	9,242	9,242
Adj. R^2	0.202	0.251	0.200	0.211	0.223	0.212
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Panel B: Patent-based TPP measures

VARIABLES	Environmental		Social	
	(1)	(2)	(3)	(4)
$TPP\ patents\ filing_{t-1}$	-1.590***		-1.412***	
	(0.464)		(0.397)	
$TPP\ patents\ issue_{t-1}$		-1.854***		-1.465***
		(0.451)		(0.373)
N of Obs.	5,651	5,900	5,651	5,900
Adj. R^2	0.636	0.639	0.555	0.550
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

***Note*:** This table presents the relationship between TPP and corporate sustainability performance with alternative dependent sustainability measures and patent-based TPP measures. The ESG data comes from the MSCI ESG KLD database. In Panel A, the dependent variables $Environmental\ KLD$ and $Social\ KLD$ are defined as the adjusted sum of strengths scores minus the adjusted sum of concerns scores for each firm-year. $Social\ KLD$ includes community, diversity, employee relations, and product attributes. The $Strength$ and $Concern$ are defined as the adjusted sum of strengths scores and the adjusted sum of concerns scores, respectively. The main variable of interest is TPP_{t-1}, technological peer pressure, which indicates the technological threats from rivals in the product market space. Panel B shows the results using an alternative patent-based TPP measure, which is constructed by replacing the proxies of R&D stock with the number of yearly patents filed and issued. Industries are defined based on the three-digit Standard Industrial Classification (SIC) codes. The Appendix Table A1 provides the definition of variables. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity.

Table 2.7: Robust tests: additional controls, different fixed effects, changes instead of levels

Panel A: Additional product market controls						
VARIABLES	Environmental			Social		
	(1)	(2)	(3)	(4)	(5)	(6)
TPP_{t-1}	-1.885***	-2.776***	-1.891***	-1.527***	-2.497***	-1.537***
	(0.264)	(0.465)	(0.265)	(0.246)	(0.382)	(0.254)
HHI_{t-1}	-5.312			2.371		
	(5.958)			(4.908)		
$TNIC-HHI_{t-1}$		0.821			-0.312	
		(1.889)			(1.622)	
$Fluidity_{t-1}$			-0.290*			0.203
			(0.172)			(0.150)
N of Obs.	12,062	8,700	9,024	12,062	8,700	9,024
Adj. R^2	0.653	0.601	0.602	0.521	0.506	0.496
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Panel B: Different level fixed effects						
VARIABLES	Environmental			Social		
	(1)	(2)	(3)	(4)	(5)	(6)
TPP_{t-1}	-4.422***	-1.616***	-1.931***	-3.327***	-1.385***	-1.435***
	(1.027)	(0.259)	(0.272)	(0.922)	(0.254)	(0.258)
N of Obs.	12,062	8,827	11,315	12,062	8,827	11,315
Adj. R^2	0.864	0.609	0.644	0.815	0.507	0.497
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	YES	YES	NO
Industry	NO	YES	NO	NO	YES	NO
Firm FE	YES	NO	NO	YES	NO	NO
State FE	NO	YES	NO	NO	YES	NO
Industry*Year FE	NO	NO	YES	NO	NO	YES

Panel C: Changes instead of levels				
VARIABLES	ΔEnvironmental		Δ Social	
	(1)	(2)	(3)	(4)
ΔTPP	-0.971	-1.569**	-1.464*	-1.460*
	(0.610)	(0.656)	(0.783)	(0.861)
N of Obs.	10,486	9,790	10,486	9,790
Adj. R^2	0.034	0.096	0.012	0.054
Controls	YES	YES	YES	YES
Year FE	YES	NO	YES	NO
Industry FE	YES	NO	YES	NO
Industry*Year FE	NO	YES	NO	YES

Panel D: Control CSR reports disclosure				
VARIABLES	Environmental		Social	
	(1)	(2)	(3)	(4)
TPP_{t-1}	-1.900***	-1.940***	-1.547***	-1.448***
	(0.264)	(0.272)	(0.247)	(0.259)
$CSR\ reports\ disclosure$	0.776	0.676	0.660**	0.589*
	(0.505)	(0.481)	(0.319)	(0.303)
N of Obs.	11,990	11,244	11,990	11,244
Adj. R^2	0.655	0.646	0.522	0.499
Controls	YES	YES	YES	YES
Year FE	YES	NO	YES	NO
Industry FE	YES	NO	YES	NO
Industry*Year FE	NO	YES	NO	YES

***Note*:** This table report four robustness tests. Panel A presents the results with extra product market competition measures: HHI_{t-1}, HHI_{t-1} and $Fluidity_{t-1}$. Panel B repeats the baseline model with different fixed effect combinations: state fixed effect, firm fixed effect, and industry*year fixed effect. Panel C reports the results of analyzing the impact of changes in TPP on changes in $Environmental$ and $Social$ performance using the control variables from the baseline model. Panel D presents the results with extra control of Corporate Social Responsibility (CSR) report disclosure. Industries are defined based on the three-digit Standard Industrial Classification (SIC) codes. The Appendix Table A1 provides the definition of variables. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity.

Table 2.8: Robustness tests: instrumental variable

VARIABLES	Frist stage	Second stage	
	TPP_{t-1}	Environmental	Social
	(1)	(2)	(3)
$Tax\ credit_{t-1}$	0.647***		
	(0.011)		
$\widehat{TPP_{t-1}}$		-0.495*	-0.094
		(0.254)	(0.290)
N of Obs.	8,823	8,823	8,823
Adj. R^2	0.838	0.444	0.395
Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Kleibergen-Paap F statistic	3,260		

***Note*:** This table presents the results of instrumental variable analysis while controlling for endogeneity. Column (1) shows the first-stage regression of the $Tax\ credit$ on TPP. Column (2) and (3) show the results of using the predicted TPP from first-stage regression to estimate the relationship between TPP and $Environmental$ and $Social$ performance. Industries are defined based on the three-digit Standard Industrial Classification (SIC) codes. The Appendix Table A1 provides the definition of variables. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity.

Table 2.9: Cross-sectional analysis: resource constraints

Panel A: Financial constraints

VARIABLES	Environmental				Social			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TPP_{t-1}	-1.474***	-2.516***	-1.625***	-1.726***	-1.306***	-1.818***	-1.270***	-1.448***
	(0.243)	(0.527)	(0.250)	(0.463)	(0.259)	(0.439)	(0.264)	(0.411)
N of Obs.	5,953	5,967	5,918	5,912	5,953	5,967	5,918	5,912
Adj. R^2	0.565	0.656	0.618	0.645	0.413	0.551	0.460	0.553
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Financial constraints proxies	Slack-high	Slack-low	Cash-high	Cash-low	Slack-high	Slack-low	Cash-high	Cash-low
Empirical p-value	0.000		0.160		0.010		0.060	

Panel B: Corporate sustainability specialization

VARIABLES	Environmental specialization		Social specialization	
	(1)	(2)	(3)	(4)
TPP_{t-1}	0.039***	0.038***	0.018***	0.017***
	(0.007)	(0.007)	(0.004)	(0.004)
N of Obs.	11,555	10,819	12,016	11,269
Adj. R^2	0.097	0.074	0.426	0.407
Controls	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
Year FE	YES	YES	YES	YES
Industry*Year FE	NO	YES	NO	YES

Panel C: Innovation efficiency

VARIABLES	Environmental				Social			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TPP_{t-1}	-1.795***	-2.441***	-1.737***	-2.368***	-1.300***	-2.479***	-1.314***	-2.064***
	(0.247)	(0.751)	(0.246)	(0.799)	(0.248)	(0.562)	(0.246)	(0.581)
N of Obs.	9,180	2,877	9,023	3,036	9,180	2,877	9,023	3,036
Adj. R^2	0.673	0.620	0.673	0.621	0.545	0.481	0.542	0.499
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Innovation efficiency	High	Low	High	Low	High	Low	High	Low
Proxies	Patents filing	Patents filing	Patents issue	Patents issue	Patents filing	Patents filing	Patents issue	Patents issue
Empirical p-value	0.010		0.000		0.000		0.000	

***Note*:** This table presents the relationship between TPP_{t-1} and firms E&S performance differentiated by the firm's finance constraints, the effect on the corporate sustainability specification, and the innovation efficiency. Panel A, we measure the degree of the financial constraint of a firm either by the financial slack and cash holding across the sample period. Following Cleary (1999), we perform Fisher's permutation test of differences in coefficient estimates between two groups. Panel B reports the relationship between TPP and $Environmental\ specification$ and $Social\ specification$, respectively. Panel C shows subsample regression results by innovation efficiency which is measured by the yearly patents filed or issued over the R&D expenditure. The Appendix Table A1 provides the definition of variables. Industries are defined based on the three-digit Standard Industrial Classification (SIC) codes. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity.

Table 2.10: Cross-sectional analysis: agency problem

Panel C: CEO perspective								
VARIABLES	Environmental				Social			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TPP_{t-1}	-3.439***	-2.984***	-3.044***	-2.963***	-2.903***	-2.697***	-3.355***	-2.064***
	(1.077)	(0.665)	(0.701)	(0.781)	(0.817)	(0.542)	(0.571)	(0.612)
N of Obs.	1,517	4,806	3,346	2,887	1,517	4,806	3,346	2,887
Adj. R^2	0.618	0.585	0.583	0.601	0.552	0.509	0.509	0.534
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Agency proxy	CEO retirement age		CEO tenure		CEO retirement age		CEO tenure	
Group	Yes	No	High	Low	Yes	No	High	Low
Empirical p-value	0.000		0.400		0.040		0.000	

Panel B: Board perspective								
VARIABLES	Environmental				Social			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TPP_{t-1}	-2.423***	-1.460***	-1.553***	-2.053***	-1.940***	-0.999***	-1.198***	-1.624***
	(0.375)	(0.307)	(0.283)	(0.329)	(0.345)	(0.296)	(0.274)	(0.353)
N of Obs.	6,364	5,649	4,361	4,332	6,364	5,649	4,361	4,332
Adj. R^2	0.636	0.698	0.669	0.601	0.541	0.539	0.529	0.491
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Agency proxy	CEO duality		Board independence		CEO duality		Board independence	
Group	Yes	No	High	Low	Yes	No	High	Low
Empirical p-value	0.000		0.050		0.000		0.060	

***Note*:** This table presents the relationship between TPP_{t-1} and corporate sustainability performance differentiated by the degree of the firm's agency problems. In Panel A, from the CEO perspective, we measure the agency concern by whether CEOs are at retirement age and the CEOs' tenure. In Panel B, we use the proxies of CEO duality and board independence to indicate the agency concerns. Following Cleary (1999), we perform Fisher's permutation test of differences in coefficient estimates between two groups. Industries are defined based on the three-digit Standard Industrial Classification (SIC) codes. The Appendix Table A1 provides the definition of variables. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity.

Table 2.11: Cross-sectional analysis: industry heterogeneity

Panel A: R&D intensity				
VARIABLES	Environmental		Social	
	(1)	(2)	(3)	(4)
TPP_{t-1}	-1.616***	-1.341**	-1.215***	-1.259***
	(0.271)	(0.526)	(0.297)	(0.439)
N of Obs.	6,018	6,036	6,018	6,036
Adj. R^2	0.666	0.623	0.517	0.536
R&D intensity	High	Low	High	Low
Empirical p-value	0.010		0.340	

Panel B: High-tech industry				
VARIABLES	Environmental		Social	
	(1)	(2)	(3)	(4)
TPP_{t-1}	-2.721***	-1.462***	-1.808**	-0.829***
	(0.933)	(0.268)	(0.716)	(0.255)
N of Obs.	3,246	8,816	3,246	8,816
Adj. R^2	0.555	0.652	0.514	0.478
High-tech industry	Yes	No	Yes	No
Empirical p-value	0.000		0.000	

Panel C: B2C industry				
VARIABLES	Environmental		Social	
	(1)	(2)	(3)	(4)
TPP_{t-1}	-1.677***	-2.475***	-1.422***	-1.606***
	(0.258)	(0.568)	(0.285)	(0.464)
N of Obs.	5,159	6,903	5,159	6,903
Adj. R^2	0.723	0.589	0.532	0.513
B2C industry	Yes	No	Yes	No
Empirical p-value	0.000		0.030	

Panel D: Dirty industry				
VARIABLES	Environmental		Social	
	(1)	(2)	(3)	(4)
TPP_{t-1}	-1.623***	-3.152***	-1.403***	-2.055***
	(0.275)	(0.698)	(0.270)	(0.568)
N of Obs.	8,139	3,923	8,139	3,923
Adj. R^2	0.681	0.582	0.536	0.490
Dirty industry	Yes	No	Yes	No
Empirical p-value	0.000		0.000	

***Note*:** This table report the heterogeneity between TPP_{t-1} and firm-level sustainability performance. Panel A and B show the heterogeneity between high-tech firms and low-tech firms. We use R&D intensity (Panel A) and R&D-intensive industry classification (Panel B) to divide our sample. Panel C reports the heterogeneity between firms in the B2C sector and the non-B2C sector. Panel D displays the difference between the firms operating in the "dirty" industries and the "green" industries. Following Cleary (1999), we perform Fisher's permutation test of differences in coefficient estimates between two groups. Each regression in this table includes the same set of control variables and industry and year fixed effects as in our baseline regressions. Industries are defined based on the three-digit Standard Industrial Classification (SIC) codes. The Appendix Table A1 provides the definition of variables. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity.

Table A1: Variable definitions

Variables	Definition
TPP	Technological peer pressure for firm i at the end of fiscal year t. $TPPi,t = ln\left[1 + \frac{1}{Gi,t}\sum^{i\neq j}\omega_{ij\times Gj,t}\right]$. Firm i's technological threat comes from a peer firm j's R&D stock $G_{j,t}$ at the end of year t weighted by the closeness ω_{ij} between these two firms, where $\omega_{ij} = \left\langle \frac{V_i}{\|V_i\|} \cdot \frac{V_j}{\|V_j\|} \right\rangle$. V_i is the vector of firm i's sales with the kth element being the share of firm i's total sales in the preceding two years made in industry (four-digit SIC) k.
Environment	Environmental pillar score of Refinitiv ESG Score.
Social	Social pillar score of Refinitiv ESG Score.
Size	Natural log of firms' total assets.
Tobin's Q	Total assets minus the book value of equity plus the market value of equity, all divided by total assets.
Leverage	The sum of long-term debt and current debt deflated by total assets.
Tangibility	Net property, plant, and equipment divided by total assets.
Environmental KLD	The adjusted sum of environment strengths scores minus the adjusted sum of environment concerns scores across in environmental dimension from MSCI KLD ESG database.
Environmental strength	The adjusted sum of environment strengths scores.
Environmental concern	The adjusted sum of environment concerns scores.
Social KLD	The adjusted sum of social strengths scores minus the adjusted sum of social concerns scores across in environmental dimension from the MSCI KLD ESG database. Social includes community, employee relations, diversity, and product.
Social strength	The adjusted sum of social strengths scores. Social includes community, employee relations, diversity, and product.
Social concern	The adjusted sum of social concerns scores. Social includes community, employee relations, diversity, and product.
TPP patents filing	The technological peer pressure based on the number of patents filed in a given year.
TPP patents issue	The technological peer pressure based on the number of patents issued in a given year.
HHI	The sum of the squared market share of all members in the focal firm's 2-digit SIC industry.
TNIC-HHI	The 10-K Text-based Network Industry Industry concentration based on the Text-based Network Industry Classifications (TNIC) introduced by Hoberg et al. (2014) and Hoberg and Phillips (2016).
CSR reports disclosure	A dummy variable indicates whether a firm discloses a separate CSR report or a section on sustainability engagement in its annual report.
Fluidity	The similarity between a firm's products and the moves made by its competitors in the firm's product market introduced by Hoberg et al. (2014) and Hoberg and Phillips (2016).
Tax credit	The degree to which peer firms are exposed to the state-level R&D tax credit.
Environmental specialization	The standard deviation of the performance on Environmental divided by the Environmental scores.
Social specialization	The standard deviation of the performance on Social divided by the Social scores.
Innovation efficiency	The annual patents applied or granted over the R&D expenditure.
Financial slack	The ratio of current assets to current liabilities.
Cash	Cash holding scaled by total assets.
CEO retirement age	A dummy variable that equals one if the CEO of the firm is above 60 years old, and zero otherwise.
CEO tenure	The number of years the CEO has become in the focal firm.
CEO duality	A binary variable that equals one if a sole individual acts as both CEO and chair of the board of a firm.
Board independence	The percentage of strictly independent board members on the board.
R&D intensity	The ratio of a firm's R&D expenditures to its total assets.
High tech Industry	The classification defined by Loughran and Ritter (2004).
B2C industry	The classification used by Lev et al. (2010).
Dirty industry	The classification defined by Berrone et al. (2013).

***Note*:** This table presents the variable definitions.

Table A2: Refinitiv ESG scores structure

Pillars	Catagories
Environmental	**Innovation:** firm's ability to create new market opportunities through new environmental technologies and processes, or eco-designed products. **Resource use:** firm's performance and capacity in reducing the use of materials, energy, or water and promoting supply chain management. **Emissions:** firm's commitment and effectiveness towards reducing environmental emissions and wastes.
Social	**Product responsibility:** firm's capacity to produce quality products, integrating the customer's health and safety, integrity and data privacy. **Community:** firm's commitment to protecting public health and adhering to business ethics. **Human rights**: firm's effectiveness in undertaking fundamental human rights initiatives. **Workforce:** firm's initiatives of providing job satisfaction, a healthy and safe workplace, maintaining diversity, and career development and training for its employees.

***Note*:** This table presents the Refinitiv ESG scores structure and definitions of the subdimensions of Environmental and Social pillars.

CHAPTER 3

Technological Peer Pressure and Acquisitions

3.1 Introduction

Innovation is a key factor for firm growth in today's knowledge-intensive economy. Firms that fall behind in the innovation race face significant risks. They may struggle to keep up with the research and development (R&D) in the product market, which can jeopardize their position and performance. In such situations, mergers and acquisitions (M&As) can be strategic tools for firms to improve their competitiveness and gain access to new technologies.[1] For example, Hoberg and Phillips (2010) show how increased ex-ante product market competition motivates firms to merge, resulting in synergies and product differentiation. Building on this analysis, Bena and Li (2014) further explain how post-merger innovation output improves through technological synergy. In this paper, we provide empirical evidence of how firms' acquisition activity responds to their product market rivals' technological advances.

There is some anecdotal evidence supporting firms' initiation of external acquisitions in response to their rivals' advances in innovation. Apple acquired Beats Music and

[1]Throughout this chapter, we use the terms acquisitions, mergers, and M&As interchangeably.

Beats Electronics in 2014 to catch up with their rivals in both the music streaming service and headphone product lines.[2] In the market of music streaming services, iTunes, a digital media service operated by Apple, was dominant during the 2010s. However, new music streaming service providers, such as Spotify, seized a large proportion of the market share since 2010. By acquiring Beats Music, Apple integrated new ideas and talents into their iTunes team. One year after the deal, Apple launched its new music app, Apple Music. In the headphone market, especially the wireless headphone market, the competition is fiercer. To catch up with the leaders and accelerate their innovation, such as Sony, Apple acquired Beats Electronics and released the AirPods two years later. This acquisition helped position Apple as one of the biggest headphone manufacturers in the world in just a couple of years.

Previous literature has documented that firms engage in M&As activities in response to various forms of competition in the product market, such as trade liberalization (Breinlich, 2008), import tariff reductions (Srinivasan, 2020), and trademark-based product market competition (Hsu et al., 2022). However, there are few studies that focus on the effect of technological competition on acquisition activities. We concentrate on technological competition rather than other dimensions of competition (such as price, customer service, and distribution) for two reasons. First, companies must maintain or increase their profitability, or even survive, in today's knowledge-based economy, especially in the United States, where technology has been the main driver of economic growth (Solow, 1956; Zingales, 2000; Eisdorfer and Hsu, 2011). Second, M&As activity is an important channel for firms to boost their innovation output (Cunningham et al., 2021; Bena and Li, 2014). By examining the competition in the technology dimension,

[2] See the news on: https://www.apple.com/uk/newsroom/2014/05/28Apple-to-Acquire-Beats-Music-Beats-Electronics/.

we can better understand the role of innovation in firms and the economy as a whole.

To investigate how acquisition activity changes in response to changes in the technological competition landscape, we use a sample of publicly listed firms in the United States (U.S.) over the period 1983-2022 to empirically examine the propensity of making acquisitions. Following Cao et al. (2018), we use the technological peer pressure (TPP) as a proxy for the measure of technological competition. TPP captures the technological threats at the firm level by comparing the R&D stocks of all competitors in an industry to the focal firm's R&D stock. The R&D stock is calculated by the focal firm's cumulative R&D expenditure in recent years. In other words, TPP measures rivals' technological advances relative to the firm's technological readiness. In robustness tests, we also use an alternative patent-based TPP as the explanatory variable to ensure that our findings are not driven by the choice of the proxy for technological peer pressure. We construct our initial dataset of all U.S. mergers and acquisitions between 1983 and 2022 from the Securities Data Company (SDC) Database. Then, we merge these M&As deal records with CRSP and Compustat datasets that provide all financial information. Finally, we identify 5,384 significant M&As events completed from 1983 to 2022. Controlling for firm- and industry-level determinants of making M&As explored in the prior literature, we find strong evidence that technological peer pressure increases the likelihood of corporate acquisition decisions. The results indicate that the probability of a firm's acquisition probability increases by 0.9%, corresponding to an approximately 8.04% increase from the average probability of the sample of 11.2%.

Our main finding is qualitatively unchanged when conducting a battery of robustness tests. Specifically, we use (1) alternative linear probability model (LPM) and probit model specifications, (2) patent-based TPP measure, and (3) subsamples by excluding industries with the largest representations.

Furthermore, we address potential sources of endogeneity in our baseline results. First, we consider omitted variable bias, wherein factors affecting both M&A activities and innovation might confound our analysis. Second, we address reverse causality; for example, rivals may accelerate innovation upon learning of a firm's acquisition plans, thereby influencing our results. To mitigate these concerns, for each completed deal, we construct three different control samples (pseudo samples) as pools of potential mergers for real acquisitions and employ a conditional logit regression following Bena and Li (2014). Using matched deal samples that share similar firm characteristics, our positive association between TPP and the propensity of becoming an acquirer remains robust. As a second identification strategy, to address potential reverse causality, we conduct a two-stage least squares (2SLS) regression analysis using the introduction of state-level R&D tax credits as an instrumental variable. We find that the introduction of state-level R&D tax credits significantly increases firms' TPP, consistent with previous studies (Cao et al., 2023, 2018). Overall, our results remain qualitatively unchanged.

Moreover, we examine the types of M&As undertaken under technological peer pressure, particularly in target selection. We find that firms tend to pursue targets in different industries, suggesting that acquirers are likely to adopt a diversifying strategy to confront threats from technology competition. Additionally, we observe that acquirers are more inclined to select innovative targets when facing heightened technological competition, aligning with the findings of Phillips and Zhdanov (2013) and Bena and Li (2014).

To further investigate the positive association between acquisition likelihood and technological peer pressure, we examine the impact of firms' responses to technology competition on shareholder wealth. If increased M&A activity is an optimal response by firms to heightened technological competition, then the announcement of such acquisitions should be viewed favorably by market participants. We run cross-sectional regressions of acquirers' cumulative abnormal returns (CAR) centered on the deal announcement day to capture the short-term effect of technological peer pressure on acquirer shareholder value. Additionally, we use buy-and-hold abnormal returns (BHAR) to evaluate the quality of M&As over the long term. The evidence indicates positive shareholder wealth creation for firms that acquire in response to fierce technological competition. Besides, we find acquirers do not overpay in M&A deals motivated by TPP. Taken together, we find robust evidence that mergers and acquisitions are an optimal response to technological peer pressure.

Lastly, we explore the cross-sectional heterogeneity of our findings and the relationship between TPP and deal characteristics. First, we examine whether M&A quality varies by industry characteristics. We find that post-merger performance is more pronounced among high-tech industries, confirming the importance of innovation in technologically competitive sectors. The firm operating in single segment also experiences higher long-term announcement returns. Second, we find that acquisitions driven by TPP show a shorter time of deal completion. Additionally, firms prefer cash financing to equity financing as a M&A payment method.

We contribute to the existing literature in three key aspects. First, we deepen the understanding of the determinants of firms' motives to become acquirers. Pioneering studies have shown that product market synergy is one of the important drivers of M&As (Hoberg and Phillips, 2010; Rhodes-Kropf and Robinson, 2008). In particular, technology synergies are an essential merger motive (e.g., Bena and Li, 2014; Acemoglu et al., 2010; Frésard et al., 2020; Phillips and Zhdanov, 2013; Ahuja and Katila, 2001). We reaffirm the findings in the previous literature but also provide new empirical evidence by showing that increased technological peer pressure in the product market triggers firms' M&A activities.

Second, we provide new evidence of firms engaging in M&As to maintain competitive advantages and explore potential growth opportunities (e.g., Hitt et al., 1996; Cassiman et al., 2005). Existing literature has well documented that fiercer product market competition induces firms to proceed with M&A activities (Bena and Li, 2014; Karim and Mitchell, 2000). However, there is a lack of studies in this field focusing on the effects of technological peer pressure on corporate decision-making. In this paper, we show how peer pressure from rivals' technological advancements influences firms' M&A activities, highlighting the important role of innovation competition in the M&A literature.

Third, we contribute to the limited but growing strand of literature on corporate consequences stemming from technological peer pressure. To the best of our knowledge, we are the first study to explore the unexpected consequences of peers' R&D investments. While it is not uncommon to conjecture that peers' R&D activities will increase the focal firm's R&D investment, the potential costs of this R&D herding phenomenon are unclear. Existing literature in related fields documents the effects of technological peer pressure on product disclosure (Cao et al., 2018), job postings (Cao et al., 2023), corporate financial policies (Qiu and Wan, 2015), and sustainability performance (Wang et al., 2024). In this paper, we complement this stream of literature by shedding new light on the role of technological peer pressure in corporate acquisition decisions.

The rest of this paper is organized as follows: Section 3.2 reviews the relevant literature and formulates our hypotheses. Section 4.3 details our variable construction, data, and sample. Section 3.4 presents both our baseline results and the findings from various robustness tests. Section 3.5 delves into cross-sectional heterogeneity, while Section 3.6 concludes.

3.2 Related literature and hypothesis development

In this section, we review the literature on mergers and acquisitions to motivate our investigation and develop our hypotheses regarding whether and how changes in the technological competition landscape in the product market trigger a deal and its post-merger performance.

3.2.1 Related literature

The rationale for firms engaging in mergers has been discussed in the literature. Previous studies have shown that the motivations behind mergers and acquisitions (M&As) are influenced by both internal and external factors. In particular, characteristics of insiders, particularly CEOs, play a significant role in corporate merger decisions (e.g., Elnahas and Kim, 2017; El-Khatib et al., 2015; Jenter and Lewellen, 2015). Additionally, compensation incentives such as CEO inside debt holding and compensation duration can affect firms' M&A decisions and post-merger performance (Li and Peng, 2021; Phan, 2014). The reduction of agency problems (Jensen, 1993) is another motivation for engaging in M&As. From an external perspective, drivers of M&As include technological industry shocks (Morck et al., 1988), demand shocks and efficiency (Yang, 2008), industry life cycle (Maksimovic and Phillips, 2008), and policy uncertainty (Nguyen and Phan, 2017).

Among the literature, product market synergies are highlighted as one of the primary motivations for M&As. For instance, Huang and Xie (2023) develop a search and matching model demonstrating that two firms would merge if bilateral knowledge spillovers between them result in a productivity gain, generating a merger surplus larger than the transaction cost. After the merger, acquirer-target firm pairs with larger bilateral knowledge spillovers generate a larger surplus. Hsu et al. (2022) discover that firms reduce overlapping product offerings post-merger to achieve cost efficiency. Lee et al. (2018) introduce a metric to evaluate the connectedness of human capital between firms, finding this relatedness linked to a higher likelihood of mergers and increased merger returns.

An emerging body of research sheds light on whether and how firms decide to engage in M&As when the product market competition landscape changes (e.g., Karim and Mitchell, 2000), and how the situations of acquirers and target firms change post-merger. Recent studies further expand on this line of inquiry. Hsu et al. (2022) develop a new trademark-based product market competition measure, revealing that firms facing greater product market competition are more likely to be acquirers. Srinivasan (2020), using import tariffs as a measure of foreign competition, establishes a causal link between product market competition and firms' propensities to engage in M&As. Notably, concerning competition in technology, Bena and Li (2014) demonstrate that companies with large patent portfolios and low R&D expenses increase the likelihood of being acquirers, with synergies resulting from combining innovation capabilities.

A relevant study by Chen et al. (2020a) examines high-tech firms' responses to their rivals' technology and product breakthroughs. They use whether the firm's rivals received R&D 100 awards as a measure of peer pressure in the technology dimension for the focal firm, and find that the probability of firms engaging in M&As increases if their rivals win the R&D 100 awards.

In our paper, we utilize technological peer pressure, which assesses the threats of rivals' technological advancements relative to the focal firm's technological preparedness, to demonstrate a significant impact of innovation competition in the product market on the acquisition decisions of U.S. firms.

3.2.2 Hypothesis Development

In a static industry, a firm with a secure position may not need to take risks such as mergers and acquisitions. However, intense industry competition can prompt firms to pursue M&As. The ways in which product market competition triggers M&As can be summarized into four parts: First, firms may merge with their product market rivals to alleviate competitive pressure and enhance monopolistic power (Nevo, 2000; Sheen, 2014). Sheen (2014) observes that prices of products decrease, and products converge in quality after two competitors in the product market merge. Second, fierce product market competition widens the gap between small and large firms. Small firms become more vulnerable and may even go bankrupt in the evolving product market landscape (Erel et al., 2015). Large firms could seize the opportunity to acquire other firms. Third, firms may seek new technologies through M&A. The competition in technology, as a specific type of product market competition, compels firms to explore new technologies. Previous literature indicates that firms engage in M&A to accelerate their innovation capabilities (e.g., Phillips and Zhdanov, 2013; Bena and Li, 2014; Lin and Wang, 2016). Firms can integrate the target's technology and innovation capabilities to offset the competitive disadvantages. Furthermore, compared to internal R&D, which requires significant time and resources to yield successful innovative outcomes, external acquisitions can be a viable option for enhancing a firm's innovation capacity (e.g., Ahuja and Katila, 2001). Fourth, the rationale behind M&A decisions may be that firms seek to expand into new markets and pursue growth opportunities beyond their current markets or existing business sectors. Recent study shows that U.S. firms have expanded their operational scope over the past three decades, primarily through acquisitions and investment in R&D. Firms that increase their scope tend to realize higher valuations and greater sales growth (Hoberg and Phillips, 2025).

Competition in the product market manifests in various dimensions such as price competition, market promotions and advertisements, product differentiation, quality, and innovations. Competition in innovation is particularly vital in this knowledge-based economy. Bloom et al. (2013) develop a comprehensive framework incorporating two types of technology spillovers and implement this model using measures of a firm's position in the technology space and product market space. The authors demonstrate that technology spillovers quantitatively dominate such that the gross social returns to R&D are at least twice as high as the private returns. Subsequently, Cao et al. (2018) devise a firm-specific measure of the technological aspect of competition, technological peer pressure (TPP), adjusted by the "closeness" of firms. Firms engage in R&D to develop new products and processes to secure future product market power. TPP captures competition within industries, offering an opportunity to analyze interaction mechanisms between firms.

Building on the arguments above, we formulate our first hypothesis regarding technology competition in the product market and M&A deal incidence as follows:

Hypothesis 1: The probability of a firm become an acquirer in M&As increases when facing intense technological competition.

To shed light on how technological synergy is achieved through M&As, we need to further test the ex-post effect of deal incidence. Some studies show new product development under product market competition after mergers. Hsu et al. (2022) demonstrate that post-merger, compared to their non-acquiring peers, acquirers reallocate their product offerings by cutting more existing product lines and developing fewer new product lines. Bena and Li (2014) find a positive causal relationship between a merger and post-merger innovation output when there is pre-merger technological overlap between merging firms. There are also papers focusing on post-merger firm value, operating performance, and shareholder value. Huang and Xie (2023) find that acquirer-target firm pairs with larger bilateral knowledge spillovers generate a larger surplus. Bereskin et al. (2018) test industry-adjusted (i.e., abnormal) post-merger operating performance, defined as earnings before interest, taxes, depreciation, and amortization. They find the abnormal increase in post-merger industry-adjusted operating performance for high-similarity mergers is 3.8%. Our second hypothesis is thus:

Hypothesis 2: M&As may lead to greater market power and economies of scale, resulting in sales growth and profitability.

In the next section, we define key variables used in the empirical analysis and present a sample overview. Then, we describe our empirical methodology used for testing the above hypotheses.

3.3 Variable construction and sample

In this section, we introduce the data sources and the construction of the main variables that will be used in the empirical analyses. We also present some variable distribution and descriptive statistics of our sample.

3.3.1 Technological peer pressure

We measure technological competition in the product market and use it as the key independent variable in our analysis. Although some recent studies have proposed measures of technological competition in the technology space (Qiu and Wan, 2015; Bloom et al., 2013; Glaeser and Landsman, 2021), we employ technological peer pressure (TPP) to measure technological competition as we think TPP is more suitable for our reseach design. The TPP measure is inspired by the product market rivalry variable proposed in Bloom et al. (2013). Cao et al. (2018) modify it and construct the TPP variable, which gauges a firm's technological threat arising from its peers' technological advances, proxied by their R&D investments. The logic behind the TPP variable is that a sample firm i's technological threat comes from a peer firm j's R&D stock $G_{j,t}$ at the end of year t, weighted by the closeness ω_{ij} between these two firms in the product market. Considering the benefits of R&D investments over an extended period, Bloom et al. (2013) apply a depreciation rate of 15% when calculating $G_{j,t}$, following Jaffe (1986): $G_{j,t} = R\&D_{j,t} + (1 - 15\%) \times G_{j,t-1}$, where $R\&D_{j,t}$ is the R&D expenditure in year t.

The closeness between two firms, ω_{ij}, is calculated in the product market space using firm i's and j's sales in every four-digit Standard Industrial Classification (SIC) industry according to the Compustat Historical Segment database.[3] We denote V_i as a K-dimensional vector for firm i's share of sales in every four-digit industry k.[4] Then,

[3]Following Bloom et al. (2013), we use sales from the entire sample span to calculate the proportions of each firm's segment sales across our analyses. Our results remain robust when using sales from the previous two years to calculate the proportions of each firm's segment sales, following Cao et al. (2018).

[4]We use 4-digit SIC codes to construct the TPP because this level provides the most granular classification available, capturing nuanced distinctions in firms' areas of focus. Since the TPP is designed to reflect detailed technological competition, the finer 4-digit classification enables us to more accurately identify overlaps in product markets and innovation domains.

ω_{ij} can be defined as the cosine of vectors V_i and V_j in the product market space:

$$\omega_{ij} \equiv \cos(\theta_{ij}) = \left\langle \frac{V_i}{|V_i|} \cdot \frac{V_j}{|V_j|} \right\rangle = \frac{\sum_{k=1}^{K} v_{ik} v_{jk}}{\sqrt{\sum_{k=1}^{K} v_{ik}^2} \sqrt{\sum_{k=1}^{K} v_{jk}^2}}. \tag{3.1}$$

Cao et al. (2018) formally calculate $TPP_{i,t}$ in Equation (3.2):

$$TPP_{i,t} = \ln\left[1 + \frac{1}{G_{i,t}} \sum_{i \neq j} \omega_{ij} \times G_{j,t}\right]. \tag{3.2}$$

The ratio inside the bracket represents the threats of rivals' technological advances relative to the firm i's own technological preparedness. For example, a TPP value of 5 indicates that a firm's competitors invest five times more in R&D than the firm itself. This suggests that firms with lower technology investment face greater competitive pressure than those with higher investment. Therefore, a higher TPP value signals intense technological competition arising from both rivals' R&D capabilities and the resulting innovations.

TPP is the best available measure for capturing technological competition in the product market and has been validated by Cao et al. (2018). It outperforms traditional competition measures based on industry structure because it accounts for all industries in which a firm operates. Moreover, TPP reflects competition intensity in a timely manner, as it is updated annually using R&D investments from the previous year combined with firms' closeness, derived from newly available segment sales data.[5]

However, there are limitations to using R&D expenditure as a proxy for innovation. Technology competition may involve factors beyond R&D investments. Critics may argue that R&D expenditure does not capture the success or output of innovation efforts.

[5] The benefits of using TPP are discussed in Cao et al. (2018).

To address this, we perform robustness checks by modifying Equation (3.2), replacing R&D stocks with the number of patents granted or applied for in a given year, which better captures the output side of innovation competition. The patent-based TPP measure complements the original TPP by gauging technological competition from the output perspective.

3.3.2 Mergers and acquisitions data

We collect our initial dataset of all U.S. mergers and acquisitions with announcement dates between January 1, 1983, and December 31, 2022, from the Securities Data Company (SDC) database. Following previous literature (e.g., Bena and Li, 2014), we focus only on completed merger deals and filter out insignificant M&A deals where the transaction value is less than 1 million US dollars. Then, we require that the acquirer holds less than 50% of the target's shares before the announcement and owns more than 90% of the target's ownership after the merger. Lastly, we keep acquisitions where both the acquirer and target are U.S. firms, and the acquirer is a public firm covered by Compustat and the Center for Research in Security Prices (CRSP).

3.3.3 Sample

We construct the sample for our investigation of the relationship between technological peer pressure and firm acquisition activities using the universe of firms included in Compustat and CRSP databases. We exclude firms from the financial (SIC 6000-6999) and utility (SIC 4900–4999) sectors due to their high regulation and distinct competition landscapes compared to other public firms (Li and Zhan, 2019).[6] Our final sample

[6] We further exclude the quasi-public firms (SIC greater than 9900), which accounts for 0.1% of the total observations. After excluding these few observations, the findings remain significant.

comprises 47,892 observations with 5,384 acquisitions across 58 different 2-digit SIC industries spanning the period 1983-2022. The key variables used in this paper are defined in Appendix Table B1.

The distributions of 2-digit SIC industry and year M&A deals are reported in Panels A and B of Table 3.1, respectively. Panel A illustrates that M&A deals concentrated in certain industries during the period 1983 to 2022, including business services (2-digit SIC 73), instruments and related products (2-digit SIC 38), electronic and electrical equipment (2-digit SIC 36), and chemicals and allied products (2-digit SIC 28). In Panel B, we observe a rapid increase in M&A deals in the mid-to-late 1990s (during the dot-com boom) followed by a significant drop in 2008 due to the financial crisis.

Summary statistics for the relevant variables are tabulated in Table 3.2. The mean probability of being an acquirer in our sample is 11.2%. The mean of TPP in our sample is 5.99, indicating that, on average, peer firms invest \$394 ($e^{5.99} - 1$) in R&D for every dollar of R&D investment by the sample firm.

[Insert Table 3.1 and Table 3.2 around here]

In Figure 3.1, we plot the changes in average TPP and the number of acquisitions over the sample period from 1983 to 2022. Both TPP and the number of M&As increased significantly during the 1990s, peaking around 2000, likely due to economic expansion and favorable market conditions during the tech boom. After 2000, the trend in acquisition activities and TPP declined and then stabilized. This graph suggests a strong correlation between technological competition and M&A activities, providing intuitive evidence supporting our hypothesis.

[Insert Figure 3.1 around here]

3.4 Empirical methodology and results

In this section, we empirically test our main hypotheses regarding the impact of technological competition in the product market on firm acquisition activity. Subsection 3.4.1 introduces the regression model used in our analysis and presents the baseline results. In addition, we address potential endogeneity concerns through instrumental variables and conditional logit estimation. We conduct a series of robustness checks in this section. Subsection 3.4.2 explores how firms select their M&A targets under pressure from rivals. Finally, subsection 3.4.3 investigates whether the increased M&A propensity associated with high TPP is an optimal choice for firms.

3.4.1 Technological peer pressure and acquisition propensity

In this subsection, to examine whether the technological peer pressure faced by a firm is associated with it becoming an acquirer, we estimate the following logit regression:

$$Pr(Acquirer_{i,t} = 1) = \Phi(\alpha + \beta TPP_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FEs + \varepsilon_{i,t}). \tag{3.3}$$

where the dependent variable, Acquireri, t, is a binary variable that equals 1 if firm i announces an M&A deal in year t, and 0 otherwise. The key independent variable, TPP, is the technological peer pressure, which captures the advancement of technological investments by a firm's product market rivals relative to the firm's own. $\mathbf{X}i, t-1$ is the vector of control variables, including both firm-level and industry-level controls. Specifically, we control for firm size (Size) because larger firms are more likely to engage in acquisitions (Almazan et al., 2010). We also include return on assets (ROA), stock returns (Stock Returns), industry sales growth (Industry Sales Growth), and book-to-market ratio (B/M), as better-performing firms and firms with higher growth opportunities are more likely to become acquirers (Gaspar et al., 2005; Harford and Uysal, 2014). We further control for cash holdings (Cash) since firms with higher liquidity are likely to engage in acquisitions (Harford, 1999). Besides, we control for firms' leverage levels (Leverage) and risks (Stock Return Volatility). Following Chen et al. (2020a), to control for other dimensions of competition in the product market, we add the Herfindahl–Hirschman Index (HHI). To alleviate the concern that TPP is correlated with other omitted variables (Xu et al., 2022), we further control whether the focal firm lacks R&D investment relative to its rivals (Lack R&D).

The main explanatory variable and control variables are measured in fiscal year $t-1$ before the M&A announcement. β is the coefficient of interest, representing the propensity of firms' acquisition decisions. We include year fixed effects to alleviate the influence of merger waves, and industry (3-digit SIC code) fixed effects to control for unobserved time-invariant industry-specific characteristics.[7] In line with the existing empirical corporate finance papers (e.g., Li and Peng, 2021; Cai et al., 2023; Cao et al., 2018), the standard errors for computing t-statistics are corrected for heteroskedasticity and clustering at the firm level in baseline regressions. All control variables have been winsorized at the 1% level in each tail. Detailed definitions of all variables are presented in Appendix Table B1.

Table 3.3 reports the logit estimation results, where Column (1) includes the firm-level controls, and Column (3) further controls for industry-level characteristics. Consistent with our hypothesis, the coefficient of our key variable, TPP, is statistically signif-

[7] We include 3-digit SIC industry fixed effects to control for unobserved heterogeneity at a reasonably granular level. The 3-digit level offers a compromise between controlling for industry-specific characteristics and retaining sufficient within-industry variation for identification. The results are qualitatively unchanged when we use 2-digit SIC codes or Fama–French industry classifications to define industries.

icant at the 1% level, indicating that the intensification of technological competition in the product market motivates firms to undertake acquisitions. Using the marginal effect of TPP from the estimated logit model in Table 3.3 Column (2), we find that the probability of a firm's acquisition likelihood increases by 0.9%, corresponding to approximately 8.04% increase from the sample acquisition probability of 11.2% (0.9%/11.2%).[8] Our results are both statistically and economically significant.

Regarding the control variables, the signs of control variables are largely consistent with previous literature. To be specific, the acquisition propensity is positively associated with firms' size, performance, and growth opportunities. On the contrary, firms with higher leverage levels and risks are negatively correlated with future propensities of conducting acquisitions. However, we don't find a relation between the general product market competition, i.e., HHI, and the propensity to become an acquirer.

[Insert Table 3.3 around here]

Moreover, we examine the potential threshold effect of TPP on the likelihood of becoming an acquirer. Appendix Table B2 presents the results, including both TPP and its quadratic term (TPP^2), to test for a possible U-shaped or inverted U-shaped relationship between TPP and the probability of becoming an acquirer. We observe a positive association with the non-squared TPP concomitant with a negative association with squared TPP, indicating an inverted U-shaped relationship between TPP and the propensity to acquire.[9] The extreme point is 9.03 for the model reported in Column (2). Considering that 90% of firms have a TPP below 8.8 in our sample, we can infer that most firms are more likely to pursue M&As when facing intense technological competition.

[8] Alternatively, we can quantify the change in another way: one standard deviation increase in TPP is associated with approximately 19.11% increase in the focal firm's acquisition probability.

[9] Following Lind and Mehlum (2010), we conduct a statistical test to check the presence of an inverted U-shaped relation. The statistical test accepts that there is an inverse U-shaped.

At moderate to high levels of TPP, firms are incentivized to acquire other firms as a way to expand their innovation capabilities and improve their competitive position. M&A serves as a strategic tool to respond to competition and consolidate market power, which increases the likelihood of firms becoming acquirers as TPP rises. At extremely high levels of technological competition, however, the environment may become overly competitive, uncertain, or saturated. Under such conditions, the costs and risks associated with M&A—such as higher acquisition premiums, integration difficulties, and intensified competition for targets—may outweigh the expected benefits.

These results highlight that while technological competition generally encourages M&A activity, beyond a certain threshold, the associated risks reduce firms' incentives to become acquirers.

Addressing endogeneity concerns

There are two potential sources of endogeneity issues in our findings, which may not indicate a causal link between technological competition and acquisition propensity. The first concern is omitted variables, i.e., factors that could affect both the probability of engaging in M&A activities and innovation. The second endogeneity issue arises from reverse causality. For example, a focal firm's rivals might accelerate their innovation to maintain competitiveness upon noticing the focal firm's intention to acquire a target before the public announcement. In the following subsections, we apply two identification tests to address these endogeneity concerns.

Conditional Logit Estimation. To address the omitted variable issue, we implement a matching method to construct a balanced matched sample in observable characteristics related to acquisition likelihood. Following Bena and Li (2014), for each completed deal, we construct three different control samples (pseudo samples) as pools of potential mergers for real acquisitions and employ a conditional logit regression. First, we randomly form the control sample. For each acquirer i of a deal in a given year t, we randomly draw five firms from the pool of firms that have ever performed an acquisition before the deal year in year $t-1$, ensuring that these firms were neither acquirers nor targets in the three years prior to the deal. Second, we match the control sample based on firm size. Similarly, for each acquirer i of a deal in a given year t, we match it with five control firms based on firm size measured as the natural log of firms' total assets. Additionally, we require the pseudo firms' sizes to be close to real acquirers' (within 20%). Furthermore, the matched firms operate in the same industry as each acquiring firm, capturing clustering in both time and firm size. Third, after matching with firms of similar size, we further refine the matching criteria by including the firm's book-to-market ratio. We use the book-to-market ratio as a matching characteristic because it represents firms' growth opportunities, overvaluation, and complementarity (Rhodes-Kropf and Robinson, 2008; Rhodes-Kropf and Viswanathan, 2004; Andrade et al., 2001).

As presented in Table 3.4, consistent with previous findings, the coefficients of TPP are statistically significant at the 1% level in the random-matched sample and size- and B/M-matched sample, reported in Columns (1) and (3).[10] These findings suggest that our baseline result is unlikely driven by omitted variables related to observable characteristics, and the positive relationship between technological competition and acquisition propensity still holds. Using the marginal effect of TPP from the estimated logit model, in Panel B Column (1), we find that the likelihood of a firm's acquisition likelihood increases by 1.2%, corresponding to approximately 7.2% increase from the sample acqui-

[10] Since B/M captures aspects of firm valuation and growth opportunities, its omission in the matching process for Column (2) likely weakens the observed relationship between technological peer pressure and M&A probability.

sition probability of 16.7%. The economic significance is smaller than that in baseline regression (8.04%).

Instrumental variable estimation. To address concerns regarding reverse causality, we implement a two-stage least squares (2SLS) regression analysis using the introduction of state-level R&D tax credit to construct the instrumental variable (IV). This event can lower the cost of R&D activities by firms headquartered in affected states, introducing exogenous increases to R&D (Wilson, 2009).[11] Thus, $Tax\ credit$ satisfies the relevance requirement for an IV. Besides, the introduction of the state-level R&D tax credit is legislature support that can promote the overall R&D in an economy (Byun et al., 2023; Wilson, 2009), so it is unlikely related to firms' acquisition activities. We therefore consider the state-level R&D tax credit as exogenous to firms' acquisition propensity.[12]

To better understand our IV, we decompose TPP into two components, see Equation (3.2). TPP can be divided by whether the state in which the peer firm is headquartered is the same state as the focal firm.

$$TPPi,t = ln\left\{1 + \frac{1}{Gi,t}\left[\sum^{i\neq j}\omega_{ij} \times G_{j,t} \times I(S_{i,t} \neq S_{j,t}) + \sum^{i\neq j}\omega_{ij} \times G_{j,t} \times I(S_{i,t} = S_{j,t})\right]\right\}, \tag{3.4}$$

where $I(\cdot)$ is an indicator function that represents if the focal firm and its peer firm are headquartered in the same state. $S_{i,t}$ is the state in which firm i headquarter located in year t.

[11]Previous studies have shown that firms have a strong incentive to operate R&D facilities in their headquarters' states (Glaeser et al., 2023) Thus, it is rational to assume that state R&D tax credit may affect R&D activities by firms headquartered in the affected states.

[12]In the Compustat database, the firms' headquarters state are the current records. Firms sometimes change headquarters. To alleviate this concern, we apply the Firm Historical Headquarter State datasets developed by Gao et al. (2021), who extract the header information from historical SEC filings. The data is shared on the author's personal website: https://mingze-gao.com/posts/firm-historical-headquarter-state-from-10k/#data-available-for-download. The Firm Historical Headquarter State datasets are merged with the dataset used in each chapter of my thesis.

Then, we can construct our instrumental variable $Tax\ credit$ as follows:

$$Tax\ credit_{i,t} = \sum^{i \neq j} \omega_{ij} \times I(Tax\ credit(S_{j,t})) \times I(S_{i,t} \neq S_{j,t}), \tag{3.5}$$

where $I(Tax\ credit(S_{j,t}))$ denotes if peer firm j is headquartered in the state that has introduced tax credit at year t. The $Tax\ credit$ captures the increases in R&D stocks for peer firms as a consequence of exogenous regulatory changes. $Tax\ credit$ is not highly correlated with TPP and is unlikely to affect the focal firm's acquisition activities.

Table 3.5 reports the results from the IV analysis. Columns (1) and (3) present the first-stage regressions, showing a strong positive relation between $Tax\ Credit$ and TPP, echoing previous findings. The Kleibergen–Papp F-statistics are high, indicating strong instruments. In columns (2) and (4), we report the second-stage regressions estimate of the instrumented TPP, which shows a positive and statistically significant relationship. Considering the economic significance in Column (4), one standard deviation increase of TPP (2.328) is associated with 9.13% from the sample acquisition probability of 12.8% (2.328*0.005/0.128), which is similar to the findings in the baseline regressions. The signs of control variables are also consistent with baseline regression and existing studies (e.g., Li and Peng, 2021; Bena and Li, 2014). Thus, the positive relationship between technological competition and acquisition likelihood documented in Table 3.3 still holds.

Overall, these findings suggest that, after addressing potential endogeneity concerns, firms facing intensified technological competition are more likely to become acquirers.

[Insert Table 3.5 around here]

Robustness checks

In this subsection, we present the results from robustness checks. First, we perform a linear probability model (LPM) and probit regression analyses to test the main hypothesis. Panel A of Table 2.6 presents the results using the same control variables and fixed effects from the baseline model. The coefficients of TPP are statistically significant at the 1% level and quantitatively similar to our baseline results. Our finding that firms are more likely to conduct M&As under technological peer pressure is not affected by the model specifications.

Second, we consider using a patents-based TPP measure to examine whether our result is driven by a specific measure of technology competition. In our baseline regressions, we construct the TPP based on R&D expenditure every year. However, there is a concern that technological competition is multidimensional. To address this concern, we modify Equation (3.2) by replacing the R&D stock with the number of patents applied and granted by the focal firm, which are commonly used to measure outputs of innovation (Glaeser and Lang, 2024). This new measure of TPP is patents-based and represents the output side competition of innovation, differentiating from the original TPP which captures the input side competition in technology.[13] As presented in Table 2.6, Panel B, the coefficient estimates of patents-based TPP are all significantly positive, and the magnitude is similar to our baseline results, consistent with our main argument.[14]

Third, we repeat the regression after excluding the top three industries, which account for over 50% of the sample. As presented in Table 3.1, firms operating in the

[13] We retrieve the patent data that links patents to firms from Kogan et al. (2017) (KPSS), which has been updated through 2022. The advantage of using KPSS is the matching identifier CRSP-PERMNO that we can later use to merge KPSS with COMPUSTAT and CRSP firm-level data. The patent data is available on: https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

[14] The number of observations is less than that used in the baseline regressions because some firms do not have patent filing records during our sample period.

business services (2-digit SIC 73), instruments and related products (2-digit SIC 38), and Electronic and other electrical equipment (2-digit SIC 36) sectors make up over half of our sample firm-years. To mitigate the concern that our findings are driven by these industries, we re-examine the main results with a model specification the same as Equation (3.3). From the first three columns in Table 2.6, Panel C, we find that the positive association between technological peer pressure and acquisition propensities is qualitatively unchanged. In Column (4), we repeat the analysis using the subsample of firms in only these top three industries. These results suggest that our finding is not subject to the largest representations in the sample.

Fourth, we use alternative combinations of fixed effects. We conduct the same regression model with firm and year fixed effect to control for unobserved time-invariant firm-specific characteristics in Appendix Table B3 Panel A Column (2). Furthermore, there is a concern that unobservable time-varying industry, and state factors, such as industry standards, regulation, and market conditions, might influence firms' acquisition decisions. To eliminate this concern, we additionally control for Year*Industry fixed effects and Year*State fixed effects in the baseline regression model. In Appendix Table B3 Panel A Column (3) and (4), we show that, after controlling for potential confounding effects, all estimated coefficients on TPP are positive and statistically significant at the 1% level. These results indicate that the firm characteristics and unobserved time-varying industry and state factors are unlikely to be the drivers of our results.

Fifth, we use alternative clustering following Abadie et al. (2023) and Angrist and Pischke (2009). Considering the presence of industry and state shocks Srinivasan (2020), we take a more conservative approach by clustering standard errors by state and industry. Additionally, we implement clustering based on industry-year or firm-year. The results are presented in Appendix Table B3 Panel B. We find that the standard errors with higher-level clustering are similar to the standard errors in the baseline regression. These findings indicate that our baseline regression results are robust.

[Insert Table 3.6 around here]

3.4.2 Target selection

Diversifying acquisition or non-diversifying acquisitions. In previous subsections, we discuss firms' reactions to fierce technological competition in the product market. Then, a natural question then arises: what type of target would the bidder select? On the one hand, firms could catch up with rivals by acquiring targets within the same industry to improve efficiency and reduce costs associated with overlapping products. When firms are aware that they have fallen behind in technology competition, firms would take over targets related to their rivals (Chen et al., 2020a). Srinivasan (2020) also find that firms are more likely to consolidate within their industries rather than pursuing diversifying acquisitions under increased product market competition.

On the other hand, firms may strategically extend their business lines through diversifying acquisitions to offset the negative effects of intensified competition. By expanding into new product lines or markets, firms seek to differentiate their offerings, enhance growth potential, and reduce risks associated with competition in their core segment. Prior studies document, as competition squeezing profit margins, firms investing in product differentiation, including altering product composition (Bao and Chen, 2018), developing more new products (Hsu et al., 2022), and investing in ESG activities (Ding et al., 2022).

To explore the type of target in an acquisition, we repeat the analyses with a model specification the same as Equation (3.3). The dependent variable is a binary variable, $Diversifying\ M\&A$, which equals one if the acquirer and target firms are in the different SIC industries, and zero otherwise. Table 3.7 presents the results from the logit regression analysis. The coefficients on TPP are all positive and statistically significant at the 5% level except for the last column. These results indicate that firms are more likely to conduct diversifying acquisitions for defensive purposes when confronting fierce technological competition.

[Insert Table 3.7 around here]

TPP and the propensity of becoming a target. Next, we examine the effect of TPP on the likelihood of being a target. Phillips and Zhdanov (2013) show that firms may acquire innovative firms and conduct less R&D themselves. However, Cunningham et al. (2021) find that acquiring innovative targets is to discontinue the target's innovation output and prevent potential competition in the future.

We re-estimate the regression in Table 3.3. Panel A of Table 3.8 presents coefficient estimates using the actual deal sample from the logit regression in Equation (3.3). We find that, in contrast to Table 3.3, there is a negative association between technological peer pressure and the propensity of a firm to become a target firm. The results are statistically and economically significant. Using the marginal effect of TPP from the estimated logit model, we find that the probability of a firm's likelihood of being a target decreases by 0.3%, corresponding to approximately an 11.54% decrease from the sample acquisition probability of 2.6%. We also conduct conditional logit regression as discussed in Section 3.4.1. As shown in Table 3.8, Panel B, the coefficients are still statistically significant at the 10% level or better. We also find that firms with better operating performance and lower stock returns are more likely to become target firms, which is consistent with previous studies (e.g., Bena and Li, 2014).

These findings suggest that firms are more likely to be acquired if they do not fall behind their rivals in their industries. Additionally, there is another interesting finding that the coefficient of $Lack\ R\&D$ is negatively significant at the 1% level, which indicates that firms are less likely to become a target if their R&D expense is below the industry median level R&D expense. Taken together, bidders prefer to purchase innovative firms when facing increased technological competition, which is in line with Phillips and Zhdanov (2013) and Bena and Li (2014).

[Insert Table 3.8 around here]

3.4.3 Technological peer pressure and post-merger performance

In this subsection, we discuss whether bids associated with intensifying technological competition benefit acquirer shareholder value. There would be a positive shareholder reaction if shareholders regard acquisitions as an appropriate response to increased competition.

TPP and announcement abnormal returns

We first examine whether TPP is associated with high combined announcement returns by using cumulative abnormal returns (CARs) around the M&A announcement date benchmarked against the market model. Following prior literature (e.g., Li and Peng, 2021; Srinivasan, 2020), we calculate CARs around the M&A announcement date over three-day (-1, +1), seven-day (-3, +3), and eleven-day (-5, +5) windows. We use 255 through 46 trading days before the M&A announcement date as the estimation period. We require that, for each M&A deal, the acquirer should have at least 30 non-missing trading days during the estimation periods.

To examine the relation between acquirer technological peer pressure and the market's reaction to acquiring firms, we use the following regression model:

$$Acquirer's\ CAR_{i,t} = \alpha + \beta TPP_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FEs + \varepsilon_{i,t}. \tag{3.6}$$

where the dependent variable is each acquirer's CAR centered on the deal announcement day. $\mathbf{X}_{i,t-1}$ is the vector of firm and deal characteristics that could affect the stock market reaction to M&As. Following earlier studies (e.g., Li and Peng, 2021), we include firm size and book-to-market ratio (B/M) to control for acquirer characteristics. We control for the following deal-level characteristics: indicators for all-cash deals and all-stock deals, whether the target is a public firm, relative deal size, diversifying M&A, and friendly deals. Year and industry fixed effects are also included in the regression. The standard errors are clustered at the firm level following Hossain et al. (2023).

Table 3.9 presents the results of CARs to the announcement of acquisitions in response to technological peer pressure. The coefficients on TPP are positive and significant at the 5% level or better over different estimation windows. The economic significance of our results is: one standard deviation (2.167) increase in TPP is associated with a 12 basic points increase in the acquirer's 3-day announcement CAR, which is around 7.8% of the sample mean.[15] Regarding the control variables, we find that acquirers with public targets show lower abnormal announcement returns and acquirers of all-cash deals experience higher abnormal announcement returns. These findings are consistent with the existing literature (Chang, 1998; Hossain et al., 2023). Hence, we document evi-

[15]The economic significance is calculated as follows: 2.167 (one standard deviation of TPP for bidders with daily stock returns from trading days -255 to -46, and with at least 30 non-missing daily stock returns) multiplied by 0.057.

dence that acquisitions made in response to intensifying technological competition can be viewed as favorable responses by acquirer shareholders.

TPP and long-term abnormal stock performance

To complement the short-run shareholder value creation analysis, we further examine the effect of technological competition on post-M&A long-run abnormal returns. Following Hossain et al. (2023), we use the buy-and-hold abnormal returns (BHARs) to measure the acquirer's long-term stock performance. BHARs are calculated based on the average difference in the aggregated performance between the included stock and benchmark (CRSP value-weighted index) returns over 12 months starting from the announcement month of the acquisition. The number of observations drops to 4912. As presented in Table 3.9 Column (4), we find that the coefficient of TPP is positive and statistically significant at the 5% level, indicating that acquisitions associated with increased technological competition positively affect acquirers' 12-month long-run returns. A one-standard-deviation increase in TPP is related to a 5.8% increase in post-merger BHAR within a year after the announcement. Overall, these results provide evidence that acquisitions made in response to fierce technological competition significantly generate higher post-acquisition abnormal stock returns for bidders in both the short and long run.

[Insert Table 3.9 around here]

Bid premium

Next, we examine the relation between TPP and acquisition premiums to better understand the mechanisms of M&A value creation. We define the bid premium as the percentage difference between the bid prices and the targets' stock prices one day, one week, and four weeks before the deal announcements. Following previous studies (e.g., Hossain et al., 2023), we control for the acquirer and deal characteristics. The results are presented in Table 3.10. We find the coefficients of TPP are insignificant across different measures of bid premium, indicating that acquisitions are not driven by over-investment concerns. The TPP-induced acquisitions are value-creating.

[Insert Table 3.10 around here]

3.5 Further discussion

We have found that firms become more likely to acquire others in response to increased technological competition, and innovation-motivated acquisitions are associated with positive shareholder wealth generation. In this section, we design multiple tests to explore factors that influence the quality of mergers and acquisitions, and how TPP influences the deal characteristics.

3.5.1 Heterogeneity between TPP and post-merger performance

First, as we focus on technological competition, we expect there could be heterogeneity between high-tech industries and non-high-tech industries. Firms in R&D-intensive industries may be more sensitive and reactive to competition within the technology dimension (Wang et al., 2024). Previous studies show that firms in high-tech industries are more likely to engage in innovation-driven acquisitions due to fast market growth, rapid product penetration, and shorter product life cycles in high-tech industries (Chen et al., 2020a). Thus, the positive shareholder reaction to TPP-motivated acquisitions may be more pronounced for high-tech companies. To test this conjecture, we use the classification defined by Cao et al. (2021) to divide the sample into high-tech and low-tech groups.[16]

Panel A of Table 3.11 presents the results of the heterogeneous effect from the industry. The coefficients of TPP are statistically significant for firms in the high-tech group. On the other hand, we do not find significant coefficients on TPP in the low R&D intensity group. These findings exist for both short-term and long-term abnormal returns. In untabulated results, we carry out the same logit analysis for acquirers' cumulative abnormal returns (CARs) over five-day and eleven-day windows, and our findings are quantitatively similar. All these results indicate positive abnormal returns associated with innovation-motivated acquisitions only exist within high-tech companies.

Second, firms may engage in product diversification to cope with intensifying product market competition (Bao and Chen, 2018). As shown in the previous section, firms tend to acquire targets in different SIC industries (i.e., diversifying M&A). However, multi-segment firms, which already operate across multiple industries, may face challenges in efficiently integrating new acquisitions and reallocating resources. As a result, they might prioritize refocusing on their most profitable segments rather than pursuing potentially riskier acquisitions (Srinivasan, 2020). This behavior likely leads to lower shareholder support and reduced announcement returns for multi-segment firms. Consequently, we expect single-segment firms to achieve higher announcement returns.

Consistent with this, Table 3.11 Panel B shows that, in the long run, single-segment firms experience higher announcement returns than multi-segment firms. This finding supports the diversification argument discussed in Section 3.2.2: firms benefit from expanding into new product lines or markets through acquisitions, creating synergies, en-

[16] Cao et al. (2021) identifies firms operating in the following four-digit SIC industries as high-tech firms: 2833–2836, 3570–3577, 3600–3674, 7371–7379, or 8731–8734. Results are quantitatively similar if we use the high-tech classification defined by Png (2017).

hancing growth opportunities. Therefore, the superior performance of single-segment firm acquisitions suggests that developing new product lines as a form of related diversification is an important value-creating strategy for acquirers. It is worth noting, however, that this effect does not appear in the short term within our sample.

[Insert Table 3.11 around here]

3.5.2 TPP, time to deal completion and payment considerations

We next examine whether M&As are completed more rapidly when facing increased technology competition. The intensifying innovation competition forces firms to complete deals quickly and achieve deal synergies. Therefore, we expect a negative relationship between TPP and M&A completion time. We investigate the effect of TPP on the time it takes to complete acquisitions by running an ordinary least squares model with acquirer- and deal-level controls. The estimation results are reported in Table 3.12 Column (1). The coefficient on TPP is negative and statistically significant, indicating that it takes the acquirers less time to complete the deals under fierce technological peer pressure. One standard deviation increase of TPP is associated with a 0.106 unit decrease in completion time, which accounts for 4.1% of the mean value of completion time.

This result is consistent with our finding that TPP-induced acquisitions are associated with positive announcement returns. Rapid integration could potentially indicate the confidence of the acquiring firm's board and management, and suggest reduced need to rely on due diligence after the announcement (Rousseau and Stroup, 2015).

We further examine the payment methods used by acquirers in acquisitions. We run a logit regression model in which the dependent variable, $Allstockdeal$, equals one for deals funded completely by stock.[17] As reported in Table 3.12 Column (2), the coefficient of TPP is negative and statistically significant. This result suggests that when experiencing an increase in TPP, acquirers prefer cash financing to equity financing as a M&A payment method. This finding is consistent with the theory that equity-financed deals should earn significantly lower returns relative to cash-financed deals (Renneboog and Vansteenkiste, 2019). Equity financing may indicate the overvaluation of a firm's stock. Overall, these results indirectly support the findings that TPP-induced acquisitions benefit acquirer shareholder value.

[Insert Table 3.12 around here]

3.6 Conclusion

Innovation stands as the primary driver of firm growth, and companies that lag behind in the innovation race face significant risks. The pressure to keep pace with competitors' research and development efforts in the product market can place firms in a precarious position. In this study, we delve into the intricate relationship between technological peer pressure and firms' mergers and acquisitions (M&As) activities. Deviating from previous research that explored the connection between product market competition and acquisition decisions, we employ a measure of technological peer pressure to capture the threats stemming from the technology dimension within the product market.

Through a comprehensive analysis of M&As transactions in the United States spanning the period from 1983 to 2022, we present compelling and robust evidence that technological peer pressure serves as a motivating factor, triggering firms to engage in acquisitions. Our findings indicate that firms are more likely to pursue diversifying M&As

[17] We also use the percentage of stock payment for a M&A deal. The finding is unchanged.

and acquire innovative targets as a strategic response to increased technological peer pressure. Furthermore, we demonstrate that acquisitions driven by technological peer pressure are associated with better cumulative abnormal returns for the acquiring firms. This suggests that companies strategically respond to heightened technology competition by engaging in acquisitions to enhance their operational efficiency and technological capabilities. Notably, firms operating in high-tech industries and single-segment firms exhibit superior post-merger performance when engaging in innovation-motivated acquisitions. Additionally, we find TPP-induced acquisitions take less time to complete. Acquirers prefer cash financing to equity financing as a M&A payment method.

In summary, our results underscore the crucial role of technological competition in the product market within the knowledge-based economy. By shedding light on how firms navigate technological challenges through strategic acquisitions, this study contributes valuable insights to our understanding of the dynamics between innovation, competition, and corporate strategies. Our findings have important implications for managerial decision-making, highlighting the significance of recognizing and responding to technological peer pressure through strategic acquisitions to maintain competitiveness and drive growth in innovation-intensive industries.

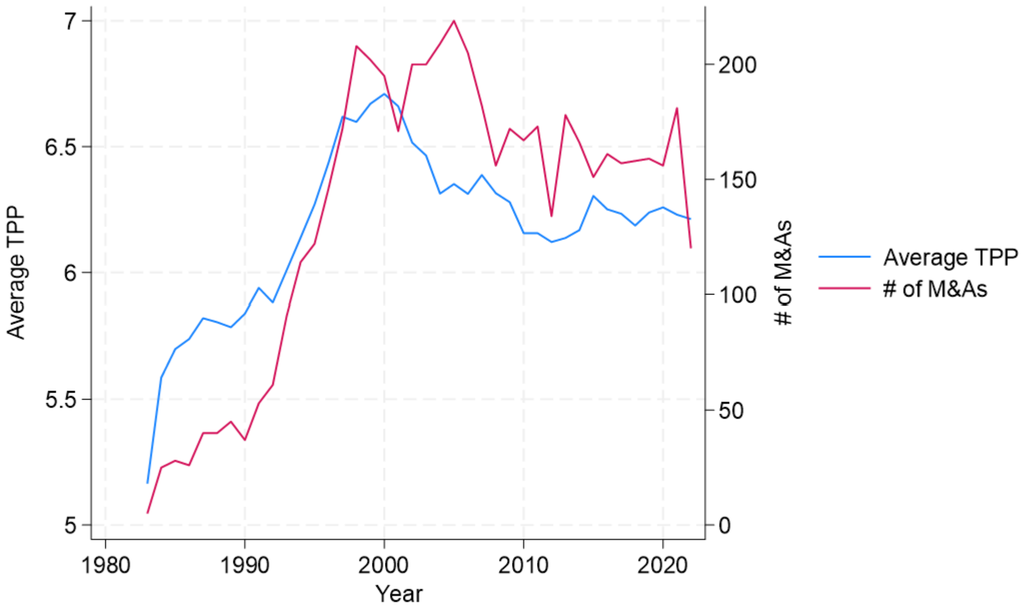

Figure 3.1: The change of TPP and number of M&A over time

Table 3.1: Distribution of the frequencies and percentages of M&As by industry and year

Panel A M&A Distribution by industries

Two-digit SIC	Industry Description	Frequency	Percentage (%)
73	Business services	1,162	21.58
38	Instruments and related products	831	15.43
36	Electronic and other electrical equipment	813	15.10
28	Chemicals and allied products	736	13.67
35	Industrial and commercial machinery and computer equipment	675	12.54
37	Transportation equipment	217	4.03
34	Fabricated Metal Products	132	2.45
20	Food & Kindred Products	108	2.01
Others	Industries with 2% representation	710	13.19
Total		5,384	100.00

Panel B M&A Distribution by year

Year	Frequency	Percentage (%)
1983	5	0.09
1984	25	0.46
1985	28	0.52
1986	26	0.48
1987	40	0.74
1988	39	0.72
1989	44	0.82
1990	37	0.69
1991	53	0.98
1992	61	1.13
1993	91	1.69
1994	114	2.12
1995	122	2.27
1996	146	2.71
1997	172	3.19
1998	208	3.86
1999	202	3.75
2000	195	3.62
2001	171	3.18
2002	200	3.71
2003	200	3.71
2004	209	3.88
2005	219	4.07
2006	205	3.81
2007	182	3.38
2008	156	2.90
2009	172	3.19
2010	167	3.10
2011	173	3.21
2012	134	2.49
2013	178	3.31
2014	166	3.08
2015	151	2.80
2016	161	2.99
2017	157	2.92
2018	158	2.93
2019	160	2.97
2020	156	2.90
2021	181	3.36
2022	120	2.23
Total	5,384	100.00

Note**:** This table reports the two-digit Standard Industrial Classification (SIC) codes industry (Panel A) and the deal subsample distribution of 5,384 completed acquisitions during 1983–2022 (Panel B).

Table 3.2: Summary statistics

Variables	N	mean	sd	p25	p50	p75
Acquirer	47,892	0.112	0.316	0.000	0.000	0.000
TPP	47,892	5.989	2.373	4.353	6.251	7.683
Size	47,892	5.156	2.271	3.448	4.869	6.688
ROA	47,892	-0.043	0.293	-0.095	0.052	0.116
Leverage	47,892	0.170	0.185	0.005	0.117	0.275
Cash	47,892	0.304	0.274	0.074	0.216	0.478
B/M	47,892	0.503	0.469	0.204	0.388	0.676
Stock return	47,892	0.125	0.635	-0.261	0.027	0.349
Stock return volatility	47,892	0.038	0.022	0.022	0.033	0.048
HHI	47,892	0.264	0.252	0.082	0.172	0.354
Lack R&D	47,892	0.509	0.500	0.000	1.000	1.000
Industry sales growth	47,422	1.338	4.849	0.130	0.262	0.736
TPP patent filing	18,579	4.354	2.065	2.740	4.453	5.892
TPP patent issue	19,233	4.374	2.061	2.785	4.489	5.902
Tax credit	42,110	12.439	1.967	11.701	12.853	13.613
Public Target	5,244	0.192	0.394	0.000	0.000	0.000
All cash	5,244	0.346	0.476	0.000	0.000	1.000
All stock	5,244	0.114	0.318	0.000	0.000	0.000
Friendly deal	5,244	0.985	0.122	1.000	1.000	1.000
Diversify deal	5,244	0.437	0.496	0.000	0.000	1.000
Relative size	5,244	0.197	0.378	0.020	0.066	0.198
CAR[-1,+1]	5,243	0.153	1.676	-0.577	0.071	0.853
CAR[-3,+3]	5,243	0.093	1.314	-0.588	0.043	0.752
CAR[-5,+5]	5,243	0.089	1.217	-0.547	0.042	0.708
12-month BHAR	4,934	-0.273	0.960	-0.519	-0.133	0.172
Complete time	4,949	2.702	1.958	0.000	3.466	4.234
1-day bid premium	898	0.310	0.319	0.160	0.287	0.439
1-week bid premium	898	0.339	0.324	0.181	0.315	0.461
4-week bid premium	895	0.371	0.339	0.202	0.342	0.508

Note: This table presents the summary statistics, including number of observations (i.e., N), mean, standard deviation (i.e., sd), quartiles (i.e., p25, p50, p75), for the key variables used in our regressions. Acquirer takes a value of one for firms that make an acquisition in year t, zero otherwise. Technological peer pressure (TPP) is the measure of technological peer pressure on firms following Cao et al. (2018). Size is the natural logarithm of total assets of 1982 constant dollars. ROA is the earnings before interest, taxes, depreciation, and amortization scaled by total assets. Leverage is the total debt scaled by total assets. Cash is cash and short-term investments scaled by total assets. B/M is the book-to-market ratio measured by the book value of equity scaled by the market value of equity. Stock return is an annualized stock return. Stock return volatility is the annualized volatility of daily stock returns. HHI is Herfindahl index of sales of all firms in the same two-digit SIC industry. Lack R&D is an indicator that equals one if a firm lacks R&D investment. Industry sales growth is the mean value of sales growth rate of a two-digit SIC industry in a given year. The mergers and acquisitions data are from the Thomson One Banker Securities Data Company (SDC) database. The Appendix Table B1 provides the definition of variables. Firm characteristics variables have been winsorized at the 1% level in each tail.

Table 3.3: Technological peer pressure and firms' probability of becoming acquirers

	(1)	(2)	(3)	(4)
	Logit	Marginal effect	Logit	Marginal effect
TPP	0.099***	0.009***	0.107***	0.010***
	(0.020)	(0.002)	(0.021)	(0.002)
Size	0.284***	0.027***	0.290***	0.027***
	(0.024)	(0.002)	(0.025)	(0.002)
ROA	0.660***	0.062***	0.685***	0.065***
	(0.125)	(0.012)	(0.126)	(0.012)
Leverage	-0.536***	-0.050***	-0.515***	-0.049***
	(0.146)	(0.014)	(0.145)	(0.014)
Cash	-0.122	-0.011	-0.145	-0.014
	(0.114)	(0.011)	(0.114)	(0.011)
B/M	-0.559***	-0.053***	-0.551***	-0.052***
	(0.056)	(0.005)	(0.056)	(0.005)
Stock return	0.295***	0.028***	0.296***	0.028***
	(0.025)	(0.002)	(0.025)	(0.002)
Stock return volatility	-6.288***	-0.591***	-6.335***	-0.600***
	(1.474)	(0.140)	(1.476)	(0.141)
HHI			-0.111	-0.011
			(0.203)	(0.019)
Lack R&D			-0.069	-0.006
			(0.049)	(0.005)
Industry sales growth			-0.000	-0.000
			(0.005)	(0.000)
Constant	-5.891***		-4.118***	
	(0.688)		(0.581)	
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.092		0.091	
No. of Observations	47,314	47,314	46,878	46,878

***Note*:** This table reports the results of the likelihood of a firm being an acquirer from 1983 to 2022. The coefficients are estimated from the logit model using the actual deal sample. The dependent variable is a M&A binary variable which equals one when the firm is an acquirer in year *t*, zero otherwise. TPP is the measure of technological peer pressure on firms following Cao et al. (2018). Regression models include year fixed effects and three-digit SIC industry fixed effects. Columns (2) and (4) present marginal effects estimated at the mean for continuous variables. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.4: Technological peer pressure and firms' probability of becoming acquirers: Pseudo deal sample

	(1)	(2)	(3)
	Random	SIC, Size	SIC, Size, B/M
TPP	0.089***	0.016	0.021*
	(0.013)	(0.011)	(0.011)
Size	0.267***		
	(0.015)		
ROA	1.080***	0.986***	0.796***
	(0.116)	(0.120)	(0.137)
Leverage	-1.181***	-0.847***	-0.455***
	(0.128)	(0.118)	(0.136)
Cash	-0.163*	-0.292***	-0.358***
	(0.097)	(0.097)	(0.104)
B/M	-0.740***	-0.749***	
	(0.054)	(0.054)	
Stock return	0.359***	0.351***	0.288***
	(0.032)	(0.033)	(0.034)
Stock return volatility	-7.202***	-8.634***	-7.377***
	(1.412)	(1.463)	(1.555)
Constant	-2.650***	-0.963***	-1.519***
	(0.132)	(0.076)	(0.081)
Deal FE	Yes	Yes	Yes
Pseudo R-squared	0.070	0.027	0.013
No. of Observations	32,304	32,304	31,219
Marginal effect of TPP	0.012***	0.002	0.003*
	(0.002)	(0.002)	(0.002)

***Note*:** This table reports the coefficients estimated from the logit model using pseudo deal samples. Following Bena and Li (2014), for each completed deal, three different pseudo samples are constructed: randomly matched; closest in firm size within the same two-digit SIC industry; and closest in firm size and B/M within the same two-digit SIC industry. Regression models include deal fixed effects. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.5: Robustness tests: Instrumental variable

	First Stage	Second Stage	First Stage	Second Stage
	TPP_{t-1}	Acquirer	TPP_{t-1}	Acquirer
	(1)	(2)	(3)	(4)
$TaxCredit_{t-1}$	0.609***		0.634***	
	(0.007)		(0.007)	
$\widehat{TPP_{t-1}}$		0.005***		0.005***
		(0.001)		(0.001)
Size	-0.887***	0.034***	-0.897***	0.035***
	(0.011)	(0.002)	(0.009)	(0.002)
ROA	1.206***	0.018**	0.788***	0.016**
	(0.059)	(0.007)	(0.052)	(0.008)
Leverage	0.395***	-0.058***	0.192***	-0.060***
	(0.081)	(0.013)	(0.074)	(0.013)
Cash	-0.508***	-0.015	-0.171***	-0.013
	(0.071)	(0.011)	(0.061)	(0.011)
B/M	0.294***	-0.037***	0.145***	-0.038***
	(0.030)	(0.004)	(0.027)	(0.004)
Stock return	-0.028***	0.030***	-0.027***	0.031***
	(0.009)	(0.003)	(0.008)	(0.003)
Stock return volatility	-1.299*	-0.303***	-0.809	-0.295***
	(0.695)	(0.104)	(0.619)	(0.104)
HHI			-0.156*	-0.002
			(0.088)	(0.018)
Lack R&D			1.004***	0.006
			(0.027)	(0.005)
Industry sales growth			0.004**	0.000
			(0.001)	(0.000)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.804	-	0.838	-
No. of Observations	42,092	42,092	41,650	41,650
Kleibergen-Paap F statistic	7862.797	-	7794.085	-

***Note*:** This table presents coefficient estimates from two stage least squares regressions. The instrumental variable is based on the introduction of state-level R&D tax credit. Column (1) and (3) show the first-stage regression of state-level R&D tax credit on the firm's TPP. In the second stage, the dependent variable is a M&A indicator, which equals one if a firm announces acquisition in year t, and zero otherwise. TPP is the measure of technological peer pressure on firms following Cao et al. (2018). Regression models include year fixed effects and three-digit SIC industry fixed effects. All specifications are the same as the baseline model, including the fixed effect and control variables. The Appendix Table B1 provides the definition of variables. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Robust standard errors are reported in parentheses with standard errors robust to heteroskedasticity.

Table 3.6: Robustness tests of likelihood to become acquirer

Panel A: Alternative model specifications				
	(1)	(2)	(3)	(4)
	LPM	LPM	Probit	Probit
TPP	0.004***	0.004***	0.048***	0.050***
	(0.001)	(0.001)	(0.010)	(0.011)
Constant	0.005	0.005	-3.019***	-2.230***
	(0.017)	(0.018)	(0.332)	(0.306)
Firm-level controls	Yes	Yes	Yes	Yes
Industry-level controls	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R^2/ Adj. R^2	0.056	0.055	0.092	0.090
No. of Observations	47,877	47,408	47,320	46,884

Panel B: Patents-based TPP				
	(1)	(2)	(3)	(4)
TPP patent filing	0.075***	0.075***		
	(0.027)	(0.027)		
TPP patent issue			0.094***	0.093***
			(0.026)	(0.026)
Constant	-5.261***	-3.618***	-5.601***	-3.827***
	(0.763)	(0.793)	(0.762)	(0.790)
Firm-level controls	Yes	Yes	Yes	Yes
Industry-level controls	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.077	0.076	0.086	0.085
No. of Observations	18,296	18,167	18,840	18,709

Panel C: Excluding industries with largest representations				
	(1)	(2)	(3)	(4)
	excluding firms in 73	excluding firms in 38	excluding firms in 36	firms in 73, 38 and 36
TPP	0.102***	0.086***	0.102***	0.118***
	(0.022)	(0.020)	(0.021)	(0.031)
Constant	-5.826***	-5.442***	-6.063***	-7.542***
	(0.691)	(0.688)	(0.723)	(1.230)
Firm-level controls	Yes	Yes	Yes	Yes
Industry-level controls	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.095	0.088	0.097	0.089
No. of Observations	40,051	40,580	39,726	21,588

***Note*:** The dependent variable is a binary variable which is equal to one when the firm is an acquirer, zero otherwise. TPP is the measure of technological peer pressure on firms following Cao et al. (2018). Regression models include year fixed effects and three-digit SIC industry fixed effects. In Panel A, The coefficients are estimated from the Linear Probability Model (LPM) and Probit model. In Panel B, we report the results from analyses in Table 3.3 with the patent-based TPP. In Panel C, we show the sample with samples excluding firms in the business services (2-digit SIC 73), instruments and related products (2-digit SIC 38), Electronic and other electrical equipment (2-digit SIC 36) sectors take over half of the sample firm-years. The Appendix Table B1 provides the definition of variables. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.7: Technological peer pressure and target choice

	(1) 2-digit SIC	(2) 2-digit SIC	(3) 3-digit SIC	(4) 3-digit SIC
TPP	0.079**	0.074**	0.072**	0.048
	(0.035)	(0.037)	(0.035)	(0.037)
Size	0.063*	0.059	0.057	0.034
	(0.038)	(0.040)	(0.039)	(0.040)
ROA	-0.596**	-0.597**	-0.481*	-0.520**
	(0.240)	(0.241)	(0.248)	(0.250)
Leverage	-0.341	-0.342	-0.431	-0.476*
	(0.259)	(0.262)	(0.268)	(0.272)
Cash	-0.553***	-0.545***	-0.568***	-0.522**
	(0.205)	(0.207)	(0.207)	(0.209)
B/M	-0.147	-0.156	-0.202*	-0.241**
	(0.107)	(0.108)	(0.112)	(0.112)
Stock return	-0.040	-0.039	-0.079	-0.075
	(0.055)	(0.055)	(0.056)	(0.055)
Stock return volatility	-0.485	-0.439	-1.799	-1.593
	(2.886)	(2.886)	(2.794)	(2.797)
HHI		0.231		0.244
		(0.359)		(0.399)
Lack R&D		0.041		0.194**
		(0.094)		(0.094)
Industry sales growth		0.010		0.009
		(0.012)		(0.012)
Constant	-0.235	0.629	1.913	2.584***
	(1.302)	(0.873)	(1.284)	(0.921)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.163	0.163	0.183	0.185
No. of Observations	5,236	5,230	5,138	5,132

***Note*:** This table reports the relationship between technological peer pressure and the diversifying M&As. The dependent variable is an indicator, which is equal to one if the acquirer bids for a target that is in the different two-digit or three-digit SIC industry of one of its rivals; zero otherwise. Regression models include year fixed effects and three-digit SIC industry fixed effects. The Appendix Table B1 provides the definition of variables. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.8: Technological peer pressure and firms' probability of becoming targets

Panel A: Actual deal sample

	(1) Logit	(2) Marginal effect	(3) Logit	(4) Marginal effect
TPP	-0.112***	-0.003***	-0.090***	-0.002***
	(0.022)	(0.001)	(0.024)	(0.001)
Size	-0.202***	-0.005***	-0.179***	-0.005***
	(0.028)	(0.001)	(0.030)	(0.001)
ROA	0.551***	0.014***	0.641***	0.017***
	(0.135)	(0.004)	(0.138)	(0.004)
Leverage	0.518***	0.013***	0.577***	0.015***
	(0.200)	(0.005)	(0.198)	(0.005)
Cash	0.569***	0.015***	0.516***	0.013***
	(0.145)	(0.004)	(0.147)	(0.004)
B/M	0.190***	0.005***	0.230***	0.006***
	(0.064)	(0.002)	(0.064)	(0.002)
Stock return	-0.155***	-0.004***	-0.159***	-0.004***
	(0.054)	(0.001)	(0.054)	(0.001)
Stock return volatility	-0.829	-0.021	-0.782	-0.020
	(1.701)	(0.044)	(1.719)	(0.045)
HHI			-0.565*	-0.015*
			(0.326)	(0.009)
Lack R&D			-0.281***	-0.007***
			(0.070)	(0.002)
Industry sales growth			-0.031**	-0.001**
			(0.014)	(0.000)
Constant	-3.936***		-3.033***	
	(0.885)		(0.705)	
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.071		0.073	
No. of Observations	45,306	45,306	44,903	44,903

Panel B: Pseudo deal sample

	(1) Random	(2) SIC, Size	(3) SIC, Size, B/M
TPP	-0.042*	-0.077***	-0.070***
	(0.025)	(0.022)	(0.023)
Size	-0.200***		
	(0.031)		
ROA	0.736***	0.331*	-0.143
	(0.172)	(0.190)	(0.216)
Leverage	0.249	0.362	0.230
	(0.259)	(0.259)	(0.301)
Cash	0.999***	0.589***	0.356*
	(0.176)	(0.179)	(0.190)
B/M	0.112	0.027	
	(0.090)	(0.086)	
Stock return	-0.187***	-0.213***	-0.209***
	(0.070)	(0.064)	(0.074)
Stock return volatility	1.149	6.237***	4.182*
	(2.232)	(2.303)	(2.510)
Constant	-0.590**	-1.628***	-1.502***
	(0.296)	(0.142)	(0.173)
Pseudo R-squared	0.024	0.007	0.009
Deal FE	Yes	Yes	Yes
No. of Observations	7,278	7,278	6,958
Marginal effect of TPP	-0.006*	-0.011***	-0.010***
	(0.003)	(0.003)	(0.003)

***Note*:** This table reports the results of the likelihood of a firm being a target from 1983 to 2022. Panel A reports the coefficient estimated from the logit model using the actual deal sample. The dependent variable is a M&A binary variable which equals one when the firm is a target in year t, zero otherwise. TPP is the measure of technological peer pressure on firms following Cao et al. (2018). Regression models include year fixed effects and three-digit SIC industry fixed effects. Columns (2) and (4) present marginal effects estimated at the mean for continuous variables. Robust standard errors clustered at the firm level are reported in parentheses. In Panel B, the coefficients estimated from the logit model are reported respectively. Following Bena and Li (2014), for each completed deal, we construct three different control samples (pseudo samples) as pools of potential mergers for real acquisitions. For each actual deal, pseudo-deals are formed by pairing the actual acquirers with up to five hypothetical matches: randomly matched; closest in firm size within the same two-digit SIC industry; and closest in firm size and B/M within the same two-digit SIC industry. Regression models include deal fixed effect. Robust standard errors clustered at the deal level are reported in parentheses. The Appendix Table B1 provides the definition of variables. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.9: Technological peer pressure and announcement return

	(1)	(2)	(3)	(4)
	3-day CAR	7-day CAR	11-day CAR	12-month BHAR
TPP	0.057**	0.060***	0.041**	0.027**
	(0.024)	(0.018)	(0.017)	(0.013)
Size	-0.015	0.005	-0.007	0.084***
	(0.025)	(0.020)	(0.019)	(0.016)
B/M	-0.033	-0.035	-0.060	-0.015
	(0.086)	(0.067)	(0.063)	(0.070)
All cash deal	0.189***	0.144***	0.118***	-0.006
	(0.056)	(0.044)	(0.042)	(0.027)
All stock deal	0.002	0.050	0.018	-0.301***
	(0.095)	(0.071)	(0.067)	(0.066)
Public target	-0.470***	-0.310***	-0.246***	0.081**
	(0.077)	(0.062)	(0.056)	(0.039)
Relative deal size	0.100	0.053	0.057	-0.304***
	(0.114)	(0.088)	(0.075)	(0.075)
Diversifying M&A	-0.055	-0.054	-0.074*	-0.048
	(0.054)	(0.043)	(0.041)	(0.031)
Friendly deal	-0.139	-0.082	-0.027	-0.070
	(0.192)	(0.147)	(0.146)	(0.103)
Constant	-0.568	-0.965	-0.968	-0.732***
	(0.925)	(0.599)	(0.618)	(0.203)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.038	0.022	0.024	0.106
No. of Observations	5,243	5,243	5,243	4,912

***Note*:** This table reports market reaction around the M&A announcement date. We use cumulative abnormal returns (CAR) to measure short-run market announcement returns benchmarked against the market model over [-1, +1], [-3, +3], and [-5, +5] windows around the M&A announcement dates. The parameters are estimated based on daily stock returns from trading days -255 to -46 with at least 30 non-missing daily stock returns. We use buy-and-hold abnormal returns (BHAR) to measure long-run market announcement returns. BHAR is calculated based on the average difference in the aggregated performance between the included stock and benchmark (CRSP value-weighted index) returns over a 12-month period starting from the announcement month of acquisition. Regression models include year fixed effects and three-digit SIC industry fixed effects. The Appendix Table B1 provides the definition of variables. Robust standard errors are at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.10: Technological peer pressure and bid premium

	(1) 1 day	(2) 1 week	(3) 4 weeks
TPP	-0.002	-0.002	0.008
	(0.010)	(0.010)	(0.012)
Size	-0.003	-0.002	0.014
	(0.013)	(0.013)	(0.015)
B/M	-0.025	-0.021	-0.021
	(0.045)	(0.046)	(0.049)
All cash deal	0.095***	0.102***	0.100***
	(0.033)	(0.035)	(0.036)
All stock deal	0.037	0.018	0.027
	(0.038)	(0.040)	(0.041)
Relative deal size	-0.019	-0.024	-0.012
	(0.032)	(0.033)	(0.034)
Diversifying M&A	0.022	0.026	0.024
	(0.024)	(0.025)	(0.025)
Friendly deal	-0.100	-0.084	-0.055
	(0.105)	(0.100)	(0.102)
Constant	0.379*	0.389**	0.226
	(0.195)	(0.191)	(0.202)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R-squared	0.064	0.067	0.100
No. of Observations	863	861	860

***Note*:** This table presents the relationship between TPP and acquisition premiums. Bid premiums are the percentage difference between the bid prices and the targets' stock prices one day, one week, and four weeks before the deal announcements. Regression models include year fixed effects and three-digit SIC industry fixed effects. The Appendix Table B1 provides the definition of variables. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.11: Heterogeneity effects of post-merger performance

Panel A: High-tech industries vs low-tech industries				
	3-day CAR	3-day CAR	12-month BHAR	12-month BHAR
TPP	0.098***	0.023	0.052**	0.016
	(0.035)	(0.032)	(0.021)	(0.016)
Constant	-0.535	0.540	-1.365***	-0.424**
	(0.498)	(0.442)	(0.340)	(0.214)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.037	0.050	0.143	0.088
No. of observations	2,323	2,898	2,170	2,741
High-tech industry	Yes	No	Yes	No
Empirical p-value	0.080		0.060	

Panel B: Single segment firms vs multi segment firms				
	3-day CAR	3-day CAR	12-month BHAR	12-month BHAR
TPP	0.005	0.035	0.079**	0.026*
	(0.055)	(0.028)	(0.038)	(0.015)
Constant	0.601	0.353	-1.314**	-0.744***
	(0.768)	(0.388)	(0.526)	(0.227)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.058	0.046	0.121	0.120
No. of observations	927	3,916	852	3,732
Single segment firms	Yes	No	Yes	No
Empirical p-value	0.290		0.040	

***Note*:** This table presents results from tests that examine the heterogeneity effect of TPP on post-merger performance by industries and the level of TPP. In Panel A, we divide the sample by whether firms operating in high-tech industries which classified by Cao et al. (2021). Panel B reports the heterogeneous effect between firms operating in single and multi segments. We use cumulative abnormal returns (CAR) to measure the short-run market announcement return benchmarked against the market model in the [-1, +1] window around the M&A announcement dates. Parameters are estimated based on daily stock returns from trading days -255 to -46 with at least 30 non-missing daily stock returns. We use buy-and-hold abnormal returns (BHAR) to measure long-run market announcement returns. BHAR is calculated based on the average difference in the aggregated performance between the included stock and benchmark (CRSP value-weighted index) returns over a 12-month period starting from the announcement month of acquisition. Following Cleary (1999), we perform Fisher's permutation test of differences in coefficient estimates between two groups. The Appendix Table B1 provides the definition of variables. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.12: Technological peer pressure, acquisition completion time and payment methods

	(1) Completion time	(2) All stock deal
TPP	-0.049*	-0.139***
	(0.028)	(0.052)
Size	0.209***	-0.305***
	(0.029)	(0.059)
B/M	-0.324***	-0.822***
	(0.094)	(0.236)
All cash deal	0.183***	
	(0.059)	
All stock deal	0.620***	
	(0.090)	
Public target	1.423***	1.946***
	(0.063)	(0.141)
Relative deal size	1.313***	0.334**
	(0.092)	(0.140)
Diversifying M&A	-0.185***	-0.015
	(0.062)	(0.123)
Friendly deal	-0.267	1.705***
	(0.297)	(0.507)
Constant	1.556***	-1.609
	(0.409)	(1.112)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted/Pseudo R-squared	0.303	0.318
No. of Observations	4,926	4,654

***Note*:** This table presents the relationship between TPP and time to deal completion (column 1) and payment considerations (column 2). Time to completion is measured as the natural logarithm of 1 plus the number of days from a M&A deal announcement to its completion. All stock deal is an indicator that takes one for deals funded entirely by stocks, zero otherwise. Regression models include year fixed effects and three-digit SIC industry fixed effects. The Appendix Table B1 provides the definition of variables. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B1: Variable definitions

Variables	Definition
M&A Dummy	An dummy variable that equals one if a firm makes a M&A announcement in a given year, and zero otherwise.
TPP	Technological peer pressure for firm i at the end of fiscal year t. $TPPi,t = ln\left[1 + \frac{1}{Gi,t}\sum^{i\neq j}\omega_{ij\times Gj,t}\right]$. Firm i's technological threat comes from a peer firm j's R&D stock $G_{j,t}$ at the end of year t weighted by the closeness ω_{ij} between these two firms, where $\omega_{ij} = \left\langle \frac{V_i}{\Vert V_i\Vert} \cdot \frac{V_j}{\Vert V_j\Vert} \right\rangle$. V_i is the vector of firm i's sales with the kth element being the share of firm i's total sales in the preceding two years made in industry (four-digit SIC) k.
Size	The natural logarithm of total assets of 1982 constant dollars.
ROA	Earnings before interest, taxes, depreciation, and amortization scaled by total assets.
Leverage	Total debt scaled by total assets.
Cash	Cash and short-term investments scaled by total assets.
B/M	The book value of equity scaled by the market value of equity.
Stock return	Annualized stock return.
Stock return volatility	Annualized volatility of daily stock returns.
HHI	The Herfindahl index of sales of all firms in the same two-digit SIC industry.
Lack R&D	Indicator variable equal one if a firm lacks R&D investment relative to its rivals, and zero otherwise. The R&D investment is measured by the R&D expenditure scaled by total assets.
Industry sales growth	The mean value of sales growth rate of a two-digit SIC industry in a given year.
All cash deal	An indicator that takes a value of one for deals funded completely by cash, zero otherwise.
All stock deal	An indicator that takes one for deals funded entirely by stocks, zero otherwise.
Public target	An indicator that takes one if the target firm is public, zero otherwise.
Relative deal size	The deal value scale by acquirer's market value of equity in the fiscal year before the announcement date.
Diversifying M&A	An indicator that equals one if the acquirer and target do not belong to the same two-digit SIC code industry, and zero otherwise.
Friendly deal	An indicator that takes one if the attitude for a deal is friendly, and zero otherwise.
CAR	Acquirer's cumulative abnormal returns over the event windows [−1, +1], [−3, +3], and [−5, +5] using market model benchmark returns (255, 46) with the CRSP value-weighted index returns.
BHAR	The average difference in the aggregated performance between the included stock and benchmark (CRSP value-weighted index) returns over a 12-month and 24-month period starting from the announcement month of acquisition.
Bid premium	The percentage difference between the bid prices and the targets' stock prices one day, one week, and four weeks before the deal announcements.
Time to completion	The natural logarithm of 1 plus the number of days from a M&A deal announcement to its completion.

***Note*:** This table presents the variable definitions. Data are collected from Compustat, CRSP, and SDC databases.

Table B2: TPP and firms' probability of becoming acquirers: Threshold effect

	(1)	(2)
TPP	0.289***	0.292***
	(0.057)	(0.057)
TPP^2	-0.016***	-0.016***
	(0.004)	(0.004)
Size	0.294***	0.298***
	(0.025)	(0.026)
ROA	0.651***	0.669***
	(0.127)	(0.128)
Leverage	-0.565***	-0.547***
	(0.144)	(0.144)
Cash	-0.172	-0.189
	(0.115)	(0.115)
B/M	-0.561***	-0.556***
	(0.056)	(0.056)
Stock return	0.295***	0.296***
	(0.025)	(0.025)
Stock return volatility	-5.775***	-5.822***
	(1.476)	(1.477)
HHI		-0.090
		(0.204)
Lack R&D		-0.050
		(0.050)
Industry sales growth		-0.000
		(0.005)
Constant	-6.250***	-4.487***
	(0.695)	(0.586)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R-squared	0.093	0.092
No. of Observations	47,320	46,884

***Note*:** This table reports the results of the likelihood of a firm being an acquirer from 1983 to 2022 influenced by the technological peer pressure (TPP) on firms following Cao et al. (2018), including the squared term of TPP (TPP^2). The dependent variable is a binary variable which is equal to one when the firm is an acquirer, zero otherwise. Regression models include year fixed effects and three-digit SIC industry fixed effects. The Appendix Table B1 provides the definition of variables. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B3: Technological peer pressure and firms' probability of becoming acquirers: Robustness checks

Panel A: Alternative combinations of fixed effects				
	(1)	(2)	(3)	(4)
TPP	0.068***	0.224***	0.079***	0.118***
	(0.015)	(0.055)	(0.019)	(0.017)
Size	0.200***	0.196***	0.253***	0.327***
	(0.017)	(0.050)	(0.024)	(0.022)
ROA	1.150***	0.654***	0.690***	0.893***
	(0.118)	(0.197)	(0.123)	(0.126)
Leverage	-1.041***	-1.355***	-0.605***	-0.888***
	(0.147)	(0.205)	(0.154)	(0.147)
Cash	-0.275***	0.930***	-0.121	-0.197*
	(0.105)	(0.173)	(0.113)	(0.109)
B/M	-0.651***	-0.379***	-0.617***	-0.478***
	(0.056)	(0.078)	(0.059)	(0.059)
Stock return	0.251***	0.286***	0.300***	0.314***
	(0.022)	(0.035)	(0.026)	(0.027)
Stock return volatility	-1.080	-4.765**	-8.112***	-5.476***
	(1.225)	(2.061)	(1.595)	(1.623)
Constant	-3.030***	-3.732***	-3.392**	-4.187***
	(0.167)	(0.697)	(1.468)	(0.666)
Firm FE	No	Yes	No	No
Year FE	No	Yes	No	No
Year*Industry FE	No	No	Yes	No
Year*State FE	No	No	No	Yes
Pseudo R-squared	0.053	0.154	0.099	0.112
No. of Observations	47,814	26,307	44,738	38,082

Panel B: Alternative clustering				
	(1)	(2)	(3)	(4)
TPP	0.099***	0.139***	0.099***	0.099***
	(0.025)	(0.022)	(0.014)	(0.013)
Size	0.284***	0.377***	0.284***	0.284***
	(0.034)	(0.020)	(0.016)	(0.015)
ROA	0.652***	0.711***	0.652***	0.652***
	(0.197)	(0.127)	(0.114)	(0.097)
Leverage	-0.540***	-0.619***	-0.540***	-0.540***
	(0.159)	(0.124)	(0.105)	(0.105)
Cash	-0.129	-0.038	-0.129	-0.129
	(0.138)	(0.122)	(0.092)	(0.084)
B/M	-0.562***	-0.418***	-0.562***	-0.562***
	(0.059)	(0.040)	(0.051)	(0.046)
Stock return	0.296***	0.313***	0.296***	0.296***
	(0.019)	(0.017)	(0.027)	(0.025)
Stock return volatility	-6.295***	-4.851***	-6.295***	-6.295***
	(1.272)	(1.404)	(1.187)	(1.187)
Constant	-5.889***	-6.398***	-5.889***	-5.889***
	(0.539)	(0.721)	(0.663)	(0.593)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SE clustering	Industry	State	Industry*Year	Firm*Year
Pseudo R-squared	0.092	0.106	0.092	0.092
No. of Observations	47,243	41,213	47,243	47,243

***Note*:** This table presents robustness test results. The dependent variable is a binary variable, which equals one if a firm makes a M&A announcement in a given year, and zero otherwise. TPP is the measure of technological peer pressure on firms following Cao et al. (2018). The Appendix Table B1 provides the definition of variables. Robust standard errors clustered at the firm level, except for the alternative clustering section, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B4: Summary statistics: Bidders and non-bidders

Panel A: Bidders						
Variables	N	mean	sd	p25	p50	p75
TPP	5,385	5.541	2.191	3.893	5.696	7.132
Size	5,385	6.026	2.116	4.441	5.903	7.482
ROA	5,385	0.051	0.181	0.023	0.088	0.139
Leverage	5,385	0.169	0.170	0.006	0.135	0.279
Cash	5,385	0.261	0.232	0.066	0.191	0.409
B/M	5,385	0.412	0.340	0.196	0.332	0.538
Stock return	5,385	0.246	0.623	-0.114	0.149	0.444
Stock return volatility	5,385	0.032	0.019	0.019	0.027	0.040
Panel B: Non-bidders						
TPP	42,509	6.045	2.389	4.434	6.330	7.745
Size	42,509	5.045	2.267	3.346	4.731	6.549
ROA	42,509	-0.055	0.302	-0.115	0.046	0.112
Leverage	42,509	0.170	0.187	0.004	0.115	0.275
Cash	42,509	0.309	0.278	0.074	0.219	0.489
B/M	42,509	0.515	0.482	0.206	0.397	0.696
Stock return	42,509	0.109	0.635	-0.280	0.010	0.333
Stock return volatility	42,509	0.039	0.023	0.023	0.034	0.049

Note: This table presents the summary statistics, including number of observations (i.e., N), mean, standard deviation (i.e., sd), quartiles (i.e., p25, p50, p75), for the key variables used in our regressions. Technological peer pressure (TPP) is the measure of technological peer pressure on firms following Cao et al. (2018). Size is the natural logarithm of total assets of 1982 constant dollars. ROA is the earnings before interest, taxes, depreciation, and amortization scaled by total assets. Leverage is the total debt scaled by total assets. Cash is cash and short-term investments scaled by total assets. B/M is the book-to-market ratio measured by the book value of equity scaled by the market value of equity. Stock return is an annualized stock return. Stock return volatility is the annualized volatility of daily stock returns. The mergers and acquisitions data are from the Thomson One Banker Securities Data Company (SDC) database. Firm characteristics variables have been winsorized at the 1% level in each tail.

Chapter 4

Green Technological Peer Pressure and Asset Prices

4.1 Introduction

Addressing environmental issues has become increasingly important for academia, businesses, and governments. Many suggest that green technologies are essential tools for alleviating environmental pressure, restoring production efficiency and competitiveness (e.g., Moscona and Sastry, 2023; Fusillo, 2023; Acemoglu et al., 2012). The Intergovernmental Panel on Climate Change (IPCC), in its most recent 6th Assessment Report, emphasizes the central role of green innovations in the global transition to climate neutrality.[1] Policymakers encourage firms to develop green technology by conducting various environmental policies.[2] Likewise, institutional investors actively promote firms to engage in more environmentally sustainable practices (Dyck et al., 2019). In

[1] See IPCC Sixth Assessment Report on: https://www.ipcc.ch/report/sixth-assessment-report-cycle/.

[2] For instance, in 2022, President Biden signed the Inflation Reduction Act (IRA) into law, incentivizing firms and investors to develop green technology in order to confront the existential threat of the climate crisis.

response, some major U.S. firms have committed billions of dollars to advancing green technologies.[3]

Green technology benefits firms in two ways. First, it enhances their capacity to reduce emissions through renewable resources, improve efficiency, and mitigate potential costs imposed by regulatory authorities, thereby reducing susceptibility to transition risks (e.g., Cheng et al., 2024; Cohen et al., 2020). Second, green innovation, such as the development of drought-resistant crops against extreme temperatures, strengthens firms' resilience against physical climate change risks (e.g., Moscona and Sastry, 2023). Consequently, investors are increasingly demanding that firms invest in green innovation, as it reduces their exposure to climate risks and enables them to capitalize on climate-related opportunities. Understanding how the market perceives green innovation is important. Despite the critical importance of green innovation, discussions on its pricing effects in stock markets remain limited and often overlook the impact of green innovation competition. This paper aims to address this gap by examining the relationship between green innovation competition and cross-sectional stock returns.

This paper contributes to the understanding of green innovation by investigating stock market reactions to firms' green innovation preparedness in comparison to their product market competitors. Prior studies mainly focus on the pricing of carbon transition risk by examining the relationship between carbon emissions or toxic pollution and cross-sectional stock returns (e.g., Hsu et al., 2023; Bolton and Kacperczyk, 2021; Zhang, 2024; Bolton and Kacperczyk, 2023; Pástor et al., 2021). An emerging strand of literature has started to explore whether financial markets pay attention to green patents, which indicate firms' capacity to cope with environmental issues (e.g., Hege et al., 2023,

[3]For example, Amazon pledged a two billion US dollars fund to invest in climate change. The original news is available at: https://www.forbes.com/sites/sergeiklebnikov/2020/06/23/amazon-launches-2-billion-fund-to-invest-in-climate-change/.

2024; Andriosopoulos et al., 2022). Despite these pioneering studies investigating how the market perceives green innovation, our understanding of the effect on firms' green innovation competition remains relatively scant. Motivated by this gap in the literature, we provide a new perspective by analyzing green innovation competition in the product market and the reactions of financial markets.

In this paper, we present empirical evidence on how the market reacts to the dynamic positioning of green innovation. Our sample consists of U.S. common stocks traded on primary exchanges, including the NYSE, AMEX, and NASDAQ, over the period from January 1980 to December 2022. To capture green innovation competition, we construct a measure called green technological peer pressure (GTPP), a modified version of the technological peer pressure measure proposed by (Cao et al., 2018). We first collect patent data documented by the United States Patent and Trademark Office (USPTO) and classify the green patents according to the Organization for Economic Co-operation and Development (OECD) guidelines for measuring environmental innovation using the CPC code. Next, we create our GTPP measure, which gauges technological threats at the firm level by comparing the green patent stocks of all competitors in an industry to the focal firm's green patent stocks. In other words, GTPP represents a firm's capacity to cope with potential environmental issues relative to its competitors. Our findings indicate that GTPP is negatively correlated with future environmental performance, validating our measure.

Utilizing this measure, we examine how financial markets incorporate green innovation competition and observe a positive return pattern, implying a risk premium demanded by the market. Specifically, we construct quintile portfolios based on GTPP and calculate each portfolio's post-formation average stock returns over the same period.

The excess returns increase from 0.883% to 1.363% across portfolios, from low to high green technological peer pressure, resulting in a return spread of 0.480% with a t-statistic of 3.341. These findings are robust after controlling existing risk factors, including the Fama and French 5 factors (Fama and French, 2015), momentum factor (Carhart, 1997), and q factor (Hou et al., 2015). In the Fama-French 5 factors model with the momentum factor, the quintile portfolios sorted from low to high exhibit excess returns of 0.189%, 0.328%, 0.518%, 0.541%, and 0.793%, respectively. More importantly, the HML portfolio shows an excess return of 0.604% with a t-statistic of 4.882, which is both economically and statistically significant. Additionally, we conduct double sorting with stock characteristics and GTPP, and our findings remain consistent, indicating that GTPP generates significant return spreads.

We then investigate whether this relationship varies with an unexpected surge in public attention toward climate change. Ardia et al. (2023) empirically tests Pástor et al. (2022)s' prediction and finds that green firms' stock prices tend to increase on days with an unexpected rise in climate change concerns. We adopt the market-wide index from Faccini et al. (2023) to capture attention to physical risks, such as those from natural disasters and rising temperatures, and transition risks, such as those from government intervention via carbon taxation and incentives to develop green technologies. As green innovation enhances firms' ability to cope with both transition and physical risks, we expect that with increased attention toward climate change, low GTPP firms will outperform high GTPP firms. Our findings reveal that considering the HML portfolio, the coefficients are negatively significant for concerns about U.S. climate policy and global warming across different models. For the high GTPP portfolio, we find that the coefficients are negative and statistically significant in relation to risks from climate change policy. Conversely, the coefficients for the low GTPP portfolio are positively insignificant across all models and various climate change concerns. These results imply that the increase in climate change attention, especially from climate change policy, has deflated the prices of companies with a substantial stock of green patents. Further analysis indicates that the effect of GTPP on stock return only exists during periods of heightened climate change concern.

Finally, we explore the potential mechanism behind this relationship. Climate change risks primarily affect a firm's long-term performance rather than its current performance, firms may choose to forgo this investment or opt for incremental investment instead of making it all at once. These firms may face a higher GTPP and higher productivity relative to their market peers in the short term. Thus, a possible explanation of our finding is that the green innovation competition may have an indirect impact on stock returns with the link to firm profitability ability. To test this hypothesis, we examine the association between GTPP and commonly used indicators of profitability or operational performance. We find a positive association between GTPP and the firm's operating performance, indicating that stock returns are indirectly affected through a link with firm fundamentals. In addition, we find this effect varies with a firm's exposure to climate change.

The contribution of this paper is threefold. First, our paper contributes to the burgeoning research regarding green innovation by looking at the association between green technological peer pressure and stock returns. To the best of our knowledge, we are the first to explore the financial market reactions toward green innovation competition. There are few studies investigating the pricing effect of green innovation (Hege et al., 2023, 2024; Leippold and Yu, 2023; Kuang and Liang, 2024; Dechezleprêtre et al., 2021; Andriosopoulos et al., 2022). Differing from existing literature, we center on the green innovation competition among firms operating in the same industries (i.e., the green technological peer pressure).

Second, our paper speaks to the broader literature research regarding climate-related asset pricing. Bolton and Kacperczyk (2021) find that the absolute value of carbon emissions has a positive relationship with realized abnormal returns during 2005-2017. Zhang (2024) documents that carbon returns shift negative in the U.S. and insignificant globally after controlling for the data release lag between accounting data and emission data. Pástor et al. (2022) use the environmental MSCI ESG Ratings to categorize "green" and "brown" stocks, and find that green stocks have lower expected returns but higher realized returns compared to brown stocks. Our contribution to this literature is that we investigate the financial market responses toward green innovation competition.

Third, we contribute to the emerging literature on investigating the impact of innovation competition on firms. Existing literature in related fields documents the effects of innovation competition or technological peer pressure on product disclosure (Cao et al., 2018), job posting (Cao et al., 2023), corporate financial policies (Qiu and Wan, 2015), and firm's engagement in sustainability actions (Wang et al., 2024). In this paper, we focus on one dimension of innovation competition (i.e., green innovation competition). We complement this stream of literature by shedding new light on the association between green innovation competition and stock returns.

The rest of this paper proceeds as follows: Section 4.2 reviews the literature. Section 4.3 describes our variable construction, data, and sample. Section 4.4 presents the model specifications and main results. 4.5 shows the potential economic mechanism behind the GTPP and stock return. Section 4.6 concludes the paper.

4.2 Related literature and hypothesis development

In this section, we first review the literature related to our topic. Then, we develop our hypothesis on whether investors in the financial market incorporate green innovation information into asset prices.

4.2.1 Related literature

Firm environmental performance and stock market returns. Our paper builds on a large body of literature examining the relationship between environmental performance and financial market reactions. The pioneering literature focuses on the pricing impact of emissions, such as greenhouse gas emissions (e.g., Zhang, 2024) or toxic emission (e.g., Hsu et al., 2023). However, this strand of literature presents mixed evidence. Some studies show that low-emission intensity stocks (i.e., green stocks) outperform high-emission intensity stocks (i.e., brown stocks) in the stock market. According to the theoretical model constructed by Pástor et al. (2021), green firms outperform as consumer preferences change and investor tastes shift when policies take effect. Investors hold green stocks not only to hedge against climate change-related risks but also for non-pecuniary motivations. Their theoretical predictions are empirically tested in Pástor et al. (2022). In the bond market, investors' environmental preferences are more directly reflected. Duan et al. (2023) examines whether carbon risk is priced in the corporate bond market and discovers that firms with higher carbon intensity earn significantly lower returns. By reviewing pricing dynamics and ownership trends in the U.S. green bond market, Baker et al. (2022) find that green bonds are often issued at a small premium (5-9 basis points) over comparable ordinary bonds.

On the contrary, some studies present evidence of a "carbon risk premium" in financial markets. Investors seek this risk premium for holding stocks in carbon-intensive companies, as these "brown" stocks are more vulnerable to climate-related risks. For example, Hsu et al. (2023) argue that a firm's profit depends on a regime shift in environmental regulation. A firm with high toxic emissions intensity is likely to experience a greater decline in profitability compared to firms with low toxic emissions if the policymaker strengthens environmental regulations. Bolton and Kacperczyk (2021) report that stocks with higher absolute levels of carbon emissions yield higher returns in the U.S., consistent with investors demanding compensation for carbon risk. However, this relationship does not hold for carbon emission intensity. Bolton and Kacperczyk (2023) further extend this work and find that this pattern is more pronounced in countries with larger energy sectors and stricter domestic climate policies.

Unexpected environment-related shocks and stock returns. Another vein of literature focuses on the effect of unexpected shocks on stock returns. One stream of literature examines the impact of physical shocks. Choi et al. (2020) find that brown stocks underperform compared to green stocks in abnormally warm weather. Pu (2023) studies firms' stock performance under abnormal local temperatures and finds a negative association. Another strand of literature examines shocks from policies, political issues, and public concerns. Ramelli et al. (2021) examine the stock price reactions and the portfolio adjustments of institutional investors following the election of Donald Trump and the appointment of Scott Pruitt as head of the Environmental Protection Agency.

Some researchers build climate change concern proxies by extracting information from news and earnings call transcripts to test financial market reactions to public climate change concerns (Engle et al., 2020; Ardia et al., 2023; Faccini et al., 2023). For example, Ardia et al. (2023) find that on days with an unexpected increase in climate change concerns, the stock prices of green firms tend to rise, while those of brown firms decrease. Sautner et al. (2023b) estimate the risk premium for firm-level climate change exposure, which captures market participants' attention to a firm's climate-related risks and opportunities.

4.2.2 Hypothesis development

A growing body of research shows that green innovation is generally rewarded by the market. For example, using quasi-random variations in patent examiner leniency, Hege et al. (2024) provide empirical evidence that firms with more fortuitous climate-related patents exhibit higher positive cumulative abnormal stock returns. Similarly, Dechezleprêtre et al. (2021) find that stock market recognizes the value of clean innovation and innovation efficiency, awarding higher valuations to firms that engage successfully in environmentally friendly research and development. This aligns with arguments by Karpoff et al. (2005) and Heinkel et al. (2001), who suggest that green innovation enhances firms' reputations, protects them from legal risks, and attracts ethical investment.[4] Furthermore, Kuang and Liang (2024) document that firms with high carbon risk and low climate patent activity significantly underperform compared to benchmark firms, whereas firms with similar carbon risk but high climate patent activity do not exhibit abnormal performance. Green innovation receives positive stock market evaluations, as it can mitigate risks associated with potential environmental regulations and physical damages (Leippold and Yu, 2023). Due to these reasons, the stock market fa-

[4] Karpoff et al. (2005) argue that green innovation protects firms from costs due to lawsuits and legal settlements. Additionally, firms benefit from engaging in green research and development by attracting funds from ethical investors who prefer firms with strong environmental performance records (Heinkel et al., 2001). Leading firms in green innovation, even those with significant current carbon emissions, are better prepared for future stringent environmental regulations, as they can more effectively achieve long-term emission reductions.

vors firms leading in green technologies, rewarding them with higher returns for their better long-term positioning.

However, there is an alternative argument. Firms that lag behind in green technological innovation face higher transition and physical risks amid tightening environmental regulations. These risks include potential carbon taxes, pollution cleanup costs, and others, which may lead to greater stock price volatility or a “risk premium”—translating into higher expected returns for investors who are compensated for bearing these risks (e.g., Hsu et al., 2023). Investors demand a carbon risk premium as compensation for exposure to such risks. In other words, laggards may exhibit higher returns because investors require compensation for uncertainty and potential losses. Building on previous studies and arguments, this paper aims to empirically test the pricing impact of green technological innovation competition.

4.3 Data and variable construction

In this section, we introduce the data sources, the construction of our green technological peer pressure measure, and other variables used in the following empirical analyses.

4.3.1 Green technological peer pressure

Measuring GTPP

We rely on publicly available patent data to measure the green innovation competition in the product market. First, we retrieve the patent data that links patents to firms from Kogan et al. (2017) (KPSS), which has been updated through 2022.[5] KPSS provides full Cooperative Patent Classification (CPC) class of every patent[6], issue date of the patent, filing date of patent application, forward citations counts and the economic value of every patent. Based on this comprehensive dataset, we then identify whether a patent could contribute to alleviating the negative environmental impacts of economic activity at a lower cost, such as minimizing wastage, global warming, air pollution, etc. Following Cohen et al. (2020) and Fusillo (2023), we classify the green patents according to the Organization for Economic Co-operation and Development (OECD) guidelines of measuring environmental innovation by the CPC code.[7] This classification identifies selected environment-related technologies (related to air and water pollution, biodiversity protection, and ecosystem health), climate change adaptation technologies (related to energy, greenhouse gases, transport, and building), and similar technologies relevant to the ocean economy.[8]

Second, we create our "Green TPP" by modifying the technological peer pressure (TPP) proposed by Cao et al. (2018). Cao et al. (2018) construct the TPP variable, which gauges a firm's technological threat arising from its peers' technological advances, proxied by their R&D investments. The logic behind the TPP variable is that a sample firm i's technological threat comes from a peer firm j's R&D stock $G_{j,t}$ at the end of year t, weighted by the closeness ω_{ij} between these two firms in the product market space. TPP

[5]The advantage of using KPSS is the matching identifier CRSP-PERMNO can be used to merge KPSS with COMPUSTAT and CRSP firm-level data. The patent data is available on: `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data`.

[6]See the detailed introduction of CPC scheme on: `https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html`.

[7]Our findings are robust to variations in green patent classification. Specifically, our results remain consistent when using the Climate Change Mitigation Technologies (CCMT) classification scheme as developed by the European Patent Office (Kuang and Liang, 2024). Launched in 2010, this classification system emphasizes patents pertaining to climate change mitigation and adaptation technologies. All CCMT-related patents are assigned to the Y02/Y04S class. The OECD classification has a wider scope and encompasses any kind of environmentally friendly technologies.

[8]Haščič and Migotto (2015) discusses the detailed algorithm for identifying environment-related technologies using patent data.

captures the innovation competition on the input side. We further modify it by replacing R&D stock with the number of patents filed by the firms.[9] In our paper, we focus on the number of green patents. Considering the benefits of new patents over an extended period, we apply a 15% annual decay rate when calculating firms' patents stock (Bloom et al., 2013; Jaffe, 1986).

The closeness between two firms, ω_{ij}, is calculated in the product market space using firm i's and j's sales in every four-digit Standard Industrial Classification (SIC) industry according to the Compustat Historical Segment database. We denote V_i as a K-dimensional vector for firm i's share of sales in every four-digit industry k. Then, ω_{ij} can be defined as the cosine of vectors V_i and V_j in the product market space:

$$\omega_{ij} \equiv \cos(\theta_{ij}) = \left\langle \frac{V_i}{|V_i|} \cdot \frac{V_j}{|V_j|} \right\rangle = \frac{\sum_{k=1}^{K} v_{ik} v_{jk}}{\sqrt{\sum_{k=1}^{K} v_{ik}^2}\sqrt{\sum_{k=1}^{K} v_{jk}^2}}. \tag{4.1}$$

Third, we formally calculate $GTPP_{i,t}$ in Equation (4.2):

$$GTPP_{i,t} = \ln\left[1 + \frac{1}{G_{i,t}} \sum_{i \neq j} \omega_{ij} \times G_{j,t}\right]. \tag{4.2}$$

The ratio inside the bracket represents the threats of rivals' green technological advances relative to firm i's green technological preparedness. A higher value of GTPP signifies that firms are under intense technological competition for green innovation.

We present the high-GTPP and low-TPP industries in Table 4.2. We find that, in Panel A, green innovation is intense in the traditional manufacturing industries. In contrast, as shown in Panel B, green innovation is less competitive in the consumer goods sector, such as the hospitality and apparel industries.

[9] We also use the number of patents filed and we gain similar results.

[Insert Table 4.2 and around here]

We also plot the trends of GTPP and patent-based TPP over the sample period from 1980 to 2022, as shown in Figure 4.1. The figure illustrates that before 2000, both GTPP and TPP were on the rise. After 2000, however, TPP leveled off, whereas GTPP continued to increase rapidly. This trend indicates that green innovation has intensified compared to general innovation competition. A potential explanation for the trend in GTPP is the rise in public awareness since the 21st century. For instance, in practice, the Kyoto Protocol was adopted at in 1997 and entered into force in early 2005. It is the first comprehensive international agreement on climate change. In academia, Stern (2006) brought climate change into mainstream discussions beyond environmental circles, influencing businesses, investors, and the general public. Additionally, the increasing frequency of extreme weather and stricter environmental regulations have prompted firms to incorporate physical and transition risks into their regular operations (e.g., Benincasa et al., 2024; Ginglinger and Moreau, 2023).

[Insert Figure 4.1 around here]

Validity of GTPP

Given that our method for measuring green innovation competition is novel, it is crucial to validate it to ensure that it accurately reflects firms' capabilities in addressing environmental challenges. We explore how GTPP affects firms' future environmental performance. Green technology plays a crucial role in mitigating environmental damage and enhancing resource-use efficiency. Therefore, a higher GTPP reflects a firm's weakness in addressing environmental issues, which could lead to poor environmental performance. To test our conjecture, we regress firms' environmental performance on

GTPP. The regression model is shown as follows:

$$Environmental\ performance_{i,t} = \alpha + \beta GTPP_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FEs + \varepsilon_{i,t}. \quad (4.3)$$

The dependent variable is the firm's environmental performance, measured using the $Emission$ and $Resourceuse$ scores from the Refinitiv ESG database (also known as Thomson Reuters ASSET 4). Refinitiv is one of the largest providers of corporate ESG scores and has been widely utilized by researchers in studies on corporate sustainability (e.g., Amiraslani et al., 2023; Asimakopoulos et al., 2023).[10] $\mathbf{X}_{i,t-1}$ is a vector of the firm-level control variables, including *Size*, *Tobin's Q*, *Leverage* and *Tangibility*. FEs are fixed effects. Given the variability of environmental performance across industries and its evolution over time, we add the industry and year fixed effects to further control the time-invariant industry-level characteristics and the variation across years to avoid omitted variables. Standard errors are clustered at the firm level to correct for cross-section correlation. We expect firms with high GTPP to exhibit poorer subsequent environmental performance due to their constrained resources in green technology.

As presented in Table 4.1, consistent with this expectation, we find a negative relationship between GTPP and $Emission$ and $Resourceuse$ score. These findings indicate that a firm's future environmental performance is worse when it does not have a stock of green patents compared to its competitors.

[Insert Table 4.1 around here]

[10]We use the $Emission$ and $Resourceuse$ scores as they capture the comprehensive level of a firm's environmental behavior. It reflects a company's environmental impact, such as energy usage, carbon emissions, and waste management. A detailed discussion of the Refinitiv ESG database can be found in Chapter 2.

4.3.2 Stock market data

We obtain firm-level stock market information from the Center for Research in Security Prices (CRSP) and accounting information sources from Compustat via the Wharton Research Data Services (WRDS). Both active and inactive firms are included to avoid survivorship bias. Our sample consists of all U.S. common stocks (with CRSP share codes 10-12) trading on the primary exchange including NYSE, AMEX, and NASDAQ (Cohen et al., 2013). Following the literature (Cao et al., 2018), we exclude financial firms (SIC 6000-6999) and utility companies (4900-4999) because the competition landscape in these industries is different from other sectors. We further drop the smallest stocks with market capitalizations of 50 million USD or less, which are considered risky for investment. We obtain monthly data on equity risk factors from Kenneth French's websites.[11] Our sample is unbalanced and spans January 1980 – December 2022.

4.3.3 Climate change risks and other related variables

We adopt the market-wide index from Faccini et al. (2023) to capture the attention to physical risks, e.g. risks stemming from natural disasters and rising temperatures, and transition risks, e.g. risks stemming from government intervention via carbon taxation and incentives to develop green technologies. Faccini et al. (2023) extract public attention to climate change from articles on Reuters news that contain the words "climate change" or "global warming". They create four relevant topics that represent the physical and transition risks in the U.S. stock market: the occurrence of natural disasters, global warming, U.S. climate policy (actions and debate), and international summits on climate change. The first two topics directly reflect the physical risks of climate change,

[11] Kenneth R. French website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

whereas the last two present the transition risks. The news-based climate concern index is updated monthly from January 2000 – December 2023.

We also obtain firm-level climate change exposure data from Sautner et al. (2023c), who extract information from the earning call and identify exposures related to opportunities, physical impacts, and regulatory changes linked to climate change. This quarterly updated firm-level climate change exposure measure is available from 2002 to 2020.

Finally, we collect yearly firm-level data on ESG scores and carbon dioxide (CO2) emissions from the Refinitiv ESG database (formally Thomson Reuters ASSET4). The CO2 emissions are measured as Scope 1 plus Scope 2 CO2 equivalent emissions to revenues USD in million. The variable definitions are presented in Appendix Table C1.

4.4 Model and empirical results

In this section, we investigate the empirical relationship between green technological peer pressure and cross-sectional stock returns. We show that GTPP is positively associated with stock returns in univariate portfolio sorts and this relation is unaffected by known return factors for other systematic risks. Then, we implement Fama and MacBeth (1973) regression to test the association at the stock level. In the second section, we test whether high-GTPP firms underperform low-GTPP firms when concerns about climate change attention increase unexpectedly.

4.4.1 GTPP and stock returns

To investigate the link between green innovation competition and the cross-section of stock returns, we employ a standard portfolio sorts approach. At month t, we construct quintile portfolios sorted on firms' GTPP and report each portfolio's postformation value-weighted average stock return. At time t-1, five portfolios are created, with the low (high) portfolios containing firms with the lowest (highest) green innovation peer pressure. After forming the five portfolio sorts (from low to high), we calculate the value-weighted monthly returns on these portfolios at time t. To examine the relationship between green innovation competition and returns, we also form a high-minus-low portfolio that takes a long position in the high-GTPP portfolio and a short position in the low-GTPP portfolio. Our sample covers the period from January 1980 to December 2022.

We conduct the following model to examine whether the portfolio yields a statistically significant abnormal performance:

$$r_{p,t} - r_{f,t} = \alpha_{p,t} + \beta_p^{'} Controls_t + \varepsilon_{p,t}, \tag{4.4}$$

where $r_{p,t}$ is the monthly value-weighted return on portfolio p, $r_{f,t}$ is the risk-free return in the market. $Controls_t$ is a vector that includes standard controls that have been found to explain the cross-section of U.S. stock excess returns, and $\varepsilon_{p,t}$ is an error term. We consider four alternative model specifications regarding the different choices of $Controls_t$ follow standard procedure: the capital asset pricing model (CAPM), the Fama-French three-factor model (Fama and French, 1996), the Fama-French five-factor model (Fama and French, 2015) with Carhart's momentum factor (Carhart, 1997), and Hou-Xue-Zhang (HXZ) q-factor model (Hou et al., 2015). To alleviate the concern of autocorrelation, standard errors are adjusted based on Newey and West (1987)s' method.

We first present portfolio-level characteristic summaries in Table 4.3. We find that stocks in the high-GTPP group are smaller, have lower profitability, and have lower asset tangibility and leverage levels.

Then, we study the relationship between green technology competition and stock return. Panel A of Table 4.4 presents monthly excess returns on the portfolios in percentage. The t-statistics are reported in parentheses. We find that the excess returns increase from 0.883% to 1.363% across portfolios from low to high green technological peer pressure, leading to a return spread of 0.480% with a t-statistics of 3.341. Thus, the firm-level GTPP measure can positively predict returns.

Next, we examine whether the positive GTPP-return can be explained by existing risk factors. From Panel B to E of Table 4.4, we report the alphas from the leading risk factor models as discussed above. The GTPP-sorted long-short portfolio alphas persist in significance. Taking Panel D as an example, the quintile portfolio sorts from low to high have excess returns of 0.189%, 0.328%, 0.518%, 0.541%, and 0.793%, respectively. More importantly, the HML portfolio has an excess return of 0.604% with a t-statistic of 4.882, which is both economically and statistically significant. Therefore, common risk factors cannot explain the cross-sectional return spread across portfolios sorted on GTPP. In sum, GTPP is positively associated with excess return and alphas.[12]

[Insert Table 4.4 and Table 4.3 around here]

4.4.2 Unexpected climate change attention

The previous section showed that the stock returns of a portfolio of firms with high GTPP are higher than the low-GTPP portfolio. We now investigate whether this relation varies when there is an unexpected surge in attention toward climate change from the public. The pioneering study from Pástor et al. (2022) shows that green firms outperform brown firms when concerns about climate change increase unexpectedly. Ardia et al.

[12]Similar results exist for equal-weighted portfolios, which are presented in Appendix Table C3. In Appendix Table C2, we report the estimation results when using alternative percentile thresholds (25-75th, 10-90th percentiles, and tercile of GTPP) of forming the portfolios. Across all cases, the results remain unchanged, and the magnitudes are similar to the findings in Table 4.3.

(2023) empirically test Pástor et al. (2022)'s prediction and find that green firms' stock prices tend to increase on days with an unexpected increase in climate change concerns. As green innovation promotes firms' ability to cope with transition risk and physical risks, we expect that, with the increased attention toward climate change, low GTPP firms outperform high GTPP firms.

To check our hypothesis, we consider a multivariate linear regression similar to Equation 4.4 as follows:

$$r_{p,t} - r_{f,t} = \alpha_{p,t} + \beta' Controls_{p,t} + \delta ClimateRisk_t + \varepsilon_{p,t}. \tag{4.5}$$

$ClimateRisk_t$ is the climate change concern of the public. We use the media-based time series index proposed by Faccini et al. (2023) to represent market-wide climate risks. Faccini et al. (2023) search English articles that contain the words "climate change" and "global warming" on Reuters news. Then, they construct four relevant topics that capture physical and transition risks and are relevant to the U.S. stock market: U.S. climate policy (actions and debate), international summits on climate change, global warming, and the occurrence of natural disasters. The first two topics are related to transition risks, whereas the last two inform the physical risks from climate change. We are interested in the coefficient δ.

Estimation results are reported in Table 4.5. Considering the HML portfolio, the coefficients are negatively significant for the concerns from U.S. climate policy (Panel A) and global warming (Panel C) across different models. For the high portfolio, we find the coefficients are negative and statistically significant to the risks from climate change policy. The coefficients of a low GTPP portfolio are positively insignificant in all models and different climate change concerns. These results imply that the increase in climate change attention, especially for attention from climate change policy, has deflated prices for companies with sufficient green patents stock.

[Insert Table 4.5 around here]

Next, we conduct regression analysis conduct a regression analysis using the following model:

$$r_{i,t} - r_{f,t} = \alpha + \gamma GTPP_{i,t} + \eta Climate\ risk_t + Controls_t + \varepsilon_t^i. \tag{4.6}$$

The regression is at the firm level and controls for the time-fixed effect. Standard errors are clustered at firm levels. To capture the changes of public concerns to climate change issues, we use the changes of measure proposed by Faccini et al. (2023). Then, we divide the sample into two groups based on whether there is an increase in concern about climate change. The regression results are reported in Table 4.6, which reveals that the effect on stock return only exists higher climate change concern period. This finding is consistent with the idea that investors are more likely to pay attention to salient climate news. In addition, investors are responding to climate change policies and global warming, which aligns with the portfolio findings presented earlier. This indicates that both transition risks and physical risks can influence stock returns.

4.4.3 Robustness tests

Industry level analysis

Furthermore, we analyze the pricing effect at the industry level.[13] We first conduct individual stock sorts of the within-industry firm-level GTPP. Shown in Table 4.7 Panel

[13]The industries are defined by the FF49 industries.

A, we find the positive return spread still significant. Second, we conduct industry sorts using industry-level GTPP. As shown in Panel B, after controlling for Fama and French's five factors (Fama and French, 2015), GTPP generates significant return spreads.

[Insert Table 4.7 around here]

Double sorting

As shown in Table 4.3, we find stock characteristics across five GTPP-sorted portfolios are different. To alleviate the concern that the return predictability is driven by other characters, we now conduct double sorts with stock characters and emission information. The analysis first sorts stocks into two portfolios by firm size, tangibility, investment level, book-to-market ratio, and financial constraints. Then, sequentially sorts stocks by GTPP into five portfolios. All the firm characters and GTPP are measured over the same period. After controlling for these factors, GTPP generates significant return spreads. For example, in Panel A of Table 4.8, the HML return spread is 0.546 for the bigger firm group, significant at the 1% level; it is 0.709 for the small firms at the 1% level. These results suggest that the GTPP-related return predictability holds in the sample without emission preferences, consistent with the baseline regression results.

[Insert Table 4.8 around here]

Fama-MacBeth regressions

We further perform a robustness test by conducting Fama-MacBeth cross-sectional regressions (Fama and MacBeth, 1973) to investigate the relationship between GTPP and stock return. This analysis allows us to control for an extensive list of firm-level characteristics that correlated with stock returns and to further examine whether the positive GTPP-return relation is driven by other known predictors at the firm level. Control variables include the natural logarithm of market capitalization (Size), the natural logarithm of the book-to-market ratio (B/M), investment rate (I/K), return on equity (ROE), tangibility, WW index (Whited and Wu, 2006), book leverage, and industry dummies based on Fama and French (1997) 49-industry classifications. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. The detailed definition of the control variables is shown in Appendix C1.

In Table C4, we examine the GTPP-return relation by running panel regressions to control for a variety of firm characteristics. The coefficient estimates represent the average slopes from monthly regressions. As shown in Column (3), the coefficient of GTPP is 0.134 and significant at 1% level after controlling other known predictors and the industry fixed effect. The results of these regressions are consistent with the results obtained when we sort portfolios on GTPP, which shows that GTPP significantly positively explains stock returns. There is a concern that the positive correlation between GTPP and returns is associated with carbon emission risk. A considerable set of literature finds strong associations between emissions (including greenhouse gas and toxic emissions) and fundamental measures of firms' financial performance such as stock returns (e.g., Hsu et al., 2023; Aswani et al., 2024; Bolton and Kacperczyk, 2023; Zhang, 2024). In the context of green innovation, a firm that lacks green patents may not be capable of emissions reduction. Accordingly, our results could be biased if high-GTPP firms are also notable emitters. To alleviate this concern, we further control firms' greenhouse gas intensity in the Fama-MacBeth regressions, which measured as Scope 1 plus Scope 2 CO2 equivalent emissions to revenues USD in millions. As shown in Table C4 Column (4), we find the coefficients between GTPP and stock return remain significant. However, the coefficients for carbon emission intensity are insignificant in our sample. Thus, the GTPP-return relationship is not ascribed to the emission risk.

4.5 Economic mechanism

We find a positive relationship between GTPP and stock return. A possible explanation for our finding is that green innovation competition may indirectly affect stock returns through its impact on a firm's profitability. Specifically, green innovation is time-consuming and requires continuous investment, which may lead to higher costs and reduced production during the transition period. Since climate change risks primarily affect a firm's long-term performance rather than its current performance, firms may choose to forgo this investment or opt for incremental investment instead of making it all at once. These firms may face higher GTPP and exhibit greater productivity relative to their market peers in the short term. Investors may expect them to devote more effort to green innovation, resulting in higher stock returns.

To evaluate this hypothesis, we examine the association between GTPP and four commonly-used indicators of profitability or operational performance (e.g., Aswani et al., 2024): (i) ROA_{it}, which is the return over assets measured as the ratio of operating income after depreciation to total book assets for firm i in year t; (ii) ROS_{it}, which is the return on sales, measured as the ratio of operating income after depreciation to sales for firm i in year t; (iii) $EBIT\ Margin_{it}$, which is the ratio of earning before interest and taxes (EBIT) to sales for firm i in year t; (iv) $EBITDA\ Margin_{it}$, which is the ratio of earning before interest, taxed, depreciation, and amortization (EBITDA) to sales for firm i in year t. We estimate the following regression:

$$Operating\ Performance_{i,t} = \alpha + \gamma GTPP_{i,t} + \eta Controls_{i,t} + Fixed\ effects + \varepsilon_t^i. \quad (4.7)$$

The dependent variable, $Operating\ Performance_{i,t}$, is one of the four measures mentioned above. The key independent variable is GTPP, which captures the green innovation peer pressure in the market. Following Bolton and Kacperczyk (2021), we add the frim-specific control variables known to be associated with firm operating performance, such as firm size, book-to-market ratio, ROE, leverage, investment level, tangibility, HHI, stock volatility, sales growth, earnings growth, momentum. The details of variable definitions are presented in Appendix Table C1. We include month-year and Fama-French 49 industry fixed effects. Standard errors are double-clustered at the firm and month-year level, following Bolton and Kacperczyk (2021).

Table 4.9 presents the results of the relationship between GTPP and operating performance. It shows that all four performance measures are positively associated with GTPP. Taking Column (1) as an example, one standard deviation of the increase of GTPP (2.19) is associated with approximately 21%(2.19*0.006/0.06) increase in ROA.

[Insert Table 4.9 around here]

In addition, we investigate whether this effect is stronger for firms with higher climate change exposure as high climate change exposed firms are expected to invest more in green R&D to reduce the emission. To assess this, we utilize a measure of firm-specific exposure to climate change developed by Sautner et al. (2023c). This time-varying measure extracts the frequency and prominence of different facets of climate change topics discussed in firms' quarterly earnings conference calls. This firm-level measure reflects the potential climate change risks in the future. Following our discussion, we expect firms with higher climate change exposure are likely to have better operating performance.

As shown in Table 4.10 Column (1), we find that both the coefficient of GTPP and the interaction term are positive. GTPP has a positive relationship with all four performance measures. We find the coefficients of interaction terms are still positive but not significant. In sum, these findings indicate that stock returns are indirectly affected through a link with firm fundamentals, and this effect varies based on a firm's exposure to climate change.

[Insert Table 4.10 around here]

4.6 Conclusion

Green technologies are essential tools to alleviate environmental pressure and restore production efficiency and competitiveness. We shed light on a less debated topic related to green innovation: the competition in green innovation and its impact on stock market returns. Using a sample of U.S. common stocks trading on primary exchanges from January 1980 to December 2022, we empirically investigate the effects of green technological peer pressure on stock returns. Our paper distinguishes itself from previous literature by focusing on competition in green patenting rather than on green innovation or carbon emissions.

We find compelling evidence indicating that green technological peer pressure has a positive relationship with stock returns. Our findings remain robust across various portfolio sorting methods and are not affected by common factors. Moreover, we discuss the positive effects during periods of increasing public concern about climate change.

Specifically, we find that this effect of green technological peer pressure on stock returns exists only during periods of higher climate change concern. Overall, our collective evidence enhances the understanding of the importance of green innovation and how the stock market values it.

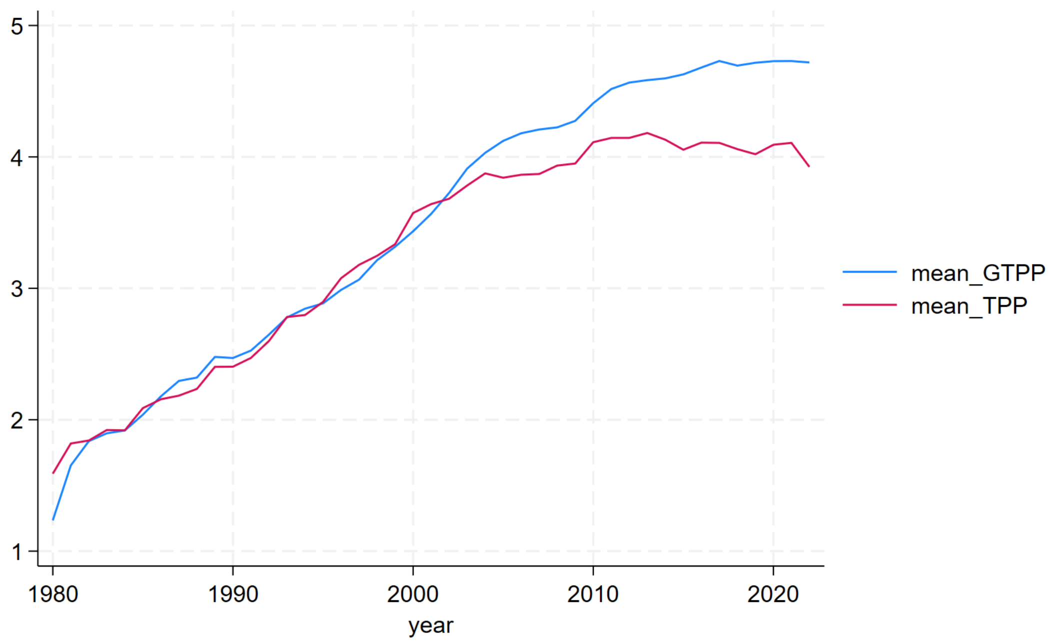

Figure 4.1: The change of GTPP and TPP over time

***Note*:** This figure plots the mean value of green technological peer pressure (GTPP) and technological peer pressure (TPP) during the sample period of 1980 to 2022. The blue line represents the annual average GTPP and the red line represents the annual average TPP.

Table 4.1: GTPP and environmental performance

VARIABLES	Emission		Resource use	
	(1)	(2)	(3)	(4)
GTPP	-1.159***	-2.028***	-1.108**	-1.644***
	(-2.796)	(-4.696)	(-2.575)	(-3.689)
Size	11.650***	12.546***	11.685***	13.306***
	(25.986)	(23.612)	(25.859)	(24.849)
Tobin's Q	1.590***	0.694*	1.383***	0.596
	(3.678)	(1.651)	(2.849)	(1.330)
Leverage	-2.538	-6.589*	2.135	-5.170
	(-0.695)	(-1.687)	(0.500)	(-1.227)
Tangibility	10.099***	12.075***	7.333***	12.357***
	(4.617)	(3.974)	(3.060)	(3.615)
Constant	-53.937***	-55.439***	-50.604***	-60.352***
	(-10.571)	(-9.578)	(-9.356)	(-10.152)
No. of Obs.	7,695	7,692	7,300	7,297
Adj. R-squared	0.440	0.580	0.412	0.582
Industry FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Clustered SE	Yes	Yes	Yes	Yes

***Note*:** This table presents the relationship between green technological peer pressure (GTPP) and corporate environmental performance. The dependent variables are *Emission* and *Resourceuse* performance, which are collected from the Refinitiv ESG database. The main independent variable is GTPP. The Appendix Table C1 provides the definition of variables. The t-statistics are reported in parentheses. Standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.2: GTPP by industry sectors

Industry	Average GTPP
Panel A: Top 5 industries	
Rubber and plastic products	5.465
Electronic equipment	5.278
Computer software	5.258
Fabricated products	5.214
Medical equipment	5.019
Panel B: Bottom 5 industries	
Apparel	0.104
Tobacco products	0.377
Candy and soda	0.930
Restaurants, hotels, motels	1.473
Beer and liquor	1.486

***Note*:** This table presents the top (Panel A) and bottom (Panel B) industries sorted by GTPP. The industry sectors are classified by Fama and French 49 industry classifications. We identify green patents using OECD's classification, i.e., green patents are the ones that contain one of the following environmental technologies: environmental management, water-related adaptation technologies, biodiversity protection, and ecosystem health, climate change mitigation technologies related to energy generation, transmission or distribution, transportation, buildings, waste-water treatment or waste management, and production or processing of goods.

Table 4.3: Portfolio characteristics

	L	2	3	4	H
GTPP	0.691	2.440	3.508	4.820	6.048
LogME	15.975	15.332	14.646	14.097	13.444
ROE	0.155	0.127	0.122	0.117	0.114
B/M	0.417	0.404	0.453	0.399	0.464
I/K	0.095	0.083	0.100	0.097	0.100
Leverage	0.247	0.227	0.203	0.167	0.158
Tangibility	0.599	0.591	0.423	0.414	0.437
WW index	-0.423	-0.404	-0.383	-0.342	-0.286

***Note*:** This table presents the time-series average of the cross-sectional medians of firm characteristics for five GTPP-sorted portfolios. logME is the natural logarithm of market capitalization. ROE is the return on equity. B/M is the book-to-market ratio. I/K is the investment rate. Leverage is the book leverage. WW index is a measure of financial constraints. The sample period spans from January 1981 to December 2022. The Appendix Table C1 provides the definition of variables.

Table 4.4: Factor alpha of GTPP portfolios

	L	2	3	4	H	HML
Panel A: Raw Return						
Raw return	0.883***	0.993***	1.130***	1.079***	1.363***	0.480***
	(4.841)	(5.263)	(4.766)	(4.538)	(5.481)	(3.341)
Panel B: CAPM						
α	0.289***	0.417***	0.397***	0.365***	0.607***	0.318**
	(3.458)	(4.718)	(3.730)	(3.370)	(4.700)	(2.346)
Panel C: Fama-French three factors						
α	0.277***	0.430***	0.472***	0.407***	0.680***	0.403***
	(3.440)	(5.147)	(4.571)	(3.893)	(5.207)	(3.180)
Panel D: Fama-French five factors with Momentum factor						
α	0.189**	0.328***	0.518***	0.541***	0.793***	0.604***
	(2.564)	(4.511)	(4.608)	(5.246)	(5.996)	(4.882)
Panel E: Hou-Xue-Zhang q factors						
α	0.232***	0.368***	0.612***	0.534***	0.842***	0.610***
	(3.001)	(4.780)	(5.212)	(4.773)	(6.110)	(4.691)

***Note*:** This table presents asset pricing factor tests for five portfolios sorted on green technological peer pressure (GTPP). The results reflect monthly data from January 1980 to December 2022. Firms in financial industries and utility industries are excluded. To adjust for risk exposure, we perform time-series regressions of GTPP-sorted value-weighted portfolios' excess returns on the market factor as the CAPM model in Panel B, on the Fama and French (1996) three factors in Panel C, on the Fama and French (2015) five factors and Carhart (1997) momentum factor, Panel D, and on the Hou et al. (2015) q-factors in Panel E, respectively. Newey and West (1987) t-statistics are reported in parentheses with five lags of autocorrelation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.5: Unexpected climate change attention

	L	H	HML
Panel A: U.S. climate policy			
CAPM	0.034	-0.342*	-0.376**
	(0.329)	(-1.956)	(-2.073)
FF3	0.044	-0.347*	-0.391**
	(0.470)	(-1.933)	(-2.285)
FF5+Mom	-0.006	-0.350*	-0.345*
	(-0.076)	(-1.939)	(-1.910)
q factors	0.027	-0.345*	-0.372**
	(0.301)	(-1.877)	(-2.032)
Panel B: International summits			
CAPM	0.102	-0.024	-0.126
	(0.930)	(-0.174)	(-0.625)
FF3	0.128	-0.027	-0.155
	(1.416)	(-0.212)	(-0.969)
FF5+Mom	0.039	0.014	-0.025
	(0.438)	(0.108)	(-0.162)
q factors	0.107	-0.034	-0.141
	(1.189)	(-0.257)	(-0.856)
Panel C: Global warming			
CAPM	0.344**	-0.313	-0.657**
	(2.212)	(-1.155)	(-2.368)
FF3	0.237	-0.222	-0.459*
	(1.536)	(-0.814)	(-1.824)
FF5+Mom	0.114	-0.170	-0.283
	(0.784)	(-0.631)	(-1.074)
q factors	0.204	-0.221	-0.426*
	(1.360)	(-0.836)	(-1.686)
Panel D: Natural disasters			
CAPM	0.081	-0.192	-0.273
	(0.559)	(-0.820)	(-1.142)
FF3	0.024	-0.165	-0.190
	(0.169)	(-0.728)	(-0.878)
FF5+Mom	0.121	-0.071	-0.192
	(0.850)	(-0.324)	(-0.885)
q factors	0.060	-0.144	-0.203
	(0.419)	(-0.659)	(-0.984)

***Note*:** This table presents asset pricing factor tests for five portfolios sorted on green technological peer pressure (GTPP) with unexpected climate change risks. The estimated coefficients of δ in Equation 4.5 are shown in this table. The dependent variable is the value-weighted return of portfolios sorted on GTPP. The results reflect monthly data from January 2000 to December 2022. To adjust for risk exposure, we perform time-series regressions of GTPP-sorted portfolios' excess returns on the market factor as the CAPM model, Fama and French (1996) three factors, Fama and French (2015) five factors plus Carhart (1997) momentum factor, and Hou et al. (2015) q-factors, respectively. Four climate change risk factors are grouped into four topics: U.S. climate policy (Panel A), international summits on climate change (Panel B), global warming (Panel C), and the occurrence of natural disasters (Panel D). The unexpected climate change data is shared by Faccini et al. (2023). Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The Appendix Table C1 provides the definition of variables.

Table 4.6: Unexpected attention factor: Regression analysis

Panel A: U.S. climate policy			
GTPP	-0.038*		0.056*
	(-1.822)		(1.845)
Constant	0.484***		-0.101
	(4.852)		(-0.710)
Controls	Yes		Yes
Industry FE	Yes		Yes
Observations	90,334		40,248
Adj. R-squared	0.179		0.16
High climate concern	No		Yes
Empirical p-value		0.010	
Panel B: International summits			
GTPP	0.009		-0.039
	(0.450)		(-1.237)
Constant	0.181**		0.636***
	(2.058)		(4.493)
Controls	Yes		Yes
Industry FE	Yes		Yes
Observations	94,517		36,065
Adj. R-squared	0.179		0.168
High climate concern	No		Yes
Empirical p-value		0.080	
Panel C: Global warming			
GTPP	-0.049**		0.056**
	(-2.275)		(2.203)
Constant	0.462***		0.010
	(4.398)		(0.081)
Observations	82,249		48,333
Controls	Yes		Yes
Industry FE	Yes		Yes
Adj. R-squared	0.183		0.164
High climate concern	No		Yes
Empirical p-value		0.000	
Panel D: Natural disasters			
GTPP	-0.035		0.027
	(-1.588)		(1.160)
Constant	0.408***		0.195*
	(3.848)		(1.707)
Controls	Yes		Yes
Industry FE	Yes		Yes
Observations	76,176		54,406
Adj. R-squared	0.184		0.164
High climate concern	No		Yes
Empirical p-value		0.030	

***Note*:** This table presents the regression analysis of monthly stock return on green technological peer pressure (GTPP). We split the sample by the changes of public climate change concerns, which were developed by Faccini et al. (2023). The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The model is estimated with data from February 2000 to December 2022. The Appendix Table C1 provides the definition of variables.

Table 4.7: Industry and GTPP sorted portfolios

	L	2	3	4	H	HML
Panel A: Fama and French 49 industries						
Raw return	0.918***	1.029***	1.168***	1.003***	1.242***	0.311*
	(4.851)	(4.716)	(5.227)	(4.445)	(4.812)	(1.946)
α	0.273***	0.332***	0.451***	0.210**	0.612***	0.333**
	(4.018)	(3.060)	(4.891)	(2.274)	(4.313)	(2.292)
Panel B: Industry-level GTPP						
Raw return	0.883***	0.814***	1.142***	0.911***	1.264***	0.381
	(4.847)	(3.536)	(4.788)	(3.670)	(4.427)	(1.618)
α	0.016	0.011	0.648***	0.114	0.961***	0.945***
	(0.182)	(0.087)	(4.589)	(0.781)	(4.796)	(4.099)

***Note*:** This table presents monthly raw returns and FF5+momentum Fama and French (2015); Carhart (1997) alphas of industry-level and firm-level sorted portfolios. The industries are defined by the FF49 industries. Panel A conducts individual stock sorts of the within-industry firm-level GTPP. Panel B conducts industry sorts using the industry level. Newey and West (1987) t-statistics are reported in parentheses with five lags of autocorrelation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.8: Factor alpha of GTPP portfolios: Double sorting

	L	2	3	4	H	HML
Panel A: Size						
L	0.186**	0.146	0.259***	0.686***	0.733***	0.546***
	(2.442)	(1.522)	(2.771)	(5.748)	(6.315)	(4.182)
H	-0.033	0.228*	0.501***	0.529***	0.676***	0.709***
	(-0.244)	(1.856)	(3.562)	(3.237)	(3.608)	(3.132)
Panel B: Tangibility						
L	0.198**	0.117	0.233**	0.473***	0.498***	0.300**
	(2.437)	(1.148)	(2.427)	(3.848)	(4.215)	(2.146)
H	0.191**	0.126	0.331***	0.463***	0.485***	0.294**
	(2.328)	(1.235)	(3.382)	(3.667)	(4.020)	(2.046)
Panel C: Investment						
L	0.010	0.087	0.297***	0.394***	0.662***	0.652***
	(0.088)	(0.793)	(2.678)	(2.859)	(4.720)	(3.826)
H	0.343***	0.397***	0.578***	0.722***	1.032***	0.689***
	(3.182)	(3.450)	(3.423)	(4.934)	(4.964)	(3.571)
Panel D: B/M						
L	0.406***	0.381***	0.842***	1.133***	1.314***	0.908***
	(4.354)	(3.554)	(6.511)	(7.128)	(6.535)	(4.820)
H	-0.573***	-0.050	-0.235	-0.205	-0.149	0.424**
	(-4.232)	(-0.392)	(-1.501)	(-1.458)	(-1.025)	(2.526)
Panel E: WW index						
L	0.160*	0.207*	0.314***	0.636***	0.618***	0.458***
	(1.738)	(1.824)	(2.946)	(4.652)	(5.210)	(3.363)
H	0.325**	0.453***	1.321***	1.294***	0.936***	0.610***
	(2.159)	(2.813)	(4.743)	(5.112)	(4.649)	(2.827)

***Note*:** This table presents monthly value-weighted portfolio returns double-sorted by technological peer pressure (GTPP) and firm-level characteristics, including firm size (Panel A), tangibility (Panel B), Investment level (Panel C), book-to-market ratio (Panel D), and financial constraints (Panel E). To adjust for risk exposure, we use the Fama and French (2015) five factors and Carhart (1997) momentum factor. The variables' definitions are shown in Appendix Table C1. Newey and West (1987) t-statistics are reported in parentheses with five lags of autocorrelation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.9: GTPP and operating performance

VARIABLES	(1) ROA	(2) ROS	(3) EBIT margin	(4) EBITDA margin
GTPP	0.006***	0.055***	0.058***	0.055***
	(3.927)	(3.635)	(3.581)	(3.635)
B/M	-0.021**	-0.015	-0.031	-0.015
	(-2.580)	(-0.162)	(-0.302)	(-0.162)
ROE	0.037***	0.113**	0.128**	0.113**
	(6.841)	(2.175)	(2.266)	(2.175)
Size	0.016***	-0.053	-0.053	-0.053
	(4.659)	(-1.352)	(-1.259)	(-1.352)
I/K	0.186***	1.248**	1.293**	1.248**
	(5.587)	(2.340)	(2.245)	(2.340)
Tangibility	0.006*	0.189***	0.190***	0.189***
	(1.685)	(4.574)	(4.293)	(4.574)
Leverage	-0.094***	-0.439**	-0.483**	-0.439**
	(-4.423)	(-1.983)	(-2.033)	(-1.983)
Sales growth	0.137***	1.444***	1.561***	1.444***
	(8.334)	(6.998)	(6.981)	(6.998)
Earning growth	-0.003	-0.155***	-0.164***	-0.155***
	(-1.505)	(-7.358)	(-7.173)	(-7.358)
HHI	-17.961**	-47.216	-45.376	-47.216
	(-2.406)	(-1.373)	(-1.264)	(-1.373)
Volatility	-4.696***	-31.820***	-34.716***	-31.820***
	(-16.609)	(-9.169)	(-9.306)	(-9.169)
Momentum	0.022***	0.168***	0.182***	0.168***
	(6.183)	(3.781)	(3.791)	(3.781)
Constant	-0.089**	0.083	0.076	0.083
	(-2.222)	(0.193)	(0.165)	(0.193)
Observations	156,976	156,880	156,959	156,880
Adj. R-squared	0.493	0.270	0.265	0.270
Industry FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes

***Note*:** This table presents the regression analysis of four measures of operating performance and profitability—ROA, ROS (return on sales), EBIT margin (the ratio of EBIT to assets), and EBITDA margin (the ratio of EBITDA to assets)—on green technological peer pressure (GTPP). All specifications include the full set of control variables along with industry and month-year fixed effects. Standard errors are two-way clustered by firm and month-year. Refer to Appendix Table C1 for variable definitions. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.10: GTPP and operating performance: The effect of climate change exposure

VARIABLES	(1) ROA	(2) ROS	(3) EBIT margin	(4) EBITDA margin
GTPP	0.004**	0.041**	0.041**	0.041**
	(2.387)	(2.578)	(2.440)	(2.578)
Climate change exposure	-4.401***	-8.252	-12.174	-8.252
	(-3.239)	(-0.508)	(-0.689)	(-0.508)
GTPP*Climate change exposure	0.806***	3.042	3.904	3.042
	(2.637)	(0.909)	(1.086)	(0.909)
B/M	-0.009	0.057	0.039	0.057
	(-0.889)	(0.567)	(0.367)	(0.567)
ROE	0.029***	0.057	0.064	0.057
	(5.693)	(1.144)	(1.178)	(1.144)
Size	0.019***	-0.050	-0.049	-0.050
	(5.063)	(-1.109)	(-1.005)	(-1.109)
I/K	0.176***	1.336**	1.409**	1.336**
	(4.364)	(2.393)	(2.340)	(2.393)
Tangibility	0.002	0.153***	0.150***	0.153***
	(0.627)	(3.292)	(3.022)	(3.292)
Leverage	-0.063***	-0.411*	-0.469*	-0.411*
	(-2.896)	(-1.761)	(-1.876)	(-1.761)
Sales growth	0.125***	1.377***	1.483***	1.377***
	(7.137)	(6.192)	(6.188)	(6.192)
Earning growth	-0.003	-0.139***	-0.146***	-0.139***
	(-1.283)	(-6.295)	(-6.019)	(-6.295)
HHI	-13.998*	-66.449*	-64.646	-66.449*
	(-1.752)	(-1.686)	(-1.569)	(-1.686)
Volatility	-4.768***	-32.876***	-35.400***	-32.876***
	(-14.204)	(-8.478)	(-8.460)	(-8.478)
Momentum	0.020***	0.150***	0.160***	0.150***
	(4.815)	(3.085)	(3.053)	(3.085)
Constant	-0.127***	0.348	0.352	0.348
	(-2.817)	(0.738)	(0.695)	(0.738)
Observations	105,657	105,639	105,648	105,639
Adj. R-squared	0.492	0.251	0.244	0.251
Industry FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes

***Note*:** This table presents the regression analysis of four measures of operating performance and profitability—ROA, ROS (return on sales), EBIT margin (the ratio of EBIT to assets), and EBITDA margin (the ratio of EBITDA to assets)—on green technological peer pressure (GTPP), and the interaction term of GTPP and firm-level climate change exposure. The climate change measure is constructed by Sautner et al. (2023a). All specifications include the full set of control variables along with industry and month-year fixed effects. Standard errors are two-way clustered by firm and month-year. Refer to Appendix Table C1 for variable definitions. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C1: Variable definitions

Variables	Definition
GTPP	Green technological peer pressure for firm i at time t. $GTPPi,t = ln\left[1 + \frac{1}{Gi,t}\sum^{i \neq j} \omega_{ij \times G j,t}\right]$. Firm i's green technological threat comes from a peer firm j's green patents stock $G_{j,t}$ at the end of time t weighted by the closeness ω_{ij} between these two firms, where $\omega_{ij} = \left\langle \frac{V_i}{\|V_i\|} \cdot \frac{V_j}{\|V_j\|} \right\rangle$. V_i is the vector of firm i's sales with the kth element being the share of firm i's total sales in industry k.
Emissions	Firm's commitment and effectiveness towards reducing environmental emissions and wastes.
Resource use	Firm's performance and capacity in reducing the use of materials, energy, or water and promoting supply chain management.
ROS	Return on sales, measured as the ratio of operating income after depreciation to year-end total sales.
ROA	Return on assets, measured as the ratio of operating income after depreciation to year-end total assets.
EBIT Margin	Ratio of earnings before interest and taxes to year-end total sales.
EBITDA Margin	Ratio of earnings before interest, taxed depreciation, and amortization to sales year-end total sales.
Sales growth	Annual firm sales normalized by prior-year sales.
Earning growth	Annual firm earnings per share normalized by prior-year earnings per share.
Volatility	Monthly stock return volatility, calculated over the one-year period.
Momentum	Total stock return over the one-year period.
ROE	Return on equity, measured as the ratio of net income divided by the value of its equity.
Size	Natural logarithm of firm's total market capitalization.
B/M	Book-to-market ratio, measured as the book value of equity scaled by the market value of equity.
I/K	Ratio of capital expenditures to total assets.
Leverage	Ratio of total debt scaled by total assets.
Tangibility	The property, plant, and equipment scaled by total assets.
HHI	Herfindahl index of sales of all firms in the same two-digit SIC industry.
WW	WW index following Whited and Wu (2006).
CO2 intensity	Scope 1 plus Scope 2 CO2 equivalent emissions to revenues USD in million.
Climate change exposure	The measure of firm-specific exposure to climate change developed by Sautner et al. (2023c)

***Note*:** This table presents the variable definitions. Data are collected from Compustat, CRSP, and Refinitiv ESG databases.

Table C2: Results of portfolios' sorting: Alternative percentile

	L	H	HML
Panel A: 25–75th percentiles			
Raw return	0.884***	1.359***	0.474***
	(4.815)	(5.519)	(3.436)
CAPM	0.286***	0.618***	0.348***
	(3.702)	(4.653)	(2.618)
FF3	0.282***	0.701***	0.419***
	(3.829)	(4.849)	(3.343)
FF5+Mom	0.209***	0.785***	0.576***
	(3.104)	(6.069)	(4.835)
q factors	0.243***	0.825***	0.582***
	(3.514)	(6.046)	(4.729)
Panel B: 10–90th percentiles			
Raw return	0.864***	1.447***	0.583***
	(4.892)	(5.184)	(3.001)
CAPM	0.272***	0.702***	0.430**
	(2.954)	(3.897)	(2.323)
FF3	0.255***	0.763***	0.508***
	(2.856)	(4.287)	(2.849)
FF5+Mom	0.135	0.723***	0.588***
	(1.537)	(4.160)	(3.186)
q factors	0.179*	0.826***	0.647***
	(1.898)	(4.681)	(3.428)
Panel C: tercile			
Raw return	0.890***	1.268***	0.378***
	((4.918)	(5.275)	(3.114)
CAPM	0.297***	0.535***	0.238**
	(4.174)	(4.899)	(2.044)
FF3	0.293***	0.597***	0.303***
	(4.444)	(5.410)	(2.769)
FF5+Mom	0.202***	0.694***	0.493***
	(3.537)	(6.865)	(5.158)
q factors	0.235***	0.720***	0.485***
	(3.911)	(6.193)	(4.443)

***Note*:** This table presents asset pricing factor tests for five portfolios sorted on green technological peer pressure (GTPP). The results reflect monthly data from January 1980 to December 2022. Firms in financial industries and utility industries are excluded. To adjust for risk exposure, we perform time-series regressions of GTPP-sorted portfolios' excess returns on the market factor as the CAPM model, on the Fama and French (1996) three factors, on the Fama and French (2015) five factors and Carhart (1997) momentum factor, and on the Hou et al. (2015) q-factors. Alternative percentile thresholds are applied (Panel A: 25-75th, Panel B: 10–90th percentiles of GTPP) for the definition of high and low GTPP stocks. Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C3: Factor alpha of GTPP portfolios: Equal-weighted returns

	L	2	3	4	H	HML
Panel A: Raw Return						
Raw return	0.711***	0.860***	0.768***	0.821***	0.940***	0.229*
	(3.208)	(3.732)	(3.217)	(3.306)	(3.509)	(1.777)
Panel B: CAPM						
α	0.021	0.160	0.014	0.071	0.156	0.135
	(0.191)	(1.521)	(0.131)	(0.629)	(1.152)	(1.059)
Panel C: Fama-French three factors						
α	-0.071	0.112	-0.032	0.064	0.153	0.224**
	(-0.793)	(1.274)	(-0.359)	(0.701)	(1.522)	(2.024)
Panel D: Fama-French five factors with Momentum factor						
α	-0.162**	0.107	0.039	0.166**	0.278***	0.440***
	(-2.216)	(1.371)	(0.482)	(2.006)	(3.110)	(4.345)
Panel E: Hou-Xue-Zhang q factors						
α	-0.144	0.141*	0.055	0.186**	0.301***	0.446***
	(-1.416)	(1.724)	(0.635)	(2.149)	(2.835)	(3.788)

***Note*:** This table presents asset pricing factor tests for five portfolios sorted on green technological peer pressure (GTPP). To adjust for risk exposure, we perform time-series regressions of GTPP-sorted equal-weighted portfolios' excess returns on the market factor as the CAPM model in Panel B, on the Fama and French (1996) three factors in Panel C, on the Fama and French (2015) five factors and Carhart (1997) momentum factor, Panel D, and on the Hou et al. (2015) q-factors in Panel E, respectively. The results reflect monthly data from January 1980 to December 2022. Firms in financial industries and utility industries are excluded. Newey and West (1987) t-statistics are reported in parentheses with five lags of autocorrelation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C4: Fama-MacBeth regressions

	(1)	(2)	(3)	(4)
GTPP	0.159***	0.125**	0.134***	0.599**
	(3.990)	(2.261)	(2.912)	(2.149)
CO2 intensity				1.148
				(1.306)
B/M	-0.721***	-0.765***	-0.822***	-0.528*
	(-10.928)	(-11.435)	(-14.460)	(-1.776)
ROE	0.444*	0.840*	0.446**	-0.057
	(1.937)	(1.711)	(2.248)	(-0.100)
Size	-0.012	0.027	0.017	0.392
	(-0.166)	(0.348)	(0.210)	(1.219)
I/K	-0.116*	-0.108	-0.119*	-0.606
	(-1.661)	(-1.529)	(-1.651)	(-1.238)
Leverage			-0.095	-0.605**
			(-1.283)	(-2.405)
Tangibility			-0.006	-0.077
			(-0.097)	(-0.208)
WW index			-0.047	0.662
			(-0.457)	(1.511)
Constant	0.947***	0.691	0.684*	0.917
	(3.896)	(1.479)	(1.825)	(0.884)
Observations	163,475	163,475	162,559	26,976
R-squared	0.084	0.274	0.293	0.544
Industry FE	No	Yes	Yes	Yes

***Note*:** This table presents Fama-MacBeth regressions of individual stock excess returns on their green technological peer pressure (GTPP) and other firm characteristics. Control variables include the firm size, B/M ratio, investment rate (I/K), return on equity (ROE), tangibility, WW index, and leverage. The industry is defined by Fama and French 49-industry classifications. All independent variables are normalized to zero mean and one standard deviation after the winsorization of the 1st and 99th percentiles to reduce the impact of outliers. Newey and West (1987) t-statistics are reported in parentheses. The Appendix Table C1 provides the definition of variables. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Chapter 5

Conclusion

5.1 Summary of thesis

In this thesis, we combine three different studies by investigating firms' reactions when facing intense technological peer pressure. More specifically, by using U.S. sample, we consider the trade-off between innovation activity and sustainability investment, the acquisition decisions, and how the green innovation peer pressure influences the performance in the stock market.

Chapter 2 sheds light on a less debated topic in relation to corporate sustainability, that is, the association between technological peer pressure and corporate sustainability. We employ a panel dataset comprising 12,062 firm-year observations from 1,536 publicly traded U.S. firms over a 20-year period to empirically examine the impact of technological competition on firm-level sustainability efforts. Unlike previous studies that focus on the relationship between product market competition and corporate sustainability, we introduce a measure of technological peer pressure to capture the competitive threats arising specifically from the technology dimension within the product market.

We focus on technological competition because it is crucial for firms' success and, in a knowledge-based economy, may even be essential for their survival.

We present compelling evidence that technological peer pressure significantly reduces corporate sustainability performance, as measured by the Refinitiv Environmental and Social pillar scores. Our results remain robust across various measures of corporate sustainability, including additional controls for other aspects of competition, fixed effects, different model specifications, alternative patent-based TPP measures, and an instrumental variable approach to address endogeneity.

In our analysis, we find evidence that resource constraints and agency problems may contribute to the negative relationship between technological peer pressure and corporate sustainability. First, we underscore the significant role of financial slack in reducing corporate social responsibility performance. Second, we show that firms tend to concentrate on a limited range of sustainability activities. Third, the negative impact is weaker for companies with higher innovation efficiency. Fourth, from the perspectives of the CEO and the board, we highlight the disciplinary function of competition on corporate sustainability engagement. Additionally, we explore the cross-sectional heterogeneity, observing that the negative association is particularly pronounced for firms in R&D-intensive, high-tech, non-B2C, and "green" industries.

In Chapter 3, we delve into the intricate relationship between technological peer pressure and firms' mergers and acquisitions activities. Different from previous research that explored the connection between product market competition and acquisition decisions, we employ a measure of technological peer pressure to capture the threats stemming from the technology dimension within the product market.

Through a comprehensive analysis of M&A transactions in the United States from

1983 to 2022, we present compelling evidence that technological peer pressure acts as a significant motivating factor, prompting firms to pursue acquisitions. Our findings reveal that firms are more inclined to engage in diversifying M&As and acquire innovative targets as a strategic response to heightened technological peer pressure. Moreover, we demonstrate that acquisitions driven by technological peer pressure are linked to improved cumulative abnormal returns for the acquiring firms. This indicates that companies strategically respond to intensified technology competition by engaging in acquisitions to bolster their operational efficiency and technological capabilities. Notably, firms operating in high-tech industries and those that are single-segment exhibit superior post-merger performance when participating in innovation-motivated acquisitions. Additionally, we find TPP-induced acquisitions take less time to complete. Furthermore, acquirers show a preference for cash financing over equity financing as a payment method for M&A transactions.

The last empirical chapter (Chapter 4) conducts an examination of the relationship between green technological peer pressure and stock returns. This relationship is robust across various portfolio sorting techniques and remains unaffected by common market factors. Furthermore, we find that the positive impact is particularly pronounced during periods of heightened public concern about climate change. Specifically, the influence of green technological peer pressure on stock returns is significant only when climate change awareness is elevated. Overall, our findings enhance the understanding of the importance of green innovation and its valuation in the stock market.

5.2 Limitations and prospects for future research

Despite its significant contributions, this thesis has limitations that present opportunities for future research. First, capturing the effect of technological competition is challenging. In this thesis, we use TPP to represent technological competition, as proposed and validated by Cao et al. (2018). TPP gauges industry rivals' technological investment, measured by R&D stock, relative to the focal firm's level of preparedness. However, R&D expenditures on financial statements could encompass costs that are not directly related to innovation activities, with significant cross-sectional and temporal variations arising from differences in tax treatment (Frésard and Phillips, 2022). In addition, firms' choice of patenting is influenced by many factors (Glaeser and Lang, 2024). Some inventors may choose trade secrets to protect their innovation instead of applying for patents (Friedman et al., 1991). Consequently, our technological competition measure cannot fully capture the dynamics process in the market.

Second, this thesis only focuses on public firms traded in the United States in all three papers. We do not explore the technological peer pressure exerted by entities such as private companies, government entities, and non-profit organizations. Although a significant portion of innovation originates from these groups, their interactions within the product market are not examined due to data limitations.

Given the scope and findings of this thesis, several directions are suggested for future research in the field of corporate finance. First, it would be interesting to expand the scope of technological peer pressure from the product market space to the broader technology space. The dynamics of technological competition in the technology space could differ significantly from those in the product market space.

Second, considering the significant differences in competitive landscapes and business environments across countries, one possible extension is to conduct the analysis in other regions to validate and complement the findings of this thesis. Additionally, future studies could expand the scope by exploring technological competition on a global scale, as innovation requires greater cooperation and communication (e.g., Bahar et al., 2023). These would enable a broader, more comprehensive understanding of how technological competition shapes firms' behavior.

Third, scholars can conduct natural language processing to measure the technological dimension of a firm's product market rivalry. Recent studies have employed computational linguistics methods to identify competitors, competitive interactions, and market structure (e.g., Hoberg and Phillips, 2025; Acikalin et al., 2022; Frésard et al., 2020), allowing for a more accurate and timely reflection of the rapid changes within the product market. Therefore, future research could develop new measures to gauge technological innovation using computational linguistics methods.

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