The Green Rivalry Threat: Evidence from Peers' Green Strategies☆

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Abstract

We examine whether and how firms subject to stringent environmental regulation have a peer effect on unconstrained firms' green innovations. Using a difference-in-differences model, we find that unconstrained firms significantly increase their green innovations in response to the heightened green innovations of constrained firms after China's Emission Trading Scheme (ETS) pilot. We document the competitive threat as the underlying mechanism, consistent with the rivalry-based theory. Our heterogeneity analyses show that peer effects are more pronounced among non-ETS firms characterized by leader status, high public scrutiny, higher financial constraints, more institutional investors, and under-investment. We further find that these peer effects significantly increase non-ETS firms' economic performance and green revenues. Our research offers valuable insights and ex-ante evidence for policymakers and practitioners to further develop decarbonization regulation.

Keywords: Green rivalry threat; Green innovation; Peer effects; Policy spillover

JEL Classifications: G34, M41, O31, Q56

☆ We are grateful to Jason Zezhong Xiao, Mark N. Harris and Min Teach for helpful comments and discussion about ealier versions of this paper. We also benefited from numerous participants from "The 2023 Annual Conference of the British Accounting Review" at the Harvard Faculty Club, "The 2023 Global Conference of the British Accounting Review" in Cape Town, "The AFAANZ Annual Conference" at Auckland, New Zealand and seminar participants at Curtin University. All errors are our own.

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1. Introduction

Climate-change issues and carbon emissions have emerged as crucial factors influencing economic development and the dynamics of financial markets (Stroebel and Wurgler, 2021; Bai and Ru, 2024). In response to climate change and carbon emissions, regions globally have enacted diverse policies aimed at reducing organizational and corporate carbon emissions.[1] However, these emissions reduction policies are still in the infancy of implementation and have not been universally applied across all jurisdictions and industries (Fankhauser *et al.*, 2022). The hot-debated but underexplored question is how unconstrained firms (focal firms) respond to the heightened green investment of their peer firms subject to stringent environmental regulations. If such peer effects exist, what are the specific reasons behind this phenomenon?

Previous studies have explored how stringent environmental regulation can reduce firms' carbon dioxide emissions (Bai and Ru, 2024; Bushnell, Chong, and Mansur, 2013), enhance operating performance (Downar *et al.*, 2021), reallocate labor resources (Walker, 2011), and foster green innovations (Nesta, Vona, and Nicolli, 2014). Liu *et al.* (2022) investigate the province-level spillover effects of regional green innovations. Li, Lian, and Xu (2023) explore the spillover effects on ESG (Environmental, Social, and Governance) performance. However, there exists a dearth of evidence on whether and how unconstrained firms adapt their strategies in response to the increased investment in green innovations of peer firms constrained by stringent environmental regulations. Thus, in this study, we explore the peer effect of constraint firms' green investment on unconstraint firms' green innovations.

On the one hand, Jaffe *et al.* (1995) and Joshi, Krishnan, and Lave (2001) find that environmental regulations impose compliance costs and additional hidden environmental costs on constrained firms. Palmer, Oates, and Portney (1995) argue that firms view efforts to reduce pollution or improve environmental performance as incurring additional costs. Given the uncertainty and substantial costs involved in adopting green technologies (Schaefer, 2009), firms not subject to environmental regulations might overlook the potential advantages of eco-friendly products and services, thereby limiting their focus and investment in green innovations. On the other hand, Porter and van der Linde (1995) posit that stringent environmental regulations can spur innovations within constrained firms and boost their resource productivity, thereby enhancing their competitive advantages. This can pose a competitive threat to unconstrained firms. To

[1] For example, climate and environmental governance has historically been defined either as a target for stabilizing atmospheric concentrations, as seen in the 1992 United Nations Framework Convention on Climate Change, or as a percentage emissions reduction target, exemplified by the 1997 Kyoto Protocol. In more recent times, the approach to climate and environmental governance has shifted towards setting specific targets for achieving net-zero emissions, often aligned with the peak temperature goals established by the Paris Agreement in 2015.

maintain competitive advantage and limit rivals, firms imitate and learn from their peers, known as the rivalry-based theory (Lieberman and Asaba, 2006). Previous studies have examined that focal firms adapt their strategies to respond to peer firms' strategies (Dou, Hung, She, and Wang, 2023; Kim and Valentine, 2021; Leary and Roberts, 2014; Park, 2023). Yet, whether and how firms subject to stringent environmental regulation have a peer effect on unconstrained firms' green innovations remains unclear and requires rigorous empirical investigation. We, therefore, aim to address this question and provide causal inferences through a quasi-natural experimental setting- the Emission Trading Scheme (ETS) pilot in China.[2]

The ETS is a worldwide regulation for curbing climate change and reducing greenhouse gas emissions. For example, the European Union (EU) ETS has been in operation since 2005 and is the world's largest and most mature ETS. It is now commonly accepted as an effective and efficient carbon emission policy. With the acceleration of China's industrialization, urbanization, and rapid economic development since the 21st century, its carbon emissions have also increased sharply. According to the Climate Trade report data, China became the world's biggest carbon emitter, with 10,065 MtCO2e in 2021, constituting approximately 30% of global emissions.[3] As the world's largest emitter of greenhouse gases, China plays a pivotal role in the battle against global climate change. China launched the pilot ETS program in 2013 to achieve carbon emission reduction targets. It eventually implemented it in seven jurisdictions in 2014 and was named China's ETS pilot.[4] However, this regulation remains in its infancy and has not yet encompassed all jurisdictions. It is urgent to provide ex-ante evidence of how unconstrained firms respond to peer firms subject to this regulation to policymakers and practitioners. This motivates us to focus specifically on China's ETS pilot in this study.

Moreover, focusing on corporate green innovation is worthwhile as it constitutes a crucial corporate strategy for enhancing financial performance, environmental performance, and market competitiveness (Amore, Schneider, and Žaldokas, 2013; Amore and Bennedsen, 2016). For example, green innovations serve as effective signals that capture the attention of investors (Sunder, Sunder, and Zhang, 2017). Nguyen, Vu, and Yin (2020) find that audit quality significantly reduces corporate innovation output (patent counts and citations). Zaman *et al.* (2021) document that corporate

[2] ETS is a market-based regulation of global climate-change governance, aims to mitigate carbon emissions covering 34 worldwide jurisdictions as of 2022, including China (World Bank, 2022).

[3] $MtCO_2e$ is the measurement unit of carbon emissions, representing the million tons of carbon emissions. Data is from the Climate Trade report in 2021, available online at: https://climatetrade.com/which-countries-are-the-worlds-biggest-carbon-polluters/

[4] In October 2011, China's National Development and Reform Commission (NDRC) issued the *Notice on Pilot Carbon Emission Trading*, mandating the implementation of ETS pilots in Shenzhen, Beijing, Shanghai, Tianjin, Guangdong, Hubei, and Chongqing. Moreover, Shenzhen ETS pilot in August 2013, Beijing ETS pilot in October 2013, Shanghai and Tianjin ETS pilots in September 2013, Guangdong ETS pilot in March 2014, Hubei ETS pilot in April 2014, and Chongqing ETS pilot in June 2014.

environmental innovation can reduce stock price crash risk.[5] In addition, firms may obtain superior and valuable investment information or enhance their competitiveness by imitating peer firms' innovations (Machokoto, Gyimah, and Ntim, 2021). Nevertheless, the peer effects of constrained firms' green innovations on unconstrained firms' green innovations remain unexplored in the literature. Previous studies mainly focus on the peer effects of corporate financial policies (Leary and Roberts, 2014), dividend policies (Adhikari and Agrawal, 2018), trade credit (Gyimah, Machokoto, and Sikochi, 2020), banks' consumer complaints (Dou *et al.*, 2023). These motivate us to examine whether and how ETS firms' green innovations affect non-ETS firms' green innovations.

Prior literature documents that peer firms' strategies positively affect focal firms' innovation or R&D. For example, Kim and Valentine (2021) find that firms enhance their investment in innovation in response to peer firms' patent disclosures. Machokoto *et al.* (2021) find that firms enhance their R&D investment in response to peer firms' R&D strategies. However, previous studies have drawn different conclusions about the reasons behind these peer effects. One the one hand, Gyimah *et al.* (2020) find that the positive peer effects on firms' trade credit are more pronounced in the highly competitive and asymmetric environment. This is consistent with the rivalry-based and information-based theories. On the other hand, Adhikari and Agrawal (2018) document that the positive peer effects on corporate payout policies are more pronounced in the highly competitive and low asymmetric environment. This is consistent with the rivalry-based theory but inconsistent with the information-based theory. Thus, we predict that non-ETS firms enhance their green innovations in response to ETS firms' green innovations, particularly in a highly competitive environment, aligning with the rivalry-based theory.

According to Leary and Roberts (2014), peer firms are defined as all firms that except focal firms in the same industry. Numerous studies use this definition to investigate diverse peer effects (e.g., Adhikari and Agrawal, 2018; Gyimah *et al.*, 2020; Machokoto *et al.*, 2021). However, this may cause a particular form of endogeneity when attempting to investigate whether group actions or characteristics can affect the actions of its individual members (so-called the "reflection problem" pointed out by Manski (1993)). Specifically, a focal firm may be conducting green innovations either due to the green innovations (the actions) of peer firms or due to other irrelevant characteristics of peer firms. One way to deal with the reflection problem is to utilize peer group heterogeneity (e.g., Aghamolla and Thakor, 2022; Bramoullé, Djebbari, and Fortin, 2009; De Giorgi,

[5] More literature pertinent to corporate green innovations in accounting and finance research. For example, Jarrar and Smith (2014) suggest that corporate innovation mediates the relationship between entrepreneurial strategies and organizational performance. Similarly, Dunk (2011) posits a positive correlation between product innovation and corporate financial performance, emphasizing the utilization of budgets as a strategic planning mechanism. Bellora and Guenther (2013) find that firms in a high research and development (R&D) industry are more inclined to enhance the quantity and quality of their innovation capital.

Pellizzari, and Redaelli, 2010; Dou *et a*l., 2023). Therefore, in this paper, following Dou *et al.* (2023), we classify focal[6] and peer firms based on whether they are subject to China's ETS pilot.[7] The rationale is that whether a firm is regulated by China's ETS pilot (peer characteristics) is entirely exogenous, and firms' green innovations are affected by environmental policies (Du, Cheng, and Yao, 2021; Hu et al., 2023).

We employ a generalized difference-in-differences (DiD) model to investigate the peer effects of ETS firms' green innovations on non-ETS firms' green innovations. We find that non-ETS firms significantly boost their green innovations in response to the increased green innovations of ETS firms. These peer effects are more pronounced among non-ETS firms operating in highly competitive environments. We, therefore, identify the competitive threat as the underlying mechanism. Our finding is in line with the rivalry-based theory of Lieberman and Asaba (2006), suggesting firms facing intensive competition are more inclined to imitate and learn from their peers. Our results are also economically significant. We document that non-ETS firms enhance the number of green patent applications, independent applications, and collaborative applications by approximately 25%, 24%, and 59% of the standard deviation in response to the augmented green innovations of ETS firms. Our heterogeneity analyses find that these peer effects are more pronounced among the non-ETS firms characterized by leader status, facing high public scrutiny, with higher financial constraints, having more institutional investors, and under-investment. We also show that these peer effects significantly enhance non-ETS firms' economic performance and green revenues.

The primary obstacle in estimating the peer effects of ETS firms' green innovations on non-ETS firms' green innovations is the issue of endogeneity. We thus adopt a number of tests to address the potential endogeneity issues. First, we investigate the parallel trend assumption using a dynamic analysis (Beck, Levine, and Levkov, 2010) to test the validity of our DiD model. Second, the endogeneity issue could result from the self-selection on covariates between non-ETS firms with higher green innovations and those with lower green innovations. Following previous studies (e.g., Basu, Naughton, and Wang, 2022; Cao, Li, and Hasan, 2023; Cazier, Merkley, and Treu, 2020), we use the entropy balancing approach to overcome this issue. The entropy balancing approach enables us to balance the differences among covariates without dropping any observations. We use the propensity score matching (PSM) approach to mitigate systematic differences to match non-ETS firms with higher green innovations and those with lower green innovations. Third, the impacts of other contemporaneous environmental policies can be the noise of policy shock. To address this issue, we conduct placebo tests to ensure our

[6] In our sample of focal firms, despite they may be in the same industry, they do not become peers of each other since we classify focal and peer firms by China's ETS pilot. That is, only firms subject to China's ETS pilot in a same industry become the peers of focal firms.

[7] Dou *et al.* (2023) divide focal and peer banks based on whether they are constrained by the Consumer Financial Protection Bureau established in the U.S. in 2011.

results are not biased by spurious correlations, confounding factors, and other related policies. Specifically, following Defusco (2018), we randomly allocate fictitious environmental policies to establish pseudo-impacted jurisdictions and simulate the placebo tests 1,000 times for green innovations. Fourth, we also exclude the impacts of the global financial crisis in 2008, COVID-19 in 2019, and China's ETS in 2021 from our results. Fifth, measurement error could be another cause of endogeneity bias. To deal with the measurement error, we estimate our results using a variety of measures of green innovations based on the different definitions. Sixth, we further incorporate alternative fixed effects to ensure our results are not sensitive to different fixed effect specifications. Seventh, the other source of the endogeneity issue comes from the omitted variable bias. To tackle this issue, we adopt Oster's (2019) bound estimate to compare the sensitivity of estimated coefficients and the change of goodness-of-fit between regression with and without control variables. Our results remain robust and consistent across all robust and endogeneity tests.

Our study advances and contributes to the literature in three ways. First, we contribute to the growing literature pertinent to the peer effects on corporate governance and strategies (e.g., Adhikari and Agrawal, 2018; Gyimah *et al.*, 2020; Leary and Roberts, 2014; Machokoto *et al.*, 2021; Seo, 2021). To the best of our knowledge, we are the first to examine the peer effects of environmental regulation-constrained firms' green patent applications on unconstrained firms' green patent applications (a real outcome of investment in green innovations). Our study sheds new light on the understanding of firms' sustainable strategies, representing a significant and economically important facet of their corporate strategies. We address the hot-debated question of the three pillars of corporate sustainability, including environmental integrity, social equity, and economic prosperity (Bansal, 2005). We provide robust evidence that environmental regulation-constrained firms' investments in green innovations can significantly increase unconstrained firms' green innovations, thereby achieving a win-win scenario between environmental sustainability and economic development.

Second, we provide *ex-ante* evidence of the intended consequences of environmental regulation for policymakers, practitioners, and investors. This is accomplished by revealing the motivations of unconstrained firms to invest in green innovations. The existing literature infers firms' innovation incentives, considering facets such as corporate governance (Amore and Bennedsen, 2016; Atanassov, 2013), environmental regulation (Du *et al.*, 2021), and managerial experience (Quan *et al.*, 2023). We posit that non-ETS firms are motivated to intensify their green innovations to sustain competitiveness and mitigate the competitive threat from ETS competitors. Our study complements the Porter Hypothesis, which suggests that stringent environmental regulations can facilitate constrained firms' innovations and enhance their resource productivity of the competition among constrained firms (Porter and van der Linde, 1995). We provide evidence that stringent environmental regulations, such as ETS, can also promote unconstrained firms' green innovations and enhance their green revenues from the competitive threat from constrained firms.

Third, we contribute to the emerging literature on the real impacts of policy spillover on firms' investment strategies in green innovations. Previous studies have investigated the impacts of policy spillovers on carbon emissions (Bartram, Hou, and Kim, 2022), two-way foreign direct investment (Ma, Qin, and Zhang, 2023), and corporate disclosure (Brown, Tian, and Wu, 2018). Our study enriches this stream of literature by examining the real effects of policy spillovers on the investment in green innovations from ETS firms to non-ETS firms. Considering that ETSs are still in the infancy stage of global implementation and have not yet covered all jurisdictions, we shed light on the spillover of green innovations under this regulation. Based on China's ETS pilot as a setting, we provide evidence that ETS fosters the spillover of constrained firms' green innovations on unconstrained firms' green innovations. This provides important implications for environmental policies' effective promotion of corporate green innovations.

The remainder of the study is organized as follows. Section 2 demonstrates the theoretical mechanisms and develops hypotheses. Section 3 describes the data used in this study and specifies the empirical model. Section 4 discusses the empirical results and conducts robustness tests. Section 5 examines the plausible reasons for the peer effects of green innovations. Section 6 provides a heterogeneous analysis of non-ETS firms with implications of imitating peer firms' green innovations, and section 7 concludes.

2. Theoretical Mechanisms and Hypothesis Development

The rapid development of emerging markets, such as China's, has led to considerable economic growth. However, this growth has also resulted in heightened air pollution (Huang *et al.*, 2014) and negative effects on public health (Vandyck *et al.*, 2018). Addressing climate change issues and mitigating carbon emissions are pivotal in ensuring a sustainable economy (Tol, 2009). Environmental and climate regulations, such as the ETS, can stimulate constrained firms to enhance their green innovations (Porter and van der Linde, 1995; Nesta *et al.*, 2014; Amore and Bennedsen, 2016; Wang, Si, and Hu, 2023). It is also important to investigate whether and how environmental regulations, such as ETS, impact unconstrained firms through peer effects.

Previous studies have investigated diverse peer effects on firms' or banks' policies. For instance, Dou *et al.* (2023) find that consumer complaints of banks constrained by the Consumer Financial Protection Bureau positively affect unconstrained banks' mortgage approval rates. Kim and Valentine (2021) show that patent disclosures of firms that the American Inventor's Protection Act constrains positively affect unconstrained firms' innovation. A large stream of literature has documented the presence of positive peer effects on firms' strategies. For instance, Leary and Roberts (2014) find a positive peer effect on firms' financial policies. Existing studies show that focal firms' payout policies, trade credit, and research and development (R&D) activities are also positively influenced by peer firms (Adhikari and Agrawal, 2018; Gyimah *et al.*, 2020; Machokoto *et al.*, 2021). Given the overwhelming evidence demonstrating the positive peer effects among firms, in the present study, we conjecture that peer firms that China's ETS pilot constraints positively affect non-ETS firms' green innovations. Hence, we propose our first hypothesis:

H1: *After China's ETS pilot, the heightened investment in green innovations of ETS firms induces non-ETS firms in the same industry to increase their green innovations.*

The rivalry-based theory demonstrates that firms imitate their peers to maintain competitiveness and limit rivals (Lieberman and Asaba, 2006). China's ETS pilot stimulates ETS firms to invest in green innovations, thereby enhancing their competitiveness (Aghion *et al.*, 2001). As a result, the green innovations of ETS firms would bring competitive threats to non-ETS firms. Competitive threats can reduce firms' management slack and provoke innovation and growth (Machokoto *et al.*, 2021). Increased competition in the market prompt firms to pursue innovative strategies to escape the competitive threats (Aghion *et al.*, 2005). Firms in a market with less competition have limited motivations to mimic their peer firms (Gyimah *et al.*, 2020). In contrast, firms in a market with fierce competition have stronger incentives to conduct innovative strategies to maintain competitiveness (Aghion *et al.*, 2005; Lieberman and Asaba, 2006). Non-ETS firms, therefore, mimic ETS firms' green innovations to maintain their own competitiveness and limit rivals. Hence, we propose our second hypothesis as follows:

H2a: *Non-ETS firms are more inclined to imitate ETS firms' green innovations when in a highly competitive environment.*

The information-based theory, however, argues that firms are more inclined to mimic their peers to obtain superior information in an environment with high levels of uncertainty and information asymmetry (Lieberman and Asaba, 2006). Information, therefore, is a crucial factor in mimicking peer firms. Previous studies (e.g., Badertscher, Shroff, and White, 2013; Foster, 1981; Kim and Valentine, 2021) find that gaining more information from other firms' disclosures of patents can contribute to a firm's innovative strategies. Kim and Valentine (2021) refer to this pattern as knowledge spillovers. Firms, therefore, are motivated to mimic their better-informed peer firms to obtain superior information (Lieberman and Asaba, 2006). The ETS firms have more information and knowledge of green innovations than non-ETS firms since they are the participants in China's ETS pilot. Non-ETS firms thus would mimic ETS firms when conducting green innovations as they believe ETS firms have superior information about green policies and green innovations. Moreover, in an environment with a high level of information asymmetry, non-ETS firms are more likely to mimic ETS firms in the same industry to obtain superior information on green innovations. Hence, we propose our third hypothesis as below:

***H2b:** Non-ETS firms are more inclined to imitate ETS firms' green innovations in a high information asymmetry environment.*

Figure 1 sketches the theoretical framework of the present study. In summary, ETS firms' green innovations can facilitate non-ETS firms to apply green innovations (i.e., hypothesis ***H1***). The motivations of firms to mimic their peers, according to Lieberman and Asaba (2006), are either consistent with the rivalry-based theory, the information-based theory, or both. Thus, we further propose two hypotheses to examine the reasons behind the peer effects of ETS firms on non-ETS firms' green innovations. On the one hand, to maintain their own competitiveness and limit rivals, non-ETS firms in a highly competitive environment are more likely to imitate ETS firms when conducting green innovations (i.e., the hypothesis ***H2a***, and we designate it as the "green rivalry threat"). On the other hand, non-ETS firms would also mimic ETS firms in a high information asymmetry environment as they believe ETS firms have superior information about green policies and green innovations (i.e., the hypothesis ***H2b***).

[Insert Figure 1 Here]

3. Data, Sample, and Research Design

3.1 Data and sample

The data on firms' green innovations are retrieved from the Chinese Research Data Services (CNRDS) platform and State Intellectual Property Office. We further collect the financial data of China's A-share listed firms from the China Stock Market and Accounting Research (CSMAR) database, the CNRDS platform, and the WIND database. Our sample period is from 2006 to 2022. We initially have 49,126 firm-year observations, and our final sample is obtained through five steps. Given their different accounting fundamentals, we first exclude the specially treated (ST) financial firms with 2,535 firm-year observations. We then drop missing relevant financial data with 6,563 firm-year observations. Third, following Dou *et al.* (2023), we restrict our sample to non-ETS firms (focal firms) and delete 10,833 firm-year observations (i.e., firm-year observations of ETS firms). Noticeably, prior to removing the ETS firms' observations, we utilize them to calculate peer firm averages of green innovations as the intensity of ETS firms' green innovations by following Leary and Roberts (2014) and Dou *et al.* (2023). Fourth, we further drop 4,144 observations with missing values of peer average variables. Finally, to mitigate the impacts of firm-specific issues with an aversion to green innovations, we eliminate firms without green patent applications from 2006 to 2022 in our sample with 9,143 firm-year observations. Our sample, therefore, comprises 15,908 firm-year observations for 1,375 unique firms across 47 industries. Table 1 shows the sample selection procedure used in this study.

[Insert Table 1 Here]

3.2 Research design

3.2.1 Model specification

We adopt a DiD framework with continuous treatment variables (Angrist and Pischke, 2009) to estimate the peer effects of ETS firms' green innovations on non-ETS firms' green innovations:

$$y_{i,j,t}=\alpha+\beta\bar{y}_{j,t}\times Post_t+\gamma\bar{y}_{j,t}+\delta X_{i,j,t}+\lambda\overline{X}_{j,t}+\varphi\nu_j+\phi\upsilon_t+\varepsilon_{i,j,t} \quad (1)$$

where the subscripts i denotes non-ETS firms (focal firms), j and t represent industry and year, respectively. The outcome variable $y_{i,j,t}$ denotes green innovations (*GP*, *GI1*, *GI2*) of non-ETS firm i (focal firms) in industry j in year t. Peer firms are defined as firms with the same China Securities Regulatory Commission (CSRC) Industry Classification (2012 version code) located in ETS-constrained jurisdictions.[8] The independent variable $\bar{y}_{j,t}$ refers to peer firm (ETS firm) averages of green innovations in industry j in year t. $Post_t$ is a dummy variable that equals one in (and post) the year of China's ETS pilot implemented, and zero otherwise. The variable of interest is $\bar{y}_{j,t}\times Post_t$, capturing the peer firm averages of green innovations in the presence of China's ETS pilot. We choose the year 2014 as the shock year because five jurisdictions (Beijing, Guangdong, Shanghai, Shenzhen, and Tianjin) officially implemented China's ETS pilot in the second half of 2013, with another two jurisdictions (Chongqing and Hubei) in 2014. Hence, China's ETS pilot, which had a total of seven jurisdictions, was eventually implemented in 2014. As China's ETS pilot does not constrain the focal firms in our study, we thus employ China's ETS pilot in 2014 rather than that in 2013 as the policy shock to non-ETS firms.

The vector $X_{i,j,t}$ is a set of control variables that captures firm-specific characteristics. We follow Amore and Bennedsen (2016), Hu, Wang, and Wang, 2021, Machokoto *et al.* (2021), and Cao *et al.* (2023) to incorporate a number of control variables in our model. Specifically, we control for financial and firm-specific factors that likely affect firms' green innovations, comprising firms' size (*Size*), the nature of firms' ownership (*SOE*), leverage (*DTA*), market-to-book ratio (*MTB*), net working capital (*NWC*), return on assets (*ROA*), Tobin's Q (*TobinsQ*), cash and cash equivalent (*Cash*), firms' listed age (*Age*), tangible assets (*Tang*), quick ratio (*Quick*), subsidy of innovation (*Subsidy*), and financial constraints (*SA*). Table A1 in the Appendix demonstrates the details of the variables' definitions.

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[8] Consistent with prior literature (e.g., Gao *et al.*, 2020; Xiao, Yu, and Guo, 2023), we define ETS-constrained jurisdictions as Shenzhen, Beijing, Shanghai, Tianjin, Guangdong, Hubei, and Chongqing since they are mandated to initiate ETS pilot by the *Notice on Pilot Carbon Emission Trading* in 2011 from NDRC.

Furthermore, in line with Adhikari and Agrawal (2018), Leary and Roberts (2014), and Machokoto *et al.* (2021), we take the vector $\overline{X}_{j,\,t}$ regarding peer firm averages into account to control the impacts of peer firms' characteristics on peer firm averages of green innovations (i.e., $\bar{y}_{j,\,t}$). Industry- and year-fixed effects are captured by $\boldsymbol{\nu}_j$ and $\boldsymbol{\upsilon}_t$, respectively; $\varepsilon_{i,\,j,\,t}$ is the error term. We use robust standard errors clustered by industry to adjust for correlation among residuals in an industry. We are interested in β (the coefficient on $\bar{y}_{j,\,t}{\times}Post_t$), capturing the peer effects of ETS firms' green innovations on non-ETS firms' green innovations.

3.2.2 Measures of investment in green innovations

Following previous studies (e.g., Amore *et al.*, 2013; Amore and Bennedsen, 2016; Sunder *et al.*, 2017; and Kim and Valentine, 2021), we use three proxies to measure firms' investment in green innovations: i) number of green patent applications (*GP*), ii) number of green patent-independent applications (*GI1*), and iii) number of green patent-collaborative applications (*GI2*). Patent characteristics can serve as valuable proxies for various facets of a firm's innovative efforts, including its investment levels and technological capabilities (Sunder *et al.*, 2017; Kim and Valentine, 2021). Patents grant inventors exclusive legal rights, safeguarding the commercial exploitation of their innovations (Acharya, Baghai, and Subramanian, 2013). This legal protection incentivizes firms to actively seek patents, positioning patent applications as a reliable indicator of their commitment to innovation (Aghion *et al.*, 2005; Fang, Tian, and Tice, 2014). In addition, the patent application process requires detailed disclosure of the technological and inventive components of the innovation (Zhong, 2018), further reinforcing its role as a reflection of the firm's innovative capabilities and strategic direction.

Thus, the *GP* offers a direct measure of firms' investment in green innovations, reflecting their dedication to developing technologies that mitigate environmental damage. The *GI1* underscores firms' internal capabilities of investment in green innovations, highlighting its reliance on internal resources to drive green technologies. In contrast, the *GI2* represents investment in green innovations achieved through partnerships, illustrating how firms draw on external expertise and resources to address sustainability challenges. Employing multiple proxies provides a more holistic perspective on investment in green innovations, capturing both individual and collaborative efforts. This multidimensional approach also mitigates measurement bias of green innovations. We define *GP* (*GI1* and *GI2*) as the logarithmic value of one plus the number of green patent applications (green patent-independent applications and green patent-collaborative applications).

3.2.3 Measures of peer firm averages

We define peer firm averages of non-ETS firms as the aggregated value of variables of

ETS firms scaled by the total number of ETS firms in the same industry minus one:

$$\overline{Peer_{j,\ t}} = \frac{\sum_{n=1}^{n=N_{j,\ t}} (Peer_{j,\ t})_n}{N_{j,\ t} - 1} \tag{2}$$

where the subscripts j denotes the industry, t represents the year, and n denotes ETS firms. $\overline{Peer_{j,\ t}}$ are the outcome variables in Model (2), which denotes the peer firm averages. $(Peer_{j,\ t})_n$ are the variables of ETS firm n in industry j in year t. $N_{j,\ t}$ is the total number of ETS firms in industry j in year t.

The reasoning behind employing this method lies in addressing endogeneity related to the reflection problem identified by Manski (1993), which arises when assessing whether group behaviors or characteristics (peer group) influence the actions of individual members (focal firms). To resolve this, peer group heterogeneity offers an effective solution (Aghamolla and Thakor, 2022; Dou *et al.*, 2023). Consistent with Dou *et al.* (2023), we implement peer group heterogeneity to differentiate focal firms from peer firms based on their participation in China's ETS pilot. Focal firms are defined as those operating in regions not covered by China's ETS pilot, while peer firms are those within the same industry but located in regions where the ETS pilot is enforced. Whether firms are regulated by China's ETS pilot (peer heterogeneity) is exogenous. Thus, focal firms in our sample, despite being in the same industry, are not classified as peers due to their differing participation status in China's ETS pilot.

4. Empirical Results

4.1 Descriptive statistics

Table 2 presents the descriptive statistics. In Panel A, the mean value of *GP* (*GI1* and *GI2*) is 0.863 (0.781 and 0.177), with a standard deviation of 1.116 (1.061 and 0.525), indicating a significant variation in green innovations among firms. The mean value of *GI1* (0.781) exceeds that of *GI2* (0.177) by approximately 4.5 times, indicating that non-ETS firms are more inclined to apply for green patents independently rather than through collaborations. Meanwhile, we find that the mean value of green utility-model patent applications (*GU3*) (0.584) is close to that of green invention patent applications (*GU4*) (0.550). This indicates that non-ETS firms have the same investment preferences for green inventions and green utility models in our sample. The mean value of *SOE* equals 0.399, indicating that 39.9% of non-ETS firms in our sample are stated-owned enterprises. Moreover, the mean value of other variables is similar to previous studies (Wu and Wang, 2022; Cao *et al.*, 2023; Huang, Gao, and Jia, 2023). We winsorize all continuous variables at the 1^{st} and 99^{th} percentiles to ensure our results are not driven by outliers.

Panel B of Table 2 reports the results of the univariate comparison for non-ETS firms before and after the China's ETS pilot. We observe that the mean values of *GP*, *GI1*, and $\overline{GI2}$ (1.102, 1.008, and 0.234) for non-ETS firms after China's ETS pilot are singnificantly higher than those (0.412, 0.353, and 0.071) for non-ETS firms before China's ETS pilot. Meanwhile, this trend is also observed in ETS firms. The mean values of $\overline{GP}$, $\overline{GI1}$, and $\overline{GI2}$ (1.282, 1.161, and 0.355) for ETS firms after China's ETS pilot are singnificantly higher than those (0.671, 0.585, and 0.169) for ETS firms before China's ETS pilot. These results preliminarily indicate that non-ETS firms increase there green innovations in response to heightened investment in green innovations of ETS firms in the presence of China's ETS pilot.

[Insert Table 2 Here]

4.2 Baseline results

Table 3 reports the results of the peer effects of ETS firms' green innovations on non-ETS firms' green innovations. In Columns (1), (3), and (5), we only include the industry- and year-fixed effects in the regression as control variables to mitigate the concern regarding the impacts of controlling other covariates on estimations (Gormley and Matsa, 2014). Specifically, Columns (1) and (2) show that the coefficients on $\overline{GP}$ are insignificant and indistinguishable from zero. This indicates that these peer effects are muted in the absence of China's ETS pilot. However, the coefficients on $\overline{GP}\times Post$ (0.249 and 0.283) are positive and significant at the 1% level, indicating that ETS firms' green patent applications significantly enhance non-ETS firms' green patent applications in the presence of China's ETS pilot. In addition, Columns (3) to (6) show that the coefficients on $\overline{GI1}\times Post$ (0.218 and 0.250) and $\overline{GI2}\times Post$ (0.274 and 0.312) are all positive and significant at the 1% level, and the coefficients on $\overline{GI1}$ and $\overline{GI2}$ are insignificant. This indicates that ETS firms' green patent-independent applications (green patent-collaborative applications) positively affect non-ETS firms' green patent-independent applications (green patent-collaborative applications) in the presence of China's ETS pilot.

Meanwhile, our results are economically significant. The economic significance is calculated as the coefficients on treatment variables scaled by the standard deviation of non-ETS firms' green innovations. Specifically, ETS firms' green patent applications (green patent-independent applications and green patent-collaborative applications) enhance the non-ETS firms' green patent applications (green patent-independent applications and green patent-collaborative applications) by approximately 25%[9] (24%[10] and 59%[11]) of the standard deviation in the presence of China's ETS pilot. These results imply that ETS firms' green innovations have significantly positive effects on non-ETS firms' green innovations in the presence of China's ETS pilot, supporting ***H1***.

[9] The coefficient on $\overline{GP}\times Post$ (0.283) / the standard deviation of GP (1.116).

[10] The coefficient on $\overline{GI1}\times Post$ (0.250) / the standard deviation of $GI1$ (1.061).

[11] The coefficient on $\overline{GI2}\times Post$ (0.312) / the standard deviation of $GI2$ (0.525).

[Insert Table 3 Here]

4.3 Parallel trends

The assumption underlying our inferences of DiD specification is that the trends in non-ETS firms' green innovations would be the same in the absence of China's ETS pilot. Following Beck *et al.* (2010), we employ a dynamic analysis to re-estimate our model by replacing $\bar{y} \times Post$ with the seven interaction terms between $\bar{y}$ and year dummy variables.

Figure 2 shows that the peer effects on non-ETS firms' green innovations (*GP*, *GI1*, and *GI2*) are insignificant before the implementation of China's ETS pilot. This implies that ETS firms' green innovations do not significantly affect non-ETS firms' green innovations before the implementation of China's ETS pilot. We find that non-ETS firms' *GP* and *GI1* significantly increase only after implementing China's ETS pilot. There is a dramatical increase in non-ETS firms' *GP* and *GI1* after China's ETS pilot. Meanwhile, the peer effects on non-ETS firms' *GI2* significantly increase until two years after the implementation of China's ETS pilot. This indicates that non-ETS firms prioritize applying for green patents independently when influenced by ETS firms' green innovations in the presence of China's ETS pilot.

[Insert Figure 2 Here]

4.4 Sample selection bias

To address the potential endogeneity issue regarding sample selection bias, we employ the entropy balancing approach and propensity score matching. The change in non-ETS firms' green innovations may be driven by firm characteristics rather than the China's ETS pilot and ETS firms' green innovations. Therefore, we follow prior studies (Cazier *et al.*, 2020; Yoon, 2021; Basu *et al.*, 2022; Cao *et al.*, 2023) to employ the entropy balancing approach to balance the groups of non-ETS firms with higher green innovations and those with lower green innovations. This approach enables balancing differences among covariates without dropping any observations (Hainmueller, 2012). This approach calculates the scalar weights to balance the distributions of covariates between two groups across mean, variance, and skewness, respectively. We use the sample median of non-ETS firms' green innovations to partition the two different groups.

Panel A of Table 4 exhibits the differences between before and after balancing the groups of non-ETS firms using the entropy balancing approach. After balancing the differences between the two groups, the differences of control variables in standard deviation are equal to zero, and the variance ratio is equal to one. Then, we perform the regression analysis of Model (1) using balanced control variables. Panel B of Table 4 shows that our results are robust after balancing the groups of non-ETS firms. In addition, to ensure these results are robust, we further exploit the PSM approach to match the groups of non-ETS firms with higher green innovations and those with lower green innovations (Heckman *et al.*, 1998). Figure A1 in the Appendix presents the differences in covariates between matched and unmatched groups. This shows that the standardized bias across covariates has been reduced after employing the PSM approach. Table A2 in the Appendix exhibits the results, indicating that our results are still robust after employing the PSM approach. These results confirm that our baseline results are robust and not driven by self-selection arising from observable firm characteristics and other confounding factors.

[Insert Table 4 Here]

4.5 Placebo tests

A potential endogeneity related to the impacts of other environmental policies or random factors may affect our results. We thus employ placebo tests to mitigate this endogeneity. We follow Defusco (2018) to randomly allocate fictitious environmental policies to establish pseudo-impacted jurisdictions and simulate the placebo tests 1,000 times. Figure 3 visualizes the probability distributions of the pseudo-estimated coefficients. This shows that the pseudo-estimated coefficients are all centralized around zero, and the random coefficients are located on the left side of the true coefficients on green innovations (0.283, 0.250, and 0.312). These placebo tests provide convincing evidence that our results are robust and not driven by other contemporaneous environmental policies and confounding factors.

[Insert Figure 3 Here]

4.6 Excluding effects of the global financial crisis in 2008, COVID-19 in 2019, and China's ETS in 2021

In this section, our results exclude the effects of the global financial crisis (GFC) in 2008, COVID-19 in 2019, and China's ETS in 2021. First, the GFC in 2008 and COVID-19 in 2019 are global traumatic events that can affect firms' decision-making. Second, China officially launched the ETS in 2021, encompassing eight jurisdictions, including the seven jurisdictions subject to China's ETS pilot and Fujian (World Bank, 2022). Thus, we restrict the sample window to the years 2010 to 2018. Table 5 indicates that the coefficients on $\overline{GI1}\times Post$ (0.216), $\overline{GI1}\times Post$ (0.222), and $\overline{GI2}\times Post$ (0.184) are all positive and significant at the 1% level. This indicates that our results in Table 3 are robust after excluding the effects of GFC in 2008. COVID-19 in 2019, and China's ETS in 2021.

[Insert Table 5 Here]

4.7 Alternative measures

To address potential endogeneity related to measurement bias, we employ alternative measures of green innovations. According to Chen, Zhang, and Zi (2021) and *Quan et* *al.* (2023), we employ green invention patent applications (*GU3*) and green utility-model patent applications (*GU4*) and their peer firm averages as the alternative variables.[12] Table 6 reports these results. Specifically, in Columns (1) and (2), the coefficients on $\overline{GU3}\times Post$ (0.258 and 0.284) are positive and significant at the 1% level. In Columns (3) and (4), the coefficients on $\overline{GU4}\times Post$ (0.276 and 0.312) are positive and significant at the 1% level. Thus, our results in Table 3 are robust after using alternative measures of green innovations.

[Insert Table 6 Here]

4.8 Controlling other fixed effects

In this section, we further test whether our results are sensitive to different fixed effect specification. We alternatively incorporate firm, region, and the interaction term of industry and region fixed effects to rerun our baseline analysis. This enables us to control for unobserved time-invariant firm-specific and region-specific characteristics and unobserved industry heterogeneity specific to different regions. Table 7 shows the results based on different conbinations of fixed effects. Our results are still robust after adding region fixed effects and relacing industry fixed effects with firm fixed effects.

[Insert Table 7 Here]

4.9 Omitted variable bias tests

The potential endogeneity of omitted variable bias may impact our regression, thereby distorting our consequences. To mitigate omitted variable bias, following Cao *et al.* (2023) and Pan, Biru, and Lettu (2021), we adopt Oster's (2019) bound estimate to compare the sensitivity of estimated coefficients and the change of R-squared between regression with and without control variables. The selection proportionality δ and maximum goodness-of-fit R_{max}[13] are utilized to testify whether our model and regressions are affected by omitted variable bias. We employ the model from Oster (2019), $\beta^{*}=\beta^{*}$ (R_{max}, δ), to capture the consistent estimates of the true coefficients.

Specifically, we conduct two omitted variable bias tests to examine the robustness of our results following Oster (2019). First, we take the value of δ as one and define R_{max} as 1.3 times the adjusted R-squared proposed value by Oster (2019). We thus compute the estimated value of β^{*}. Our results are robust if the estimated value of β^{*} falls within the 95% confidence interval of our treatment variables. Table 8 shows that the estimated values of β^{*} of *GP* (0.361), *GI1* (0.326), and *GI2* (0.327) are all within the 95%

[12] Green innovation patents refer to green techniques for products or production activities; green utility-model patents are green technical solutions that aim to improve the practical use of shape, structure, and utility of products.

[13] According to Oster (2019), the maximum R-squared in the test is defined as the maximum goodness-of-fit for regressions if potential omitted variables can be captured and observed.

confidence interval. Second, we take the value of β^* as zero and define R_{max} as 1.3 times the adjusted R-squared. We compute the estimated value of δ. Our results are robust if the estimated value of δ is larger than one or less than minus one ($\delta > 1$ or $\delta <$ -1). Table 8 reports that the estimated value of δ of *GP* (2.248), *GI1* (1.790), and *GI2* (27.520) are all larger than one. These results indicate that our baseline results are not driven by the omitted variable bias.

[Insert Table 8 Here]

5. Reasons Behind the Peer Effects

5.1 Is the rivalry-based theory?

The rivalry-based theory proposes that firms imitate their peers to enhance competitiveness and limit rivals (Lieberman and Asaba, 2006). Thus, firms operating in a highly competitive environment are more likely to imitate their peer firms to maintain their competitiveness and limit rivals. For example, Pástor and Veronesi (2003) find that learning from a competitive industry can reduce firms' future performance uncertainty. Aghion *et al.* (2001) suggest that firms maintain competitiveness and improve growth prospects by imitating their peers.

Following Adhikari and Agrawal (2018), Gyimah *et al.* (2020), and Machokoto *et al.* (2021), we examine whether the peer effects of green innovations conform to the rivalry-based theory. Giroud and Mueller (2011) and Machokoto *et al.* (2021) employ a concentration index to investigate the impacts of market competition on equity prices and R&D investment, respectively. We thus use the concentration index based on the sales revenue of the top-eight firms (*CR8*) in the industry to proxy product market competition. A higher value of *CR8* indicates a more concentrated market, implying lower market competition. We categorize firms operating in a highly (low) competitive environment when the concentration index (*CR8*) is below (above) the median.

Table 9 shows that the peer effects on green innovations are more pronounced among firms operating in a highly competitive environment. Specifically, the coefficients on $\overline{GP}\times Post$, $\overline{GI1}\times Post$, and $\overline{GI2}\times Post$ (0.270, 0.297, and 0.343) for highly competitive (low *CR8*) are larger than the coefficients on those (0.191, 0.158, and 0.199) for low competitive (high *CR8*). These results are consistent with previous studies (Leary and Roberts, 2014; Adhikari and Agrawal, 2018; Machokoto *et al.*, 2021; Aghamolla and Thakor, 2022). In addition, to ensure the difference in the coefficient estimate for green innovations between a highly and low competitive environment is significant, we follow Cleary (1999) to assess the empirical p-value between two subsamples. The empirical p-values are all significant at the 1% level after employing Fisher's permutation tests and bootstrap 1,000 times, indicating that the coefficients for different subsamples are significantly different. These results support ***H2a***.

[Insert Table 9 Here]

5.2 Is the information-based theory?

However, the information-based theory argues that firms would imitate their peers when in a high information asymmetry environment (Lieberman and Asaba, 2006). In Section 5.1, we find that the peer effects of ETS firms' green innovations on non-ETS firms align with the rivalry-based theory. In this section, we further examine whether these peer effects are more pronounced in a high information asymmetry environment that is aligned with the information-based theory.

We proxy the information asymmetry by the level of stock price synchronicity, with a higher level of stock price synchronicity indicating greater information asymmetry (Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009). Information asymmetry arises when one group of firms in a transaction has more or better information than the other group of firms (Aboody and Lev, 2000). This leads to a situation where firm-specific information may not be fully reflected in stock prices due to the asymmetry (Chan, Menkveld, and Yang, 2008; El Ghoul *et al.*, 2013). In environments with reduced information asymmetry, investors have a clearer understanding of the unique prospects and risks associated with firms, allowing stock prices to incorporate firm-specific information more accurately (Chan *et al.*, 2008). This results in less synchronicity since investors trade based on nuanced understandings of each company's unique situation (Boubaker, Mansali, and Rjiba, 2014).

Table 10 shows the results of the tests of the information-based theory. We define firms operating in a high (low) information asymmetry environment when the level of stock price synchronicity (*Synchron*) is above (below) the median. Columns (1) to (6) show that the coefficients on $\overline{GP}\times Post$, $\overline{GI1}\times Post$, and $\overline{GI2}\times Post$ remain positive and significant at the 1% level. However, Columns (1) to (4) show that the coefficients on $\overline{GP}\times Post$ and $\overline{GI1}\times Post$ (0.244 and 0.224) for high information asymmetry (High *Synchron*) are insignificantly[14] lower than those (0.033 and 0.291) for low information asymmetry (Low *Synchron*). Columns (5) and (6) present that the coefficient on $\overline{GI2}\times Post$ (0.331) for high information asymmetry (High *Synchron*) is insignificantly larger than that (0.293) for low information asymmetry (Low *Synchron*). These results indicate that the results of heterogeneity analyses of information asymmetry are not stable. Thus, we provide evidence that the peer effects of ETS firms' green innovations on non-ETS firms' green innovations are not driven by information asymmetry. In summary, these results in Sections 5.1 and 5.2 support ***H2a*** but do not support ***H2b***.

[Insert Table 10 Here]

[14] The empirical p-values of these heterogeneity analyses (0.112 and 0.235) are larger than 0.100, indicating that the coefficients for different subsamples are insignificantly different.

6. Additional Analyses

6.1 Which non-ETS firms are imitating? Leaders versus followers

This section investigates which non-ETS firms are more inclined to mimic ETS firms. On the one hand, the learning motive of the information theory (e.g., Scharfstein and Stein, 1990; Leary and Roberts, 2014) documents that followers learn from leaders to obtain superior information and maintain competitiveness. On the other hand, the feedback theory of predation (e.g., Brander and Lewis, 1986; Bolton and Scharfstein, 1990) posits that leaders are motivated to learn from their followers as a strategy to maintain their market leadership and potentially compel the followers out of business (Gyimah *et al.*, 2020). Given that non-ETS firms are not subject to China's ETS pilot, leader non-ETS firms may be more inclined to intensify their green innovations in response to the increased green innovations of ETS firms.

For example, Park (2023) infers that the effect of peer CEO turnover on real earnings management is more pronounced among high-growth firms. Leary and Roberts (2014) classify firms into leaders and followers by using profitability, market share, and stock return to partition the sample into three terciles. They define leaders as the firms in the top tercile and followers as the firms in the middle and lower terciles of these distributions. Adhikari and Agrawal (2018) classify firm-level samples into three terciles based on firms' size. They define leader firms as those in the top tercile and follower firms as those in the bottom tercile. We thus, following Leary and Roberts (2014) and Adhikari and Agrawal (2018), classify non-ETS firms into three terciles by market share based on enterprises operating revenue.[15] We define leader non-ETS firms as those in the top tercile and follower non-ETS firms as those in the middle and bottom terciles.

Table 11 exhibits the results of distinguishing non-ETS firms into leaders and followers. We find that ETS firms' green innovations positively affect either leader or follower non-ETS firms. However, we provide evidence that the peer effects of green innovations are more pronounced among leader non-ETS firms. The coefficients on $\overline{GP}\times Post$, $\overline{GI1}\times Post$, $\overline{GI2}\times Post$ (0.439, 0.412, and 0.381) for leader firms are larger than the coefficients on those (0.261, 0.219, and 0.325) for follower firms. This indicates that leader non-ETS firms are more responsive to the peer effects of green innovations.

Moreover, in Columns (3) and (5) of Table 11, our results show that leader non-ETS firms are more responsive to the peer effects of green patent-independent applications (the coefficient on $\overline{GI1}\times Post$ equals 0.412) than those of collaborative applications (the coefficient on $\overline{GI2}\times Post$ equals 0.381). In Columns (4) and (6) of Table 11, we document that follower non-ETS firms are more responsive to the peer effects of green patent-collaborative applications (the coefficient on $\overline{GI2}\times Post$ equals 0.325) than those of

[15] We compute market share by dividing firm's operating revenue by total operating revenue of firms in the same industry.

independent applications (the coefficient on $\overline{GI1}\times Post$ equals 0.219). This is because leader non-ETS firms have sufficient strength, so they pay more attention to green patent-independent applications. However, follower non-ETS firms are more responsive to green patent-collaborative applications due to their limitations on independent applications.

In addition, in Table A3 in the Appendix, following Gyimah *et al.* (2020), Machokoto *et al.* (2021), and Dou *et al.* (2023), we further classify non-ETS firms based on size, age, and tangible assets. We classify large-size, older, and more tangible (small-size, younger, less tangible) firms if each of the variables' values is above (below) the median values. We find that the peer effects of green innovations are more pronounced among larger, older, and more tangible assets non-ETS firms.

[Insert Table 11 Here]

6.2 Heterogeneous analyses of non-ETS firms

6.2.1 Public scrutiny

In this section, we explore the heterogeneity analysis of public scrutiny. Dangelico and Pujari (2010) suggest that firms under increased public scrutiny are more inclined to focus on environmental activities. The number of analysts following also represents crucial information in financial markets. Prior studies document that analyst followings significantly affects the firms' decision makings and corporate strategies (Womack, 1996; Jegadeesh *et al.*, 2004; Kelly and Ljungqvist, 2012; Adhikari, 2016). Samuels, Taylor, and Verrecchia (2021) argue that more analyst followings reflect higher public scrutiny. Thus, we follow Samuels *et al.* (2021) to adopt the number of analyst followings of firms (Alt) as a proxy to measure the intensity of public scrutiny.

We classify the high (low) public scrutiny when Alt is above (below) the median. Panel A of Table 12 reports the results of this heterogeneity analysis. Specifically, the coefficients on $\overline{GP}\times Post$, $\overline{GI1}\times Post$, and $\overline{GI2}\times Post$ (0.372, 0.341, and 0.429) for high public scrutiny (High Alt) are significantly larger than those (0.276, 0.254, and 0.277) for low public scrutiny (Low Alt). This indicates that the peer effects of ETS firms' green innovations on non-ETS firms' green innovations are more pronounced among firms subject to high public scrutiny.

6.2.2 Financial constraints

Prior literature (Leary and Roberts, 2014; Adhikari and Agrawal, 2018) documents that the peer effects are more pronounced among firms with higher financial constraints.[16]

[16] Leary and Roberts (2014) utilize WW index from Whited and Wu (2006) to investigate that firms with higher financial constraints are more inclined to mimic their peers. Adhikari and Agrawal (2018) employ credit rating to examine that peer effects on the dividend are more pronounced among firms with higher

They argue that financial constraints allow firms to imitate their peers and divorce them from awkward situations. Thus, we anticipate that financial constraints will provoke non-ETS firms to mimic their peers to mitigate the threat of green rivalry from ETS firms. We use the absolute value of the SA index (Hadlock and Pierce, 2010) to proxy firms' financial constraints. The higher absolute value of the SA index indicates firms have higher financial constraints.[17] We define firms as having high (low) financial constraints when the absolute SA index (*SA*) is above (below) the median.

Panel B of Table 12 supports our anticipation. The coefficients on $\overline{GP}\times$ *Post*, $\overline{GI1}\times$ *Post*, and $\overline{GI2}\times$ *Post* (0.277, 0.287, and 0.327) for firms with higher financial constraints (High *SA*) are significantly larger than those (0.214, 0.198, and 0.294) for firms with lower financial constraints (Low *SA*). We find that the peer effects of green patent applications (*GP*), green patent-independent applications (*GI1*), and green patent-collaborative applications (*GI2*) are more pronounced among non-ETS firms with higher financial constraints (High *SA*). Our results document that non-ETS firms with higher financial constraints are more inclined to imitate ETS firms to keep their competitiveness when conducting green innovations.

6.2.3 Institutional investors

Establishing a sustainable economy is paramount, and institutional investors can affect this process (Azar *et al.*, 2021; Cohen *et al.*, 2023). Firms with a larger proportion of institutional ownership tend to reduce their carbon emissions (Azar *et al.*, 2021). ESG Pay (the executive compensation related to Environmental, Social, and Governance metrics) is positively affected by the percentage of institutional ownership (Cohen *et al.*, 2023). Thus, we posit that non-ETS firms with more institutional investors (*INS*) are more dedicated to environmental and sustainable issues and, thus, more responsive to the peer effects of green innovations.

We define firms with more (low) institutional shareholdings when *INS* is above (below) the median. Panel C of Table 12 provides evidence that non-ETS firms with a larger proportion of institutional shareholdings (High *INS*) are more inclined to respond to the peer effects of ETS firms' green innovations. Specifically, the coefficients on $\overline{GP}\times$ *Post*, $\overline{GI1}\times$ *Post*, and $\overline{GI2}\times$ *Post* (0.304, 0.278, and 0.324) for firms with more institutional investors (High *INS*) are significantly larger than those (0.237, 0.187, and 0.265) for firms with less institutional investors (Low *INS*). We suggest that non-ETS firms with more institutional investors are more responsive to the peer effects of ETS firms' green innovations, consistent with the findings of Azar *et al.* (2021) and Cohen *et al.* (2023).

financial constraints.

[17] SA index is more robust to measure firms' financial constraints since it is computed from two related exogenous indicators, total firms' assets and firms' age. Thus, SA index is not affected by endogenous issues such as financing methods and operating conditions. SA=-0.737$\times$*Size*+0.043$\times$*Size*^{2}-0.040$\times$*Age*

6.2.4 Investment efficiency

Biddle, Hilary and Verdi (2009) document that corporate financial reporting quality negatively (positively) affects over-investment (under-investment) firms. Cheng, Dhaliwal and Zhang (2013) also find that financially constrained (unconstrained) firms are more inclined to under-invest (over-invest). We posit that under-investment non-ETS firms are more inclined to mimic ETS firms to enhance their capability of investing in green innovations and, thus, are more responsive to the peer effects of green innovations. We classify non-ETS firms into over-investment and under-investment firms by the following model (Biddle *et al.*, 2009):

$$Investment_{i,\ t+1}=\alpha+\beta Sales\ Growth_{i,\ t}+\varepsilon_{i,\ t+1} \tag{3}$$

where $Investment_{i,\ t+1}$ is the total investment of firm i in year t+1 and $Growth_{i,\ t}$ is defined as the percentage change in sales from year t-1 to t of firm i in year t. We follow Biddle et al. (2009) to obtain investment inefficiency (over-investment or under-investment) by employing the residuals ε_{it+1} (positive value or negative value), which is proxied as the deviations from expected investment.

We obtain 13,301 firm-year observations regarding investment inefficiency in our sample, comprising 4,642 firm-year observations of over-investment and 8,659 firm-year observations of under-investment. Panel D of Table 12 exhibits the results of heterogeneity analysis of investment inefficiency. The coefficients on $\overline{GP}\times Post$, $\overline{GI1}\times Post$, and $\overline{GI2}\times Post$ (0.288, 0.266, and 0.338) for firms facing under-investment are significantly larger than those (0.250, 0.244, and 0.159) for firms facing over-investment. This shows that the peer effects of green innovations are more pronounced among under-investment firms. However, the empirical p-value of green patent-independent applications (*GI1*) is 0.180, indicating that the subsample analysis in *GI1* is insignificant. The empirical p-value of green patent applications (*GP*) is 0.056, which is significant at the 10% level, and the empirical p-value of green patent-collaborative applications (*GI2*) is 0.000, which is significant at the 1% level. This indicates that the subsample analysis in *GI2* is more significant than that in *GP*. We provide evidence that under-investment non-ETS firms are more responsive to the peer effects of green patent-collaborative applications.

[Insert Table 12 Here]

6.3 Economic performance and the peer effects of green innovations

We further investigate the implications of imitating peers' green innovations on firms' economic performance. In previous literature, total factor productivity (TFP) is used as the proxy of firms' economic performance (Giannetti, Liao, and Yu, 2015; Ren, Yang, Hu, and Chevallier, 2022; Wu and Wang, 2022). We employ the method of Levinsohn and Petrin (2003) to compute the TFP of non-ETS firms. Thus, we establish the following TFP model:

$$Y_{i,\ t}=\alpha+\beta L_{i,\ t}+\gamma K_{i,\ t}+\delta M_{i,\ t}+\lambda I_{i,\ t}+\varepsilon_{i,\ t} \tag{4}$$

where $Y_{i,\ t}$ is firms' operating revenue. $L_{i,\ t}$ represents the number of firms' employees. $K_{i,\ t}$ denotes firms' total assets. $M_{i,\ t}$ is proxied as firms' expenditure on materials and other inputs.[18] $I_{i,\ t}$ is cash used for fixed assets, tangible assets, and other long-term assets. The residuals $\varepsilon_{i,\ t}$ are used to measure firms' TFP. In addition, dependent variable and independent variables are entirely logarithmic in Model (4).

To assess the implications of imitating ETS firms' green innovations on non-ETS firms' economic performance, we construct the following model to test how the peer effects of green innovations affect firms' economic performance (i.e., TFP):

$$TFP_{i,\ j,\ t+1}=\alpha+\beta\bar{y}_{j,\ t}\times Post_t\times y_{i,\ j,\ t}+\delta X_{i,\ \ j,\ t}+\lambda\overline{X}_{j,\ t}+\varphi\nu_j+\phi\upsilon_t+\varepsilon_{i,\ j,\ t} \tag{5}$$

where $TFP_{i,\ j,\ t+1}$ denotes the TFP of firm i in industry j in year t+1. $\bar{y}_{j,\ t}\times Post_t\times y_{i,\ j,\ t}$ represents the intensity of the peer effects of green innovations. We incorporate $\bar{y}_{j,\ t}$ into $\overline{X}_{j,\ t}$ in Model (5).

Table 13 reports that the coefficients on $\overline{GP}\times Post\times GP$ (0.012), $\overline{GI1}\times Post\times GI1$ (0.014), and $\overline{GI2}\times Post\times GI2$ (0.024) are all positive and significant. Our results show that the peer effects of green innovations improve non-ETS firms' economic performance.

[Insert Table 13 Here]

6.4 Green revenues and the peer effects of green innovations

In this section, we investigate whether and how peer effects of green innovations affect non-ETS firms' green revenues. We obtain information on corporate revenues from diverse business activities through the WIND database to categorize corporate green revenues. We then identify corporate green revenues based on the *2019 Green Industry Guiding Catalogue* (GIGC) issues by China's National Development and Reform Commission. The GIGC includes six primary categories of business activities related to green, encompassing a total of 211 segmented activities. We classify corporate revenues stemming from business activities listed in the GIGC as "green revenues". We quantify non-ETS firms' green revenues (*GR*) as the aggregated value of green revenues scaled by total revenues. We replace total factor productivity (*TFP*) with corporate green revenues (*GR*) in Model (5). Table 14 shows that the coefficients on $\overline{GP}\times Post\times GP$ (0.011), $\overline{GI1}\times Post\times GI1$ (0.012), and $\overline{GI2}\times Post\times GI2$ (0.017) are all positive and significant at 1% level. These results indicate that the peer effects of green innovations significantly increase non-ETS firms' green revenues.

[Insert Table 14 Here]

[18] M = Operating costs + Sales costs + Management costs + Financial costs – Depreciation – Employee costs

7. Conclusions

We investigate the peer effects of ETS firms' green innovations on non-ETS firms' green innovations. We find that the non-ETS firms significantly enhance their green innovations in response to the augmented green innovations of ETS firms. We identify the competitive threat as the underlying mechanism. We suggest that the peer effects of green innovations are more pronounced among leader non-ETS firms. We document that these peer effects are more pronounced among firms characterized by leader status, high public scrutiny, higher financial constraints, more institutional investors, and under-investment. We further find these peer effects significantly increase non-ETS firms' economic performance and green revenues.

Our study has important implications for policymakers regarding environmental regulations, offering new insights into regulation spillover. We provide policymakers and practitioners with ex-ante evidence on the peer effects of environmental regulation-constrained firms on unconstrained firms' green innovations. We provide robust evidence regarding the motivations of non-ETS firms to imitate ETS-firms' green innovations. Overall, our findings suggest that unconstrained firms imitate the green innovations of peer firms subject to environmental regulation to maintain their competitiveness and limit rivalry, consistent with the rivalry-based theory (Lieberman and Asaba, 2006).

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Table 1: Sample selection and distribution

Total number of firm-year observations from 2006-2022	49,126
Removal of observations with ST and financial firms	(2,535)
Removal of observations with missing relevant financial data	(6,563)
Restrict the initial sample to non-ETS firms	(10,833)
Removal of peer average variables with missing values	(4,144)
Removal of firms without any green patent application from 2006 to 2022	(9,143)
Final firm-year observations	15,908
Number of firms	1,375
Number of industries	47

Note: This table shows the sample selection strategies of our study. The total number of firm-year observations from 2006-2022 is 49,126. First, we removed 2,535 observations with specially treated (ST) and financial firm-year observations because of the differences in the accounting fundamentals from our samples. We then exclude 6,563 firm-year observations with missing relevant financial data. According to Dou et al. (2023), we restrict our initial sample to non-ETS firms (focal firms), thus deleting 10,833 firm-year observations in our initial sample. We also remove the observations with missing the value of our key variables. To mitigate the issues with firms' preferences and firm-specific disturbance, we thus remove firms without any green patent application from 2006 to 2022 (9,143 firm-year observations). Ultimately, the final firm-year observations in our sample are 15,908 with 1,375 firms and 47 industries.

Table 2: Descriptive statistics

Panel A. Descriptive statistics of full sample								
Variable	N	Mean	SD	Min	P25	Median	P75	Max
Firm-specific factors								
GP	15,908	0.863	1.116	0.000	0.000	0.000	1.609	5.112
GI1	15,908	0.781	1.061	0.000	0.000	0.000	1.386	4.820
GI2	15,908	0.177	0.525	0.000	0.000	0.000	0.000	3.526
GU3	15,908	0.550	0.899	0.000	0.000	0.000	0.693	4.500
GU4	15,908	0.584	0.887	0.000	0.000	0.000	1.099	4.078
Size	15,908	22.142	1.228	19.440	21.256	21.998	22.880	26.132
SOE	15,908	0.399	0.490	0.000	0.000	0.000	1.000	1.000
DTA	15,908	0.446	0.200	0.073	0.286	0.441	0.598	0.961
MTB	15,908	0.633	0.243	0.114	0.449	0.632	0.815	1.271
NWC	15,908	0.194	0.241	-0.494	0.028	0.187	0.362	0.804
ROA	15,908	0.035	0.066	-0.487	0.012	0.035	0.064	0.272
TobinsQ	15,908	1.941	1.111	0.787	1.227	1.582	2.226	8.764
Cash	15,908	0.148	0.114	0.003	0.067	0.116	0.195	0.710
Age	15,908	2.833	0.370	1.099	2.639	2.890	3.091	3.555
Tang	15,908	0.930	0.084	0.453	0.922	0.957	0.977	1.000
Quick	15,908	1.592	1.454	0.131	0.701	1.106	1.871	9.173
Subsidy	15,908	7.600	8.370	0.000	0.000	0.000	16.561	20.423
SA	15,908	3.530	0.865	0.538	3.561	3.770	3.952	4.496
Peer firms' average characteristics								
$\overline{GP}$	15,908	1.070	0.753	0.000	0.508	1.004	1.470	5.162
$\overline{GI1}$	15,908	0.961	0.716	0.000	0.430	0.884	1.287	4.980

$\overline{GI2}$	15,908	0.291	0.317	0.000	0.063	0.218	0.425	2.207
$\overline{GU3}$	15,908	0.727	0.593	0.000	0.298	0.671	1.053	4.646
$\overline{GU4}$	15,908	0.714	0.596	0.000	0.266	0.567	1.015	3.596
$\overline{Size}$	15,908	24.207	2.503	21.441	22.533	23.482	24.752	35.050
$\overline{SOE}$	15,908	0.439	0.291	0.000	0.250	0.333	0.607	1.500
$\overline{DTA}$	15,908	0.473	0.112	0.287	0.393	0.450	0.548	0.943
$\overline{MTB}$	15,908	0.679	0.185	0.253	0.537	0.657	0.776	1.436
$\overline{NWC}$	15,908	0.230	0.144	-0.279	0.164	0.247	0.314	0.667
$\overline{ROA}$	15,908	0.042	0.028	-0.106	0.029	0.042	0.056	0.195
$\overline{TobinsQ}$	15,908	2.144	0.612	1.102	1.702	2.080	2.450	5.464
$\overline{Cash}$	15,908	0.183	0.069	0.033	0.135	0.170	0.211	0.577
$\overline{Age}$	15,908	3.099	0.354	2.467	2.860	3.070	3.252	4.755
$\overline{Tang}$	15,908	1.008	0.101	0.784	0.937	0.986	1.042	1.460
$\overline{Quick}$	15,908	1.881	0.739	0.470	1.316	1.822	2.341	7.108
$\overline{Subsidy}$	15,908	8.219	8.876	0.000	0.000	0.000	17.280	25.161
$\overline{SA}$	15,908	3.837	0.940	0.812	3.824	4.000	4.191	6.037

Panel B. Univariable comparison before and after China's ETS pilot

Variables	Pre China's ETS Pilot (N = 5,517)		Post China's ETS Pilot (N = 10,391)		Difference (Pre – Post)	
	Mean	Median	Mean	Median	*t*-statistic	Wilcoxon Z
GP	0.412	0.000	1.102	0.693	-38.825***	-38.565***
GI1	0.353	0.000	1.008	0.693	-38.772***	-38.747***
GI2	0.071	0.000	0.234	0.000	-18.755***	-18.240***
$\overline{GP}$	0.671	0.578	1.282	1.179	-52.832***	-53.259***
$\overline{GI1}$	0.585	0.498	1.161	1.069	-52.344***	-53.910***
$\overline{GI2}$	0.169	0.087	0.355	0.291	-36.613***	-45.421***

Size	21.745	21.614	22.353	22.219	-30.553***	-30.084***
SOE	0.508	1.000	0.341	0.000	20.808***	20.531***
DTA	0.468	0.472	0.435	0.427	9.908***	10.239***
MTB	0.659	0.673	0.619	0.610	9.776***	11.312***
NWC	0.172	0.159	0.206	0.200	-8.558***	-9.182***
ROA	0.039	0.037	0.032	0.034	6.698***	4.297***
TobinsQ	1.803	1.486	2.014	1.640	-11.469***	-11.312***
Cash	0.169	0.130	0.136	0.109	17.766***	13.236***
Age	2.556	2.639	2.980	2.996	-82.258***	-69.313***
Tang	0.949	0.964	0.919	0.953	21.240***	20.121***
Quick	1.496	0.944	1.642	1.191	-6.056***	-16.641***
Subsidy	0.000	0.000	11.635	15.934	-111.299***	-79.217***
SA	2.890	3.528	3.869	3.872	-80.550***	-72.597***

Note: This table presents the descriptive statistics of variables employed in the main analyses for 15,098 firm-year observations corresponding to 1,375 firms and 47 industries. We define peer firms in China's ETS pilot based on the CSRC Industry Classification 2012 version code. This table shows the number (*N*), means (*Mean*), standard deviation (*SD*), minimum value (*Min*), value at 25 percent (*P25*), median value (*Median*), value at 75 percent (*P75*), and maximum value for variables (*Max*), respectively. Firm-specific factors denote variables regarding non-ETS firm *i*'s value in year *t*. Peer firms' average characteristics denote variables measured as the average value of ETS firms (peer firms) in industry *j* and year *t*. Table A1 in the Appendix details the variable definitions.

Table 3: The impacts of ETS firms' green strategies on non-ETS firms' green strategies

Variables	*Green patent application* (GP)		*Green patent-independent application* ($GI1$)		*Green patent-collaborative application* ($GI2$)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{GP} \times Post$ (β1)	0.249***	0.283***				
	(3.849)	(5.653)				
$\overline{GP}$ (β2)	-0.014	-0.022				
	(-0.216)	(-0.384)				
$\overline{GI1} \times Post$ (β3)			0.218***	0.250***		
			(3.322)	(5.342)		
$\overline{GI1}$ (β4)			0.001	0.001		
			(0.021)	(0.020)		
$\overline{GI2} \times Post$ (β5)					0.274***	0.312***
					(4.143)	(5.868)
$\overline{GI2}$ (β6)					0.013	-0.035
					(0.214)	(-0.581)
Size		0.421***		0.370***		0.146***
		(8.925)		(8.900)		(5.258)
SOE		0.143***		0.121**		0.062***
		(3.160)		(2.559)		(3.302)
DTA		0.168		0.218		-0.042
		(1.218)		(1.634)		(-0.515)
MTB		-0.297*		-0.278**		-0.035
		(-1.971)		(-2.182)		(-0.414)
NWC		0.276*		0.260*		0.063

		(1.746)		(1.764)		(1.047)
ROA		-0.105		-0.065		-0.081
		(-0.545)		(-0.343)		(-0.923)
TobinsQ		-0.033**		-0.030**		-0.004
		(-2.045)		(-2.166)		(-0.388)
Cash		0.402**		0.343**		0.147*
		(2.352)		(2.223)		(1.887)
Age		0.106		0.046		0.251***
		(1.548)		(0.724)		(4.435)
Tang		-0.057		-0.128		0.172*
		(-0.225)		(-0.552)		(1.691)
Quick		-0.040**		-0.037*		-0.005
		(-2.206)		(-1.980)		(-0.786)
Subsidy		0.036***		0.035***		0.011***
		(4.651)		(4.510)		(2.943)
SA		-0.534***		-0.454***		-0.464***
		(-3.029)		(-2.735)		(-4.091)
Peer Averages	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 + β2 (*p*-value)	0.000***	0.000***				
F-test: β3 + β4 (*p*-value)			0.000***	0.000***		
F-test: β5 + β6 (*p*-value)					0.002***	0.001***
Observations	15,908	15,908	15,908	15,908	15,908	15,908
Adjusted R^2	0.218	0.395	0.207	0.363	0.101	0.205

Note: This table reports the peer effects of green innovations on non-ETS firms' green innovations. *GP*, *GI1*, and *GI2* represent green patent applications, green patent-independent applications, and green patent-collaborative applications, respectively. Columns (1), (3), and (5) only include the industry- and year-fixed effects in the regression as control variables to mitigate the concern regarding the different impacts of controlling related covariates on investigations (Gormley and Matsa, 2014). Columns (2), (4), and (6) show the results of controlling all control variables, peer average variables, and industry- and year-fixed effects. $\overline{GP}\times Post$, $\overline{GI1}\times Post$, and $\overline{GI2}\times Post$ denote the peer effects of green innovations. *Post* equals one in and after 2014, and zero otherwise. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 4: The results of using the Entropy balancing approach

Panel A. Before and after the entropy balancing approach

Before balancing	$High\_GP = 1$			$High\_GP = 0$			Std.	Var.
	mean	variance	skewness	mean	variance	skewness	Diff.	Ratio
Size	22.550	1.548	0.426	21.750	1.154	0.617	0.170	1.341
SOE	0.412	0.242	0.360	0.387	0.237	0.466	0.005	1.021
DTA	0.464	0.037	0.068	0.429	0.043	0.262	-0.016	0.856
MTB	0.659	0.062	0.057	0.608	0.055	0.020	0.013	1.117
NWC	0.186	0.053	0.047	0.202	0.063	-0.039	-0.020	0.848
ROA	0.034	0.004	-2.043	0.035	0.005	-2.129	-0.005	0.872
TobinsQ	1.848	1.067	2.390	2.031	1.380	2.200	-0.142	0.774
Cash	0.140	0.011	1.539	0.155	0.015	1.440	-0.019	0.714
Age	2.909	0.113	-0.893	2.760	0.149	-0.792	-0.050	0.758
Tang	0.925	0.007	-2.477	0.934	0.007	-2.969	0.003	1.063
Quick	1.499	1.649	2.489	1.681	2.548	2.070	-0.312	0.647
Subsidy	10.070	71.470	-0.318	5.200	56.990	0.787	0.905	1.254
SA	3.736	0.316	-3.844	3.329	1.088	-1.711	-0.482	0.290
After balancing	$High\_GP = 1$			$High\_GP = 0$			Std.	Var.
	mean	variance	skewness	mean	variance	skewness	Diff.	Ratio
Size	22.550	1.548	0.426	22.550	1.548	0.426	0.000	1.000
SOE	0.412	0.242	0.360	0.412	0.242	0.360	0.000	1.000
DTA	0.464	0.037	0.068	0.464	0.037	0.068	0.000	1.000
MTB	0.659	0.062	0.057	0.659	0.062	0.057	0.000	1.000
NWC	0.186	0.053	0.047	0.186	0.053	0.047	0.000	1.000
ROA	0.034	0.004	-2.043	0.034	0.004	-2.043	0.000	1.000
TobinsQ	1.848	1.067	2.390	1.848	1.067	2.390	0.000	1.000
Cash	0.140	0.011	1.539	0.140	0.011	1.539	0.000	1.000
Age	2.909	0.113	-0.893	2.908	0.113	-0.893	0.000	1.000
Tang	0.925	0.007	-2.477	0.925	0.007	-2.477	0.000	1.000
Quick	1.499	1.649	2.489	1.499	1.649	2.489	0.000	1.000
Subsidy	10.070	71.470	-0.318	10.070	71.470	-0.318	0.000	1.000
SA	3.736	0.316	-3.844	3.736	0.316	-3.842	0.000	1.000

Panel B. Peer-firm effects on green innovations after entropy balancing

Variables	*Green patent application* (*GP*)		*Green patent-independent application* (*GI1*)		*Green patent-collaborative application* (*GI2*)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{GP} \times Post$ (β1)	0.168***	0.208***				
	(2.707)	(3.285)				
$\overline{GP}$ (β2)	-0.011	-0.024				

	(1)	(2)	(3)	(4)	(5)	(6)
	(-0.149)	(-0.272)				
$\overline{GI1}$ × *Post* (β3)			0.137**	0.172***		
			(2.222)	(2.829)		
$\overline{GI1}$ (β4)			0.012	0.013		
			(0.176)	(0.167)		
$\overline{GI2}$ × *Post* (β5)					0.211***	0.252***
					(4.518)	(4.791)
$\overline{GI2}$ (β6)					-0.047	-0.112*
					(-0.968)	(-1.877)
Controls	No	Yes	No	Yes	No	Yes
Peer Averages	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 + β2 (*p*-value)	0.000***	0.000***				
F-test: β3 + β4 (*p*-value)			0.000***	0.000***		
F-test: β5 + β6 (*p*-value)					0.000***	0.000***
Observations	15,908	15,908	15,908	15,908	15,908	15,908
Adjusted R^2	0.168	0.243	0.161	0.225	0.080	0.148

Note: This table shows the peer effects of ETS firms' green innovations on non-ETS firms' green innovations after conducting the entropy balancing approach. We employ the entropy balancing approach to balance the differences between non-ETS firms with higher green innovations and those with lower green innovations, thus mitigating the self-selection bias. Panel A reports the results of conducting the entropy balancing approach and the differences between before and after. Panel B exhibits the results of using control variables after being balanced to estimate Model (1). This shows that our results are robust after conducting the entropy balancing approach. Table A1 in the Appendix provides the variable definitions. The standard errors are clustered by industry. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 5: Excluding the GFC in 2008, COVID-19 in 2019, and China's ETS in 2021

Variables	*Green patent application (GP)*		*Green patent-independent application (GI1)*		*Green patent-collaborative application (GI2)*	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{GP} \times Post$ (β1)	0.217***	0.216***				
	(4.288)	(4.952)				
$\overline{GP}$ (β2)	-0.048	-0.048				
	(-1.046)	(-0.745)				
$\overline{GI1} \times Post$ (β3)			0.231***	0.222***		
			(4.129)	(4.701)		
$\overline{GI1}$ (β4)			-0.062	-0.059		
			(-1.510)	(-1.028)		
$\overline{GI2} \times Post$ (β5)					0.172**	0.184***
					(2.493)	(3.865)
$\overline{GI2}$ (β6)					-0.026	-0.051
					(-0.484)	(-1.043)
Controls	No	Yes	No	Yes	No	Yes
Peer Averages	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 + β2 (*p*-value)	0.000***	0.000***				
F-test: β3 + β4 (*p*-value)			0.000***	0.000***		
F-test: β5 + β6 (*p*-value)					0.006***	0.003***
Observations	8,700	8,700	8,700	8,700	8,700	8,700
Adjusted R^2	0.160	0.322	0.156	0.296	0.066	0.147

Note: This table reports the results after excluding the observations before 2010 and after 2018 to exclude the effects of the GFC in 2008, COVID-19 in 2019, and China's ETS in 2021. This indicates that our baseline results are still robust after excluding these effects. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 6: Alternative measures

Variables	*Green invention patent application* (*GU3*)		*Green utility-model patent application* (*GU4*)	
	(1)	(2)	(3)	(4)
$\overline{GU3} \times Post$ (β1)	0.258***	0.284***		
	(3.820)	(5.760)		
$\overline{GU3}$ (β2)	-0.024	-0.023		
	(-0.387)	(-0.405)		
$\overline{GU4} \times Post$ (β3)			0.276***	0.312***
			(4.152)	(5.632)
$\overline{GU4}$ (β4)			0.033	0.023
			(0.494)	(0.420)
Controls	No	Yes	No	Yes
Peer Averages	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F-test: β1 + β2 (p-value)	0.000***	0.000***		
F-test: β3 + β4 (p-value)			0.008***	0.000***
Observations	15,908	15,908	15,908	15,908
Adjusted R^2	0.171	0.339	0.209	0.355

Note: This table reports the results after conducting alternative measures. To mitigate measurement bias, we conduct alternative measures. *GU3* and *GU4* denote green invention patent applications and green utility-model patent applications. Columns (2) and (4) show that our results are still robust after conducting alternative measures. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 7: Other fixed effects

Variables	Green patent application (GP)		Green patent-independent application ($GI1$)		Green patent-collaborative application ($GI2$)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{GP} \times Post$ (β1)	0.261***	0.303***				
	(4.564)	(6.492)				
$\overline{GP}$ (β2)	-0.067	-0.073				
	(-1.136)	(-1.283)				
$\overline{GI1} \times Post$ (β3)			0.227***	0.273***		
			(4.106)	(6.194)		
$\overline{GI1}$ (β4)			-0.041	-0.041		
			(-0.886)	(-0.887)		
$\overline{GI2} \times Post$ (β5)					0.263***	0.302***
					(4.876)	(5.763)
$\overline{GI2}$ (β6)					-0.012	-0.075
					(-0.210)	(-1.444)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes
Industry FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE × Region FE	No	Yes	No	Yes	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 + β2 (p-value)	0.000***	0.000***				
F-test: β3 + β4 (p-value)			0.000***	0.000***		
F-test: β5 + β6 (p-value)					0.002***	0.001***
Observations	15,908	15,882	15,908	15,882	15,908	15,882
Adjusted R^2	0.403	0.634	0.370	0.600	0.212	0.446

Note: This table reports the robustness test results in which firm, year, and region are included in the regression. These results show that ETS firms' green innovations positively affect non-ETS firms' green innovations after controlling other fixed effects. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 8: Omitted variable bias test

Panel A. The peer effects of green patent applications (*GP*)		
	(1)	(2)
Standard	Estimated value	Omitted variables bias
$\beta^*(R_{max}, \delta) \in [0.209, 0.396]$	$\beta^*\ (R_{max}, \delta)=0.361$	Unlikely
$\delta > 1$ or $\delta < -1$	$\delta = 2.248$	Unlikely
Panel B. The peer effects of green patent-independent applications (*GI1*)		
	(1)	(2)
Standard	Estimated value	Omitted variables bias
$\beta^*(R_{max}, \delta) \in [0.184, 0.362]$	$\beta^*\ (R_{max}, \delta)=0.326$	Unlikely
$\delta > 1$ or $\delta < -1$	$\delta = 1.790$	Unlikely
Panel C. The peer effects of green patent-collaborative applications (*GI2*)		
	(1)	(2)
Standard	Estimated value	Omitted variables bias
$\beta^*(R_{max}, \delta) \in [0.196, 0.407]$	$\beta^*\ (R_{max}, \delta)=0.327$	Unlikely
$\delta > 1$ or $\delta < -1$	$\delta = 27.520$	Unlikely

Note: This table reports the results of the omitted variable test. According to Oster (2019), we compare the sensitivity of estimated coefficients and the change of R-squared between regression with and without control variables. The selection proportionality δ and maximum goodness-of-fit R_{max} are utilized to testify whether our model and regressions are shocked by omitted variable bias. We thus employ the model from Oster (2019), $\beta^*=\beta^*\ (R_{max}, \delta)$, which captures the consistent estimates of the true coefficients. These results show that omitted variables bias is not an issue in our study.

Table 9: The tests of the rivalry-based theory

Variables	*Green patent application* (*GP*)		*Green patent-independent application* (*GI1*)		*Green patent-collaborative application* (*GI2*)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low competitive (High *CR8*)	Highly competitive (Low *CR8*)	Low competitive (High *CR8*)	Highly competitive (Low *CR8*)	Low competitive (High *CR8*)	Highly competitive (Low *CR8*)
$\overline{GP} \times Post$ (β1)	0.191***	0.270***				
	(4.862)	(5.595)				
$\overline{GP}$	0.006	0.025				
	(0.086)	(0.245)				
$\overline{GI1} \times Post$ (β2)			0.185***	0.297***		
			(4.411)	(5.501)		
$\overline{GI1}$			0.005	0.056		
			(0.080)	(0.504)		
$\overline{GI2} \times Post$ (β3)					0.199***	0.343***
					(3.749)	(3.674)
$\overline{GI2}$					0.008	-0.330***
					(0.166)	(-5.323)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 across subsamples	0.004***					

(p-value)						
F-test: β2 across subsamples			0.000***			
(p-value)						
F-test: β3 across subsamples					0.000***	
(p-value)						
Observations	7,796	7,740	7,796	7,740	7,796	7,740
Adjusted R^2	0.388	0.407	0.356	0.374	0.207	0.219

Note: This table reports the peer effects of ETS firms' green innovations on non-ETS firms in different production market competitions. To investigate the reasons behind the peer effects, we distinguish production market competition into high and low. We employ a concentration index based on the sales revenue of the top-eight firms (*CR8*) to proxy product market competition. The higher value of *CR8* indicates a more concentrated market and lower competition. Thus, we define firms facing more (less) intense competition in the product market when the concentration index (*CR8*) is below (above) the median, in line with previous studies (Leary and Roberts, 2014; Adhikari and Agrawal, 2018; Machokoto *et a*l., 2021). Our results support the rivalry-based theory. According to Cleary (1999), we examine the difference in the coefficient estimate for the peer effects of green innovations between higher (Low *CR8*) and lower product market competition (High *CR8*). Thus, we employ Fisher's permutation tests and bootstrap 1,000 times to compute the empirical p-value. The empirical p-values are all less than 0.01, indicating that these subsample analyses are significant. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 10: The tests of the information-based theory

Variables	*Green patent application* (*GP*)		*Green patent-independent application* (*GI1*)		*Green patent-collaborative application* (*GI2*)	
	(1)	(2)	(3)	(4)	(5)	(6)
	High asymmetry (High *Synchron*)	Low asymmetry (Low *Synchron*)	High asymmetry (High *Synchron*)	Low asymmetry (Low *Synchron*)	High asymmetry (High *Synchron*)	Low asymmetry (Low *Synchron*)
$\overline{GP}$ × *Post* (β1)	0.244***	0.330***				
	(5.314)	(4.919)				
$\overline{GP}$	0.026	-0.089				
	(0.367)	(-1.224)				
$\overline{GI1}$ × *Post* (β2)			0.224***	0.291***		
			(5.224)	(4.361)		
$\overline{GI1}$			0.056	-0.079		
			(0.920)	(-1.312)		
$\overline{GI2}$ × *Post* (β3)					0.331***	0.293***
					(3.688)	(4.363)
$\overline{GI2}$					-0.049	-0.018
					(-0.756)	(-0.255)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 across subsamples (*p*-value)	0.112					
F-test: β2 across subsamples (*p*-value)			0.235			

F-test: β3 across subsamples (p-value)					0.304	
Observations	7,623	7,625	7,623	7,625	7,623	7,625
Adjusted R^2	0.401	0.395	0.363	0.368	0.227	0.191

Note: This table reports the peer effects of ETS firms' green innovations on non-ETS firms in different information environments. We distinguish information environments into high and low information asymmetry to examine the reasons behind the peer effects. *Synchron* denotes the level of stock price synchronicity. The information asymmetry is high (low) when the *Synchron* is above (below) the median. According to Cleary (1999), we examine the difference in the coefficient estimate for the peer effects of green innovations between higher information asymmetry (High *Synchron*) and lower information asymmetry (Low *Synchron*). Thus, we employ Fisher's permutation tests and bootstrap 1,000 times to compute the empirical p-value. The empirical p-values are all larger than 0.100, indicating that these subsample analyses are insignificant. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 11: Leader versus follower non-ETS firms

Variables	*Green patent application (GP)*		*Green patent-independent application (GI1)*		*Green patent-collaborative application (GI2)*	
	(1)	(2)	(3)	(4)	(5)	(6)
	High market share (Leader)	Low market share (Follower)	High market share (Leader)	Low market share (Follower)	High market share (Leader)	Low market share (Follower)
$\overline{GP} \times Post$ (β1)	0.439***	0.261***				
	(4.791)	(4.055)				
$\overline{GI1} \times Post$ (β2)			0.412***	0.219***		
			(4.233)	(3.227)		
$\overline{GI2} \times Post$ (β3)					0.381***	0.325***
					(4.333)	(4.998)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 across subsamples (p-value)	0.000***					
F-test: β2 across subsamples (p-value)			0.000***			
F-test: β3 across subsamples (p-value)					0.013**	
Observations	5,168	10,738	5,168	10,738	5,168	10,738
Adjusted R^2	0.528	0.314	0.497	0.284	0.298	0.138

Note: This table reports the peer effects of green innovations on non-ETS firms in different market positions. We follow Leary and Roberts (2014) and Adhikari and Agrawal (2018) to classify non-ETS firms into three terciles by market share based on enterprises operating revenue. We define leader non-ETS firms as non-

ETS firms in the top tercile and follower non-ETS firms as non-ETS firms in the middle and bottom terciles. Our results show that leader non-ETS firms are more responsive to the peer effects of green innovations. According to Cleary (1999), we examine the difference in the coefficient estimate for the peer effects of green innovations between leader non-ETS firms (Leader) and follower non-ETS firms (Follower). Thus, we employ Fisher's permutation tests and bootstrap 1,000 times to compute the empirical p-value. The empirical p-values are all less than 0.05, indicating that these subsample analyses are significant. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 12: Heterogeneity analyses of non-ETS firms

Panel A. Public scrutiny						
Variables	*Green patent application* (*GP*)		*Green patent-independent application* (*GI1*)		*Green patent-collaborative application* (*GI2*)	
	(1)	(2)	(3)	(4)	(5)	(6)
	High public scrutiny (High *Alt*)	Low public scrutiny (Low *Alt*)	High public scrutiny (High *Alt*)	Low public scrutiny (Low *Alt*)	High public scrutiny (High *Alt*)	Low public scrutiny (Low *Alt*)
$\overline{GP} \times Post$ (β1)	0.372***	0.276***				
	(5.450)	(4.394)				
$\overline{GI1} \times Post$ (β2)			0.341***	0.254***		
			(4.381)	(4.434)		
$\overline{GI2} \times Post$ (β3)					0.429***	0.277***
					(3.653)	(4.339)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Peer Average	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 across subsamples (*p*-value)	0.000***					
F-test: β2 across subsamples (*p*-value)			0.003***			
F-test: β3 across subsamples (*p*-value)					0.000***	
Observations	5,346	5,818	5,346	5,818	5,346	5,818

Adjusted R^2	0.476	0.373	0.443	0.338	0.275	0.179

Panel B. Financial constraints

Variables	*Green patent application* (*GP*)		*Green patent-independent application* (*GI1*)		*Green patent-collaborative application* (*GI2*)	
	(1)	(2)	(3)	(4)	(5)	(6)
	(Higher *SA*)	(Lower *SA*)	(Higher *SA*)	(Lower *SA*)	(Higher *SA*)	(Lower *SA*)
$\overline{GP} \times Post$ (β1)	0.277***	0.214***				
	(3.459)	(4.506)				
$\overline{GI1} \times Post$ (β2)			0.287***	0.198***		
			(2.970)	(4.581)		
$\overline{GI2} \times Post$ (β3)					0.347***	0.294***
					(3.715)	(3.178)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 across subsamples (*p*-value)	0.018**					
F-test: β2 across subsamples (*p*-value)			0.002***			
F-test: β3 across subsamples (*p*-value)					0.065*	
Observations	7,961	7,947	7,961	7,947	7,961	7,947
Adjusted R^2	0.384	0.392	0.349	0.365	0.185	0.226

Panel C. Institutional shareholdings

Variables	*Green patent application* (*GP*)		*Green patent-independent application*		*Green patent-collaborative*	

			(GI1)		*application (GI2)*	
	(1)	(2)	(3)	(4)	(5)	(6)
	(High *INS*)	(Low *INS*)	(High *INS*)	(Low *INS*)	(High *INS*)	(Low *INS*)
$\overline{GP} \times Post$ (β1)	0.304***	0.237***				
	(5.567)	(3.262)				
$\overline{GI1} \times Post$ (β2)			0.278***	0.187**		
			(5.215)	(2.529)		
$\overline{GI2} \times Post$ (β3)					0.324***	0.265**
					(4.653)	(2.661)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 across subsamples (*p*-value)	0.006***					
F-test: β2 across subsamples (*p*-value)			0.002***			
F-test: β3 across subsamples (*p*-value)					0.033**	
Observations	7,891	8,016	7,891	8,016	7,891	8,016
Adjusted R^2	0.442	0.348	0.403	0.328	0.260	0.125

Panel D. Investment efficiency

Variables	*Green patent application (GP)*		*Green patent-independent application (GI1)*		*Green patent-collaborative application (GI2)*	
	(1)	(2)	(3)	(4)	(5)	(6)
	(Over)	(Under)	(Over)	(Under)	(Over)	(Under)

$\overline{GP} \times Post$ (β1)	0.250***	0.288***				
	(3.830)	(5.290)				
$\overline{GI1} \times Post$ (β2)			0.244***	0.266***		
			(3.816)	(5.082)		
$\overline{GI2} \times Post$ (β3)					0.159**	0.338***
					(2.253)	(3.675)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test: β1 across subsamples (*p*-value)	0.056*					
F-test: β2 across subsamples (*p*-value)			0.180			
F-test: β3 across subsamples (*p*-value)					0.000***	
Observations	4,640	8,658	4,640	8,658	4,640	8,658
Adjusted R^2	0.395	0.408	0.372	0.373	0.190	0.220

Note: Panel A shows the results for subsamples of non-ETS firms with high or low public scrutiny. The results demonstrate that the peer effects of ETS firms' green innovations are more pronounced among non-ETS firms and are subject to high public scrutiny. Panel B exhibits the results for subsamples of non-ETS firms facing higher or lower financial constraints. These results demonstrate that the peer effects of green innovations are more pronounced among non-ETS firms with higher financial constraints. Panel C shows the results for subsamples of non-ETS firms that have more or less institutional investors. These results show that non-ETS firms with more institutional investors are more responsive to the peer effects of green innovations. Panel D reports the results for subsamples of non-ETS firms facing over- or under-investment. These results show that under-investment firms are more responsive to the peer effects of green innovations. According to Cleary (1999), we examine the difference in the coefficient estimate for the peer effects of green innovations between subsamples. Thus, we employ Fisher's permutation tests and bootstrap 1,000 times to compute the empirical p-value to calculate the significance of subsample analyses. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 13: The implications on non-ETS firms' economic performance

Variables	*Total factor productivity* ($TFP_{i,\,j,\,t+1}$)		
	(1)	(2)	(3)
$\overline{GP} \times Post \times GP$	0.012***		
	(4.274)		
$\overline{GI1} \times Post \times GI1$		0.014***	
		(4.496)	
$\overline{GI2} \times Post \times GI2$			0.024*
			(1.915)
Controls	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	13,877	13,877	13,877
Adjusted R^2	0.740	0.740	0.740

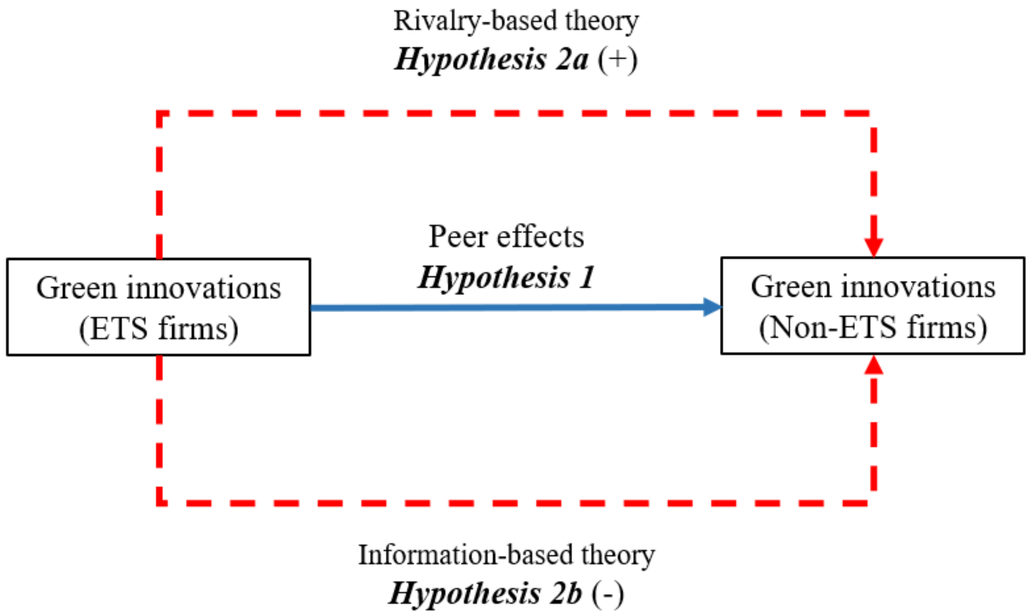
Note: This table reports the implications of non-ETS firms' green innovations on firms' economic performance influenced by the threat of green rivalry. Previous literature (Giannetti *et al.*, 2015; *Ren et al.*, 2022; Wu and Wang, 2022) employs the TFP to denote firms' economic performance. We employ the method of Levinsohn and Petrin (2003) to compute non-ETS firms' TFP. $TFP_{i,\,j,\,t+1}$ denotes the TFP of firm i in industry j in year t+1. These results show that the peer effects of green innovations positively affect firms' TFP, thus enhancing firms' economic performance. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 14: The implications on non-ETS firms' green revenues

Variables	*Corporate green revenues* ($GR_{i,\,j,\,t+1}$)		
	(1)	(2)	(3)
$\overline{GP} \times Post \times GP$	0.011***		
	(9.710)		
$\overline{GI1} \times Post \times GI1$		0.012***	
		(9.126)	
$\overline{GI2} \times Post \times GI2$			0.017***
			(2.934)
Controls	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	14,164	14,164	14,164
Adjusted R^2	0.200	0.199	0.190

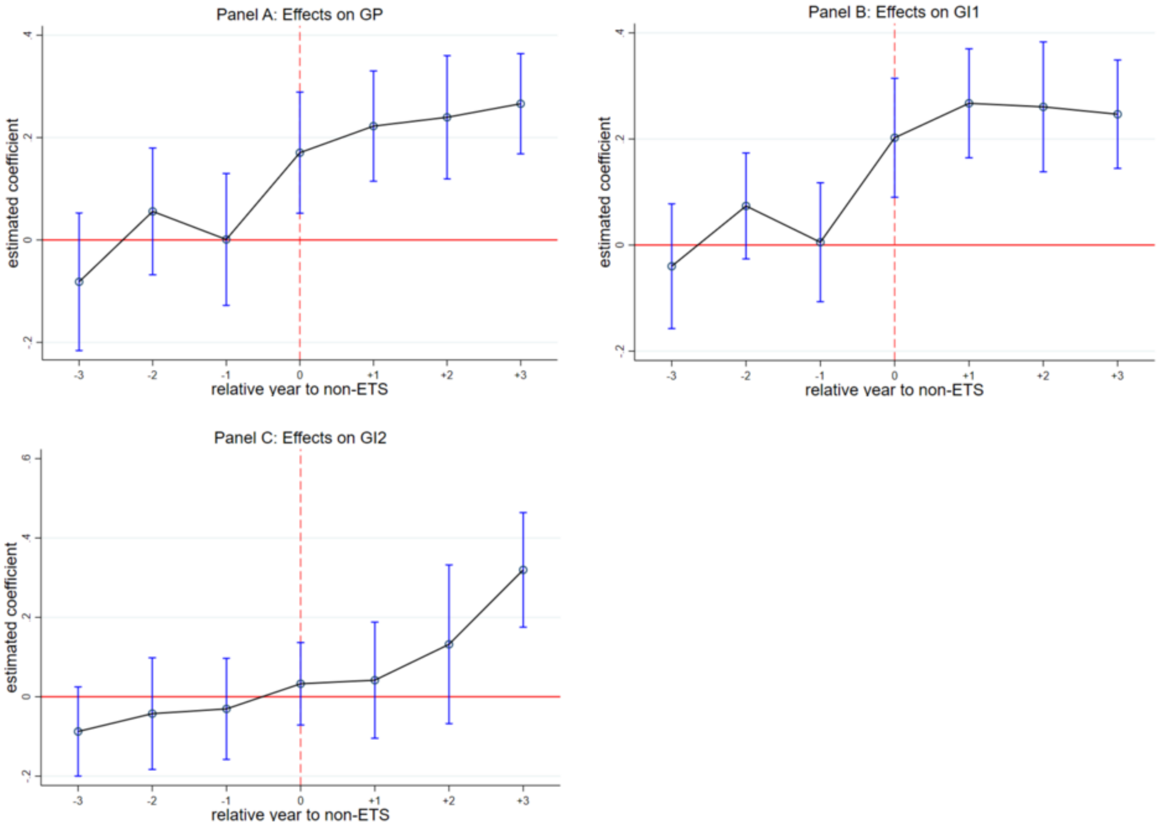
Note: This table exhibits the implications of peer effects of green innovations on non-ETS firms' green revenues. $GR_{i,\,j,\,t+1}$ represents the corporate green revenues scaled by total revenues. We find that the peer effects of green innovations significantly increase non-ETS firms' green revenues. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Figure 1. Theoretical mechanism



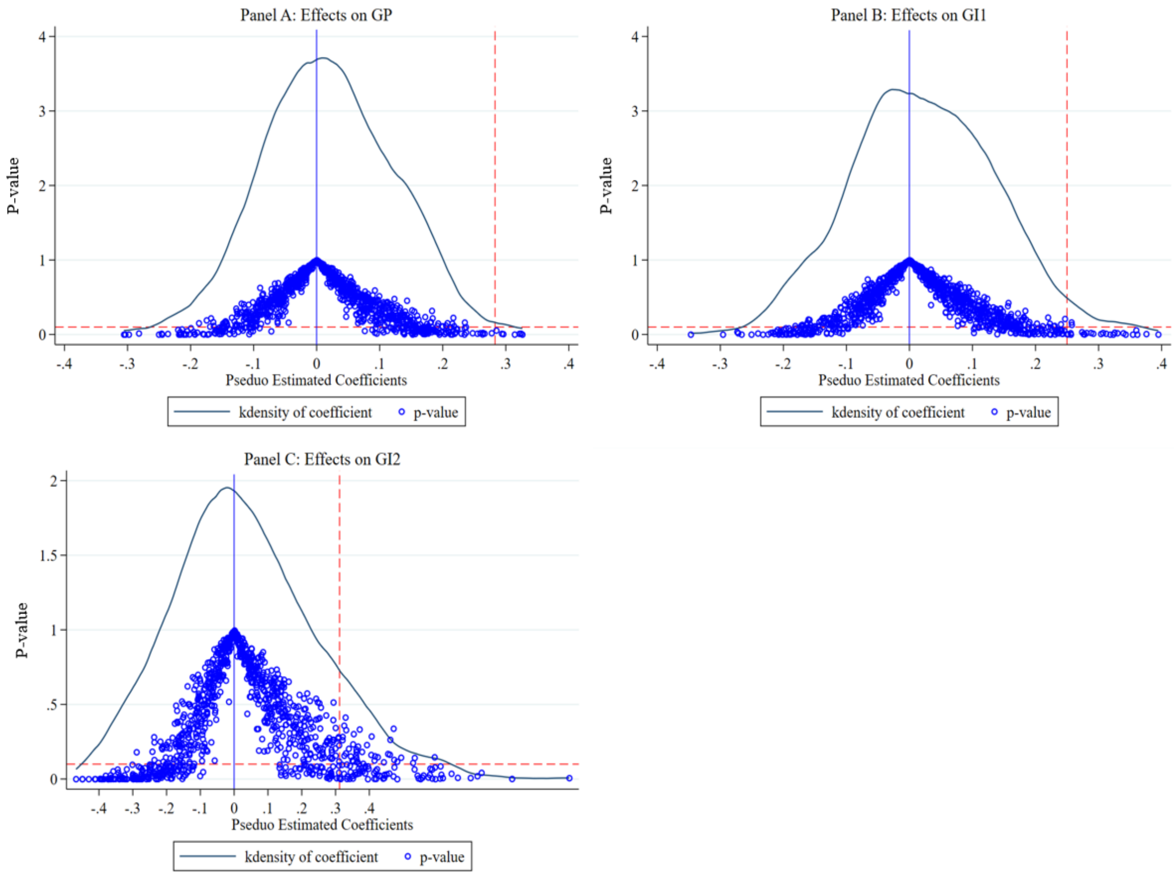
Note: This figure sketches the theoretical mechanism of this study. The solid lines denote the direct impacts, and the dashed lines represent the reasons behind the peer effects of ETS firms' green innovations. ETS firms would affect non-ETS firms when conducting green innovations despite China's ETS pilot not constraining non-ETS firms directly. This is consistent with ***H1***. According to Lieberman and Asaba (2006), the motivations of firms to mimic their peers are either the rivalry-based theory, the information-based theory, or both. Thus, we further propose two hypotheses to examine the reasons behind the peer effects of ETS firms' green innovations on non-ETS firms' green innovations. ETS firms' green innovations can enhance ETS firms' competitiveness (Porter and van der Linde, 1995; Nesta *et al.*, 2014; Amore and Bennedsen, 2016; Wang *et al.*, 2023), the motivations to imitate ETS firms' green innovations to maintain competitiveness and limit rivals become more prominent among non-ETS firms. Thus, we propose ***H2a*** that non-ETS firms in a higher rivalry pressure environment are more likely to imitate ETS firms when conducting green innovations, which we designate as the green rivalry threat. However, non-ETS firms would mimic ETS firms since they believe ETS firms have superior information about policy and green innovations. Non-ETS firms are more inclined to imitate ETS firms to obtain superior information on green innovations when information asymmetry is high. Thus, we propose ***H2b*** that non-ETS firms in a higher information asymmetry environment are more inclined to imitate ETS firms to enhance their green innovations.

Figure 2. Parallel trend tests



Note: This figure shows the results of parallel tend tests of peer effects of green patent applications, green patent-independent applications, and green patent-collaborative applications, respectively. We conduct a dynamic analysis to re-estimate Model (1) by replacing $\bar{y}\times Post$ with the seven interaction terms between $\bar{y}$ and year dummy variables. The peer effects of ETS firms' green innovations on non-ETS firms' green innovations (*GP*, *GI1*, and *GI2*) enhance significantly only after the shock of China's ETS pilot. The peer effects on *GP* and *GI1* dramatically increase after this shock, indicating that ETS firms' green patent applications and green patent-independent applications have immediate impacts on non-ETS firms. However, the peer effect of *GI2* is significant and increases saliently until one year after this shock.

Figure 3: Placebo tests



Note: This figure shows the results of placebo tests of the peer effects of green patent applications, green patent-independent applications, and green patent-collaborative applications, respectively. We follow Defusco (2018) to randomly allocate fictitious policies to establish pseudo-impacted jurisdictions and simulate the placebo tests 1,000 times for three green innovations. These results show that the coefficients are all centralized around zero, and the random coefficients are located on the left side of the true coefficients (0.283, 0.250, and 0.312).

Appendix

Table A1: Definition of variables

Variable	Definition
Outcome and treatment variables	
GP	Logarithmic value of one plus the number of green patent applications
GI1	Logarithmic value of one plus the number of green patent-independent applications
GI2	Logarithmic value of one plus the number of green patent-collaborative applications
GU3	Logarithmic value of one plus the number of green invention patents application
GU4	Logarithmic value of one plus the number of green utility-model patents application
Post	The indicator variable equals one in the year 2014 and after, and zero otherwise
Mechanism and additional variables	
CR8	The concentration Index based on sales revenue for the top 8 firms in an industry denotes the product market competition
Synchron	Stock price synchronicity, with a higher value indicating high information asymmetry
Alt	The number of analyst followings, with higher value indicating high public scrutiny
Investment	Firms' investment inefficiency, measured by the model of Biddle et al. (2009)
TFP	Total factor productivity based on the semi-parametric method from Levinsohn and Petrin (2003)
GR	Logarithmic value of one plus the amount of corporate green revenues scaled by total revenues
Control variables	
Size	Logarithm of one plus total assets
SOE	The structure of the firm's ownership equals one when firm i is a state-owned enterprise in year t, and 0 otherwise
DTA	Debt-to-Asset ratio
MTB	Book-to-market ratio
NWC	Net working capital scaled by total assets
ROA	Logarithmic value of one plus return on assets
TobinsQ	Logarithmic value of one plus Tobin's Q
Cash	Cash and cash equivalent to total assets
Age	Logarithmic value of one plus firms' age
Tang	Total tangible assets scaled by total assets
Quick	The quick ratio, measured as the sum of cash, short-term investments, and receivables scaled by current liabilities

Subsidy	Logarithmic value of one plus firms' subsidy of innovation
SA	The SA index[19] developed by Hadlock and Pierce (2010) to test firms' financial constraints, we take the absolute value

[19] SA=-0.737×Size+0.043×Size^2-0.040×Age

Table A2: The peer effects of green innovations after PSM

Variables	*Green patent application (GP)*		*Green patent-independent application (GI1)*		*Green patent-collaborative application (GI2)*	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{GP} \times Post$	0.219***	0.256***				
	(3.789)	(4.964)				
$\overline{GP}$	-0.009	-0.027				
	(-0.143)	(-0.452)				
$\overline{GI1} \times Post$			0.195***	0.224***		
			(3.033)	(4.297)		
$\overline{GI1}$			-0.012	-0.018		
			(-0.202)	(-0.369)		
$\overline{GI2} \times Post$					0.260***	0.304***
					(4.769)	(6.410)
$\overline{GI2}$					-0.010	-0.063
					(-0.198)	(-1.132)
Controls	No	Yes	No	Yes	No	Yes
Peer Averages	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,776	13,776	13,776	13,776	13,776	13,776
Adjusted R^2	0.185	0.324	0.177	0.297	0.082	0.161

Note: This table shows the results after conducting PSM to mitigate self-selection bias. These results provide evidence that our results are robust after conducting PSM. The balancing results of key variables of non-ETS firms are in Figure A1 in the Appendix. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table A3: Which non-ETS firms are mimicking? (Size, Age, and Tangible)

Panel A. Larger and smaller size						
Variables	*Green patent application (GP)*		*Green patent-independent application (GI1)*		*Green patent-collaborative application (GI2)*	
	(1)	(2)	(3)	(4)	(5)	(6)
	(Larger)	(Smaller)	(Larger)	(Smaller)	(Larger)	(Smaller)
$\overline{GP} \times Post$	0.177***	0.110				
	(3.030)	(1.526)				
$\overline{GI1} \times Post$			0.165***	0.084		
			(2.775)	(1.189)		
$\overline{GI2} \times Post$					0.292***	0.074
					(3.861)	(1.261)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Empirical P-value	0.009***		0.005***		0.000***	
Observations	7,931	7,977	7,931	7,977	7,931	7,977
Adjusted R^2	0.395	0.173	0.361	0.167	0.222	0.045

Panel B. Firms' listed age						
Variables	*Green patent application (GP)*		*Green patent-independent application (GI1)*		*Green patent-collaborative application (GI2)*	
	(1)	(2)	(3)	(4)	(5)	(6)
	(Older)	(Younger)	(Older)	(Younger)	(Older)	(Younger)
$\overline{GP} \times Post$	0.330***	0.193***				
	(4.239)	(3.701)				
$\overline{GI1} \times Post$			0.367***	0.173***		
			(3.946)	(3.564)		
$\overline{GI2} \times Post$					0.304***	0.200***
					(2.823)	(3.588)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Empirical P-value	0.000***		0.000***		0.002***	
Observations	8,378	7,529	8,378	7,529	8,378	7,529

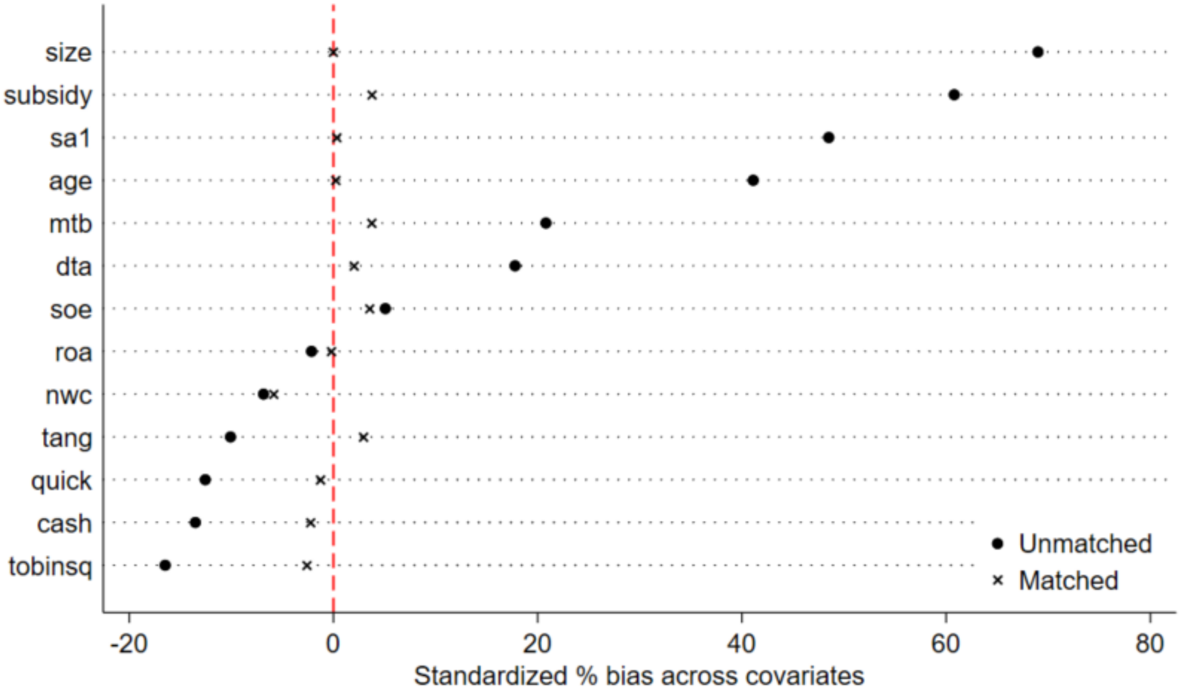
Adjusted R^2	0.418	0.326	0.375	0.316	0.234	0.107

Panel C. Tangible assets

Variables	*Green patent application (GP)*		*Green patent-independent application (GI1)*		*Green patent-collaborative application (GI2)*	
	(1)	(2)	(3)	(4)	(5)	(6)
	(More tangibles)	(Less tangibles)	(More tangibles)	(Less tangibles)	(More tangibles)	(Less tangibles)
$\overline{GP} \times Post$	0.298***	0.256***				
	(6.049)	(4.333)				
$\overline{GI1} \times Post$			0.278***	0.219***		
			(4.978)	(3.558)		
$\overline{GI2} \times Post$					0.344***	0.252***
					(6.751)	(3.572)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer Averages	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Empirical P-value	0.046**		0.013**		0.004***	
Observations	7,401	8,507	7,401	8,507	7,401	8,507
Adjusted R^2	0.410	0.393	0.379	0.359	0.220	0.200

Note: This table reports the heterogeneous analyses of non-ETS firms based on size, age, and tangible. Panel A shows that the peer effects of green innovations are only significant on large firms measured by firms' size. Our findings show that ETS firms' green innovations only affect large-size non-ETS firms. Small-size firms are not responsive to the threat of green rivalry since investments in green innovations have strong barriers to techniques and capability and, thus, are unresponsive to the peer effects of green innovations. Panel B reports the results of non-ETS firms with different listed ages in response to the peer effects of green innovations. We find that older non-ETS firms are more inclined to respond to ETS firms' green innovations. Panel C presents the results of non-ETS firms with different levels of tangible assets in response to the peer effects of green innovations. Our results show that the peer effects of green innovations are more pronounced among non-ETS firms with more tangible assets. Overall, we find that larger, older, and more tangible assets non-ETS firms are more likely to respond actively to ETS firms' green innovations. According to Cleary (1999), we examine the difference in the coefficient estimate for the peer effects of green innovations between subsamples. Thus, we employ Fisher's permutation tests and bootstrap 1,000 times to compute the empirical p-value to calculate the significance of subsample analyses. Table A1 in the Appendix provides the variable definitions. The t-statistics are reported in parentheses. The standard errors are clustered by industry. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Figure A1: The unmatched and matched results of PSM



Note: This figure plots the differences between the standardized biases of key covariates before and after implementing PSM. This shows that the standardized biases of covariates are significantly reduced after conducting PSM, and these matched results are all centred around zero value of standardized bias.