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Essays on Environmental Regulation, Green Finance, and Government Guarantees in China's Green Transition

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Abstract

This thesis examines the joint effects of market mechanisms, arising from the interaction between finance and technology, and government interventions, including green finance policies, environmental regulations, and government guarantees, on corporate environmental governance and financial stability, thereby supporting green transition and long-term economic growth in China. The key research questions are: (1) how do financial development (FD) and technological innovation (TI) co-evolve to influence corporate greenwashing? (2) How do green finance policies affect firms' stability through green innovation efficiency? (3) How do stringent environmental regulations reshape corporate green innovation? and (4) under what conditions do government guarantees complement or undermine these market- and state-led mechanisms, particularly across heterogeneous firms?

Using data on Chinese listed firms and provinces, this thesis employs logistic co-evolution and coupling coordination modelling, single-period and staggered difference-in-differences (DID), propensity score matching (PSM), and two-stage stochastic frontier analysis (SFA). These approaches capture co-evolutionary dynamics between FD and TI, regional degrees of coupling coordination between FD and TI, and disaggregated corporate green innovation efficiency at both R&D and commercialisation stages, while ensuring robust identification of how market and government governance shapes corporate environmental performance.

Chapter 1 examines the co-evolution of FD and TI and evaluates how their coupling coordination affects corporate greenwashing. It identifies that FD and TI in China co-evolve in an asymmetric, mutually beneficial pattern, producing a coupling coordination relationship with significant positive spatial autocorrelation across provinces. Higher FD-TI coupling coordination reduces corporate greenwashing, with government guarantees strengthening this market discipline in non-state-owned enterprises (non-SOEs) but weakening it in state-owned enterprises (SOEs). This work contributes to the literature on institutional complementarity and corporate environmental misconduct.

Chapter 2 evaluates the Green Finance Reform and Innovation Pilot Zone (GFRIPZ) policy as a quasi-natural experiment. The policy significantly reduces firms' stock price crash risk by enhancing green innovation efficiency, particularly at the commercialisation stage. However, excessive government guarantees weaken this risk-mitigating effect, particularly among high-tech certified firms. This chapter advances research on green finance and financial stability by highlighting the role of green innovation efficiency and government guarantees which act as government contingent liabilities.

Chapter 3 examines the Environmental Fee-to-Tax Reform (EFTR) as a case of stringent environmental regulation. The EFTR increases the quantity but reduces the quality of green innovation, reflecting both compensation and crowding-out effects. Government guarantees exacerbate quality losses in SOEs but alleviate them in non-SOEs. High-tech certified firms benefit more from government guarantees in offsetting the EFTR's adverse impact on green innovation quality than non-high-tech firms. This study contributes to environmental economics and corporate governance by revealing the trade-offs between green innovation quality and quantity under stringent regulation.

Overall, this thesis highlights the complementarities and boundaries of institutional arrangements in shaping corporate environmental strategies. It contributes to sustainable finance, corporate governance, and environmental economics by offering insights into coordinated governance frameworks that align regulatory objectives, market incentives, and government support. The findings provide valuable implications for policymakers, managers, and financial institutions in advancing green transitions that are both environmentally effective and economically sustainable.

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List of Abbreviations

FD..... Financial Development
TI..... Technological Innovation
FD-TI.....Financial development and technological innovation
CCD.....Coupling Coordination Degrees
CGG.....Corporate Government Guarantees
IMF.....International Monetary Fund
CCA..... Contingent Claims Analysis
CELMA.....China Electronic Local Government Bond Market Access
SOE..... State owned Enterprises
CSMAR.....China Stock Market and Accounting Research database
DID.....Difference in Differences
GFRIPZ.....Green Finance Reform and Innovation Pilot Zone policy
SFA.....Stochastic Frontier Analysis
R&D.....Research and development
PSM..... Propensity Score Matching
DDD.....Difference in Differences in Differences
GIE.....Green Innovation Efficiency
CNRDS.....Chinese Research Data Services Platform
EFTR.....Environmental Fee-to-Tax Reform policy
CNIPA.....China National Intellectual Property Administration
WIPO.....World Intellectual Property Organisation

Introduction

Research background

Over the past several decades, the significant economic growth in China has been accompanied by intensive resource consumption and high levels of pollutant emissions, resulting in severe environmental degradation. Addressing the paradox between sustaining long-term economic development and protecting the environment has therefore become a central priority of national policy in China. Promoting environmentally responsible production at the firm level has been identified as a crucial pathway to balancing these competing objectives. In response, the Chinese government has introduced a comprehensive set of governance tools aimed at internalising the externalities of environmental protection, fostering corporate green transformation, while maintaining financial stability alongside economic growth. Four thematic pillars, grouped into two broad dimensions, namely state-led interventions and market-based mechanisms, stand at the core of this process and form the foundation of this thesis.

Within the dimension of state-led interventions, there are three critical thematic pillars. First, stringent environmental regulations, such as taxation instruments, impose direct constraints on corporate polluting behaviours. Second, green finance policies directly link firms' accessibility to external funding with their environmental performance, thereby aligning financing incentives with sustainability objectives. Finally, government guarantees act as government contingent liabilities that can release financing constraints for firms during the green transformation, but may also create risks of moral hazard and adverse selection. Within the dimension of the market-based mechanisms, cross-sector initiatives that go hand in hand play a crucial role in supporting government efforts. By fostering industrial complementarities, particularly between financial development and technological innovation, these initiatives enhance state-led efforts in promoting firms' capacity and motivation to address environmental challenges through green innovation and efficient resource allocation.

Although each of these mechanisms has been widely examined in isolation, relatively little is understood about how they interact across different institutional and policy settings, how their combined effects reshape firms' environmental strategies while ensuring long-term stability, and under what conditions these governance mechanisms from both market and government interventions complement or undermine one another.

Research motivation

Accordingly, this thesis examines how these market mechanisms and government interventions jointly influence corporate environmental governance and green outcomes, while safeguarding corporate financial stability and supporting long-term economic growth during China's green transition. A unifying theme across all three main chapters is the role of government guarantees as a double-edged instrument. On the one hand, guarantees may complement market discipline and stringent environmental regulations by alleviating corporate financing constraints and signalling government endorsements. On the other hand, they may weaken the regulatory effectiveness of both market-led and state-led governance by providing firms with a financial cushion, which reduces the cost of non-compliance and encourages risk-taking, thereby increasing financial risks. Moreover, given the distinctive corporate attributes in China, most notably state ownership and high-tech certification, which grant certain firms preferential access to government resources, the role of government guarantees in promoting corporate green transformations is likely to vary across firm types.

Based on this, the thesis follows a deliberate progression: it begins by analysing broad institutional dynamics within market and government, moves to examine the effectiveness of targeted market-oriented interventions, and finally considers stringent environmental regulations in shaping sustainable development.

Research Contributions

This research is motivated by a growing body of literature that examines the dynamic interactions and interdependence across sectors and industries (e.g., Jiang et al., 2018; Wang and Tan, 2021; Zhou et al., 2022), standalone effects of government-led instruments such as green finance (e.g., Irfan et al., 2022; Lee and Lee, 2022) and environmental regulations (e.g., Hu et al., 2023), and the role of market forces in shaping corporate environmental responses and financial performances (e.g., Jia et al., 2024; Deng et al., 2025; Dogah et al., 2025). Previous studies also highlight firms' heterogeneous responses contingent on ownership and technological attributes (e.g., Geng and Pan, 2024). The main contribution of this thesis is primarily built on three types of limitations of existing literature, both from theoretical and practical perspectives.

First, from a theoretical perspective, existing studies primarily focus on the consequences of either market mechanism or state interventions in isolation on environmental outcomes (e.g., Liu and Wang, 2023; Li et al., 2025a). This thesis contributes by extending theories of institutional complementarity and substitution by demonstrating how market mechanisms and state interventions jointly influence corporate environmental and financial outcomes, and the

boundary conditions under which they complement or substitute each other. Specifically, it provides new evidence on their combined effects on corporate greenwashing, stock price crash risk, and the quantity and quality of green innovation.

Second, from a methodology perspective, this thesis applies and develops a diverse set of empirical strategies using an interdisciplinary approach. Prior research has typically examined the impact of financial development (FD) and technological innovation (TI) on each other, but few have explored their co-evolutionary dynamics by drawing on symbiotic theory from biology and coupling theory from physics. This thesis also introduces measures of the specific degrees of the coupling coordination between FD and TI to capture the magnitude of the resulting market forces and links them to corporate environmental governance from the perspective of sustainable strategy and stakeholder theory.

Third, from an empirical perspective, this thesis builds on conventional proxies of green outcomes. A two-stage stochastic frontier analysis (SFA) is employed to measure firm-level green innovation efficiency, distinguishing between the R&D and commercialisation stages across industries. Moreover, it includes disaggregated indicators of green innovation quantity and quality, enabling a deeper understanding of how policies and market forces differentially affect corporate green outcomes. This approach improves upon existing studies that rely only on quantity-based proxies (e.g., Du et al., 2021), or focus only on regional-level efficiency (e.g., Zeng et al., 2021). Furthermore, this thesis contributes by constructing continuous firm-level measures of government guarantees as government contingent liabilities, rather than the binary indicators commonly used in prior research (Hao et al., 2025a), or only theoretical discussions (e.g., Jin et al., 2022; Zolfagharinia et al., 2023). This enables an analysis of how varying levels of government guarantees interact with market-based and regulatory mechanisms, and how these effects differ across firms with different characteristics.

Research objectives and frameworks

The central objective of this thesis is to investigate how government guarantees, together with the cross-sectoral interaction and co-evolution between finance and technology, influence the effectiveness of environmental regulation and green finance in shaping corporate environmental strategies, innovation capacity, and financial risk during China's green transition. By sequencing the research across three chapters, the thesis not only examines each policy domain individually but also identifies underlying mechanisms of institutional complementarity and the boundary conditions under which market and state governance mechanisms interact effectively.

The analytical framework integrates four layers: (1) market mechanisms, namely the co-evolution of financial development (FD) and technological innovation (TI), and their resulting coupling coordination relationship at the provincial level in China; (2) market-government combined mechanisms, including green finance policy and environmental regulations; (3) state interventions in the form of government guarantees as complementary or substitutive governance tools; (4) Firm heterogeneity in terms of the differences in responses arising from ownership structure and technological intensity. The research framework, objectives, and specific focus of each chapter are structured as follows.

The first chapter examines the macro-institutional relationship between FD and TI by empirically testing their co-evolution in China using a period-superimposed logistic co-evolution model, and by measuring the degree of coupling coordination between them at the regional level. Based on this, it evaluates whether this market force shaped by FD-TI coupling coordination effectively mitigates corporate greenwashing, and investigates how government guarantees interact with this market force, with moderating effects of government guarantees differing between state-owned and non-state-owned enterprises.

The second chapter evaluates the effectiveness of market-oriented regulatory tools in promoting green transformation while ensuring corporate stability. Using the Green Finance Reform and Innovation Pilot Zone (GFRIPZ) policy, implemented in two batches in 2017 and 2019, as a quasi-natural experiment, it applies a staggered difference-in-differences model to assess whether the policy effectively reduces corporate stock price crash risk. It further examines the moderating role of government guarantees, with a particular focus on heterogeneity in terms of high-tech certification. Based on this, it highlights the underlying mechanism role of two-stage corporate green innovation efficiency, including the R&D and the commercialisation stages.

Finally, the third chapter investigates the impact of stringent government-led environmental regulations by analysing the Environmental Fee-to-Tax Reform (EFTR), implemented in 2017. It assesses dual effects of the policy, including both “crowding-out” and “compensation” effects, by distinguishing between the quantity and quality of green innovation using difference-in-differences models. It then examines the moderating role of government guarantees in mitigating the EFTR’s adverse effect on corporate green innovation quality, and explores heterogeneous impacts by ownership types and high-tech certification status.

Research implications

This thesis demonstrates that the effectiveness of government-led environmental regulatory tools, whether in the form of green finance policies or environmental taxation, cannot be fully

understood without considering their interaction with ongoing cross-sector dynamics, state-led interventions such as government guarantees, and firm-level heterogeneity in ownership and technological attributes. By integrating market- and state-based perspectives, the research contributes to debates in sustainable finance, corporate governance, and environmental economics, offering a more comprehensive view of institutional design for green transitions in China and other emerging economies.

For policymakers, the findings highlight the importance of coordinated governance frameworks that align market incentives with regulatory objectives while carefully calibrating the allocation of government guarantees. Guarantee allocations need to avoid diluting the effectiveness of green finance policies, prevent further quality loss in green innovation under stringent environmental regulations, and instead avoid greenwashing under FD-TI coupling coordination. Tailoring policy design to ownership structures and technological capabilities ensures that regulatory instruments are both environmentally effective and economically sustainable.

CHAPTER ONE

How do Financial Development and Technological Innovation co-evolve to Mitigate Corporate Greenwashing? The Role of Government Guarantees

Abstract

China's rapid economic growth has caused substantial environmental pollution, prompting stringent environmental regulations that have led many companies to adopt greenwashing strategies to appear environmentally responsible. Simultaneously, the market-driven forces, particularly the integration of financial development (FD) and technological innovation (TI), are reshaping corporate environmental incentives. This chapter examines the co-evolution of FD and TI in China, focusing on their coordination degree (CCD) and its impact on corporate greenwashing. It further explores the role of government guarantees and ownership structure. We find that FD and TI in China co-evolve in an asymmetric, mutually beneficial pattern. Provincial CCD exhibits significant positive spatial autocorrelation and spillovers from coastal to inland provinces. Higher CCD significantly reduces greenwashing, with government guarantees complementing this market discipline, though the effect varies by firm ownership structure. Guarantees weaken CCD's impact in state-owned enterprises (SOEs) but enhance it in non-SOEs. These findings highlight the complementary effects and boundaries of market and state governance in shaping corporate environmental strategy, offering policy insights for China and other emerging countries.

Keywords

Financial Development; Technological Innovation; Co-evolution; Coupling Coordination; Greenwashing; Government Guarantees.

1.1. Introduction

Global consensus holds that economic growth must be pursued within the boundaries of environmental sustainability. While China has achieved remarkable economic growth in recent decades, this progress has come at the expense of environmental degradation driven by intensive resource consumption and emissions. In response, the government has established comprehensive policy frameworks, including cross-sector initiatives that go hand in hand, aimed at fostering institutional complementarities, especially between the two pillar industries of finance and technology, to address environmental challenges (Mazzucato, 2013). Technological innovation has become increasingly important for enhancing green productivity (Wang and Tan, 2021), while the financial sector remains key to optimising resource allocation and directing capital towards sustainable activities in line with stakeholder expectations.

Technological innovation relies heavily on continuous external financing and has significantly reshaped financial service models, improving the efficiency and diversity of financial products. Schumpeterian models highlight the dynamic interplay between finance and technological innovation, demonstrating that regions with more advanced financial systems typically exhibit stronger technological progress, and vice versa (Meierrieks, 2014). In China, initiatives such as the *Pilot Policy Promoting the Integration of Technology and Finance* implemented in batches in 2011 and 2016, and the *Establishing Pilot Zones for Green Finance Reform and Innovations programme* implemented in batches in 2017 and 2019, demonstrate a continued commitment to promote sustainability by coordinated growth between financial industry and technological innovation (e.g., Lee and Lee, 2022; Xu et al., 2023; Li et al., 2025a). These policies reflect deliberate attempts to align market-based mechanisms with regulatory frameworks, enhancing institutional complementarities that can shape corporate environmental strategies.

The integration of financial development (FD) and technological innovation (TI) in China has accelerated, exhibiting increasingly pronounced co-evolutionary characteristics. This is evident not only from recent policy initiatives but also from how their development trajectories influenced one another. FD and TI exhibit synchronised cycles of expansion and contraction. TI often follows a like-saw trajectory, characterised by experiencing repeated

transitions between exploratory Innovation and exploitative innovation, which are significantly positively correlated with the efficiency of financial resource allocation (Juliao-Rossi et al., 2020). A coupling coordination relationship appears to have emerged between FD and TI (Hendrikse et al., 2020). Coupling coordination refers to a dynamic equilibrium in which the two systems evolve interactively and mutually reinforce one another, creating optimal institutional synergies that enhance firms' access to resources, reduce information asymmetry, and ultimately influence corporate strategic choices (Jiang et al., 2018), including environmental commitment or greenwashing behaviour. While many studies have discussed the individual impact of FD and TI on regional development, or their impacts on each other, few have explored their co-evolutionary dynamics from the perspective of sustainable strategy or stakeholder theory or the implications of the resulting coupling coordination between them for corporate environmental governance.

Moreover, with government intervention through stringent regulations aimed at internalising environmental externalities, firms are facing rising environmental compliance costs. Corporate environmental commitments are often shaped by strategic incentives of enhancing reputation and meeting stakeholder expectations for financing and profitability. In this context, many firms engage in greenwashing, exaggerating their sustainable efforts at low cost, without delivering substantial environmental improvements. Such behaviour is facilitated by information asymmetry and misaligned incentives, often reinforced by political factors (Coen et al., 2022; Khan et al., 2024), raising growing concerns over the credibility of corporate sustainability claims. The role of market-driven institutional arrangements, such as FD-TI coupling coordination, as a disciplining mechanism for greenwashing remains underexplored, representing a key gap this study addresses.

Consequently, in the context of government-led efforts to promote interactions between FD and TI for sustainable development, examining their co-evolutionary dynamics and the resulting coupling coordination in China offers valuable insights into the effectiveness of these policies. Building on this, exploring how such dynamic interaction influences corporate green behaviours can help evaluate whether the current institutional design in China effectively supports green transformation. In parallel, government guarantees have been introduced as a complementary tool to alleviate firms' financial constraints in green-oriented

production activities. It is therefore essential to explore how government guarantees interact with the FD-TI coupling coordination in shaping corporate green strategies. This allows for examining the institutional complexity, namely how market forces and government intervention interact, thus extending our understanding of the complementarity between market-driven and state-driven governance. However, government guarantees may act differently across ownership structures, as state-owned enterprises (SOEs) and non-SOEs in China have long experienced distinct access to government resources (Geng and Pan, 2024). Understanding these ownership-contingent effects can further clarify the moderating role of government guarantees.

This chapter contributes to the ongoing debate on the integration of the financial industry with technological advancement and its implications for firm-level green performance, with particular attention to the role of government guarantees in four key aspects: (1) using a period-superimposed logistic co-evolution model and drawing on symbiotic theory from biology, we examine the co-evolutionary relationship between FD and TI, providing more precise evidence of coupling coordination between them; (2) we measure the provincial coupling coordination degree of FD and TI (CCD) in China from 2012 to 2020 using a coupling coordination model from physics, and apply global and local spatial autocorrelation analyses to reveal its temporal and spatial characteristics; (3) we assess the impact of this FD-TI coupling coordination on corporate greenwashing using fixed-effects OLS regressions with a series of robustness checks; and (4) we construct a continuous firm-level measure of government guarantees for A-share listed firms in China from 2012 to 2020, enabling explorations of how varying levels of government guarantees moderate the effect of this FD-TI coupling coordination on corporate greenwashing, thereby identifying the complementarity or substitution effects between market and state governance mechanisms. Additionally, we analyse its different roles in SOEs and non-SOEs. To our knowledge, the co-evolution and coupling coordination of FD and TI remains underexplored, and few have measured government guarantees as a form of government contingent liability at the firm level or explored their interactive effect with the FD-TI coupling coordination, which influences corporate greenwashing.

This chapter is structured as follows. Section 1.1 presents the research background, objectives and main contributions. Section 1.2 reviews the key insights from the relevant literature and develops research hypotheses accordingly. Section 1.3 describes the data and model specifications. Section 1.4 reports the empirical results and their interpretation. Section 1.5 concludes the chapter and provides policy recommendations.

1.2. Literature Review and Hypotheses Development

1.2.1. The Co-evolution and Coupling Coordination of FD and TI

Extensive research has confirmed the bidirectional interaction between financial development (FD) and technological innovation (TI), which forms the basis of their long-term co-evolution. FD consistently supports the transformation of TI into commercial outcomes, thereby increasing firms' profitability, improving credit ratings, and attracting additional financial resources. In turn, the commercialisation of TI enhances the stability and resilience of the financial system by improving the quality and diversifying the structure of financial products and services. This reciprocal relationship promotes the iterative optimisation of the financial and innovation systems over time.

Specifically, a dynamic bidirectional feedback mechanism between FD and TI demonstrates their self-reinforcing co-evolution, with financial systems both enabling and being transformed by technological innovation. On the one hand, TI projects, particularly in their early R&D stages, require substantial external financing despite uncertain returns. A well-functioning financial system thus provides the essential resource base for their success (Amore et al., 2013). Mature financial markets, characterised by competitive banking institutions (Spatareanu et al., 2019; Giebel and Kraft, 2020), stock market liberalisation (Brown et al., 2013; Moshirian et al., 2021), and greater risk appetite of venture capital and private equity sectors (Gu and Qian, 2019), help reduce information asymmetries, enabling risk sharing and alleviating financing constraints for TI-driven projects. Consequently, FD can shape the pace and trajectory of TI in terms of quality, peer influence and marketability. On the other hand, TI also feeds back into the financial system by reshaping product structure, enhancing efficiency, and expanding service scope (Umar et al., 2021). The Fourth Industrial

Revolution has transformed financial services through TI, such as artificial intelligence, bio-technology, blockchain, digital platforms, Insurtech and Robo-advising (Chen et al., 2019; D'Acunto et al., 2019; Thakor, 2020). Despite short-term profitability pressures on traditional financial institutions when conducting TI transformation (Buchak et al., 2018), these TI applications have reduced service and compliance costs, improved risk management, increased refinancing efficiency (Fuster et al., 2019), and diversified financial instruments, thereby strengthening the overall resilience and long-term profitability of the financial sector.

Moreover, China's institutional environment and targeted policy interventions have further strengthened the co-evolutionary relationship between FD and TI, creating a solid foundation for the coupling coordination mechanism. The government has established a multi-dimensional policy framework strategically integrating technological advancement with financial resource allocation. For instance, the Pilot Policy Promoting the Integration of Technology and Finance, implemented in batches in 2011 and 2016, aims to enhance resource allocation efficiency and reduce structural frictions between FD and TI (Huang et al., 2025). Similarly, the Establishing Pilot Zones for Green Finance Reform and Innovations programme, implemented in batches in 2017 and 2019, directs financing resources toward green technological innovation projects (Ge et al., 2023). These initiatives reflect an institutional design in which FD and TI are embedded within an integrated framework, fostering mutually reinforcing rather than independent development.

The significant interdependence between FD and TI, together with their dynamic interaction in their co-evolution processes, suggests an objective progression towards a coupling coordination development pattern. Originating in physics, the concept of "coupling" refers to the mutual interaction between circuits in terms of energy input and output. In the context of industrial systems, it has been increasingly applied to describe the dynamic interplay between sectors that are interconnected through resource flows and embedded within the same institutional or environmental framework (e.g., Xing et al., 2019; Tan et al., 2022). A higher level of coordination state indicates that industries evolve in a balanced, mutually supportive pattern rather than in conflict or misalignment, reflecting the extent to which their development trajectories are synchronised (Yin and Xu, 2022). Accordingly, the degree of

coupling coordination between FD and TI provides a meaningful measure of their structural interdependence and dynamic balance.

Historical and empirical evidence show that FD and TI follow synchronised trajectories and share structural interdependence, reinforcing the emergence of coupling coordination between them. Boom-and-bust cycles in FD and TI often occur in tandem, while historical observations indicate that successive technological revolutions have been accompanied by expansions in financial capital, reflecting a structurally interdependent relationship (Perez, 2002). This is consistent with the theoretical essence of coupling coordination, which emphasises a reciprocal, dynamic interaction in which both sectors rely on and complement each other, rather than a one-way influence. In China's institutional and policy context, FD and TI have progressively co-evolved, forming a coupling coordination relationship in which the two systems remain distinct in function yet interdependent and mutually reinforcing within a specific temporal and spatial framework.

Consequently, we can develop the first hypothesis as follows:

H1: Financial development (FD) and technological innovation (TI) in China are not entirely independent but co-evolve, with a coupling coordination relationship gradually taking shape between them.

1.2.2. The Impact of the Coupling Coordination between FD and TI on Corporate Greenwashing

Firms face growing institutional and market pressure to pursue green transformation, driven by rising environmental awareness among customers, investors, and governments. In stakeholders' evaluations, corporate environmental performance is increasingly prioritised over profitability metrics (Kyaw et al., 2022). In China, stringent environmental regulations have intensified these pressures, prompting firms to disclose more environmental information to signal compliance with policy mandates and alignment with external expectations.

Genuine green transformation is primarily driven by clean-oriented technological innovation, which requires substantial capital investment, long development cycles, and high risk tolerance (Du et al., 2021). Although such innovation offers significant long-term profitability

(Darendeli et al., 2022), firms often face short-term performance pressures. Moreover, ESG-related information frequently lacks robust auditing and consistent verification mechanisms, exacerbating information asymmetry and creating spaces for opportunistic behaviour. Consequently, some firms, despite undertaking certain environmental efforts, engage in greenwashing by deliberately overstating their environmental achievements to construct a greener image without substantive improvements (Walker and Wan, 2012; Yu et al., 2020), a practice of growing concern to both academics and regulators. FD-TI coupling coordination fosters the renewal of corporate strategies toward substantive green transformation by shaping dynamic market conditions. In regions with a higher degree of coupling coordination between FD and TI, industrial boundaries are often reconfigured through continuous structural adjustments, generating market turbulence. While typically perceived as a source of instability, such turbulence can prompt firms to reassess and optimise strategic orientations (Hu et al., 2021). In this environment, firms are more incentivised to adopt innovation-driven strategies aligned with long-term sustainability objectives, generating both environmental value and financial benefits (Qiu et al., 2020). Therefore, the FD-TI coupling coordination reduces corporate reliance on greenwashing.

Specifically, first, higher FD-TI coupling coordination enhances financial institutions' ability to assess the actual value of green innovation projects, thereby easing financing constraints and lowering borrowing costs for genuinely green firms while discouraging symbolic compliance (Bai et al., 2024). Under stringent environmental regulations, environmental performance has become a key criterion for financing approval. Many firms, however, face resource shortages, which are the key driver of greenwashing (O'Reilly et al., 2024). Severe information asymmetries hinder accurate evaluation of these environmental commitments by financial institutions; however, the integration of FD and TI has facilitated financial innovations, such as digital finance, which improve the efficiency and accuracy of information exchange between lenders and borrowers (Ji et al., 2022). This enables financial institutions to differentiate firms engaging in symbolic disclosure from those undertaking genuinely impactful green innovations, thereby directing capital toward firms with stronger tendencies to improve their social and environmental performance and reducing firms' reliance on greenwashing (Cheng et al., 2014).

Second, FD-TI coupling coordination reduces greenwashing by constraining managerial short-termism and incorporating substantive green transformation outcomes into financing criteria. Greenwashing often arises from managerial myopia, where executives prioritise short-term profits over long-term sustainability (Zhao and Wang, 2025). FD-TI coupling coordination mitigates this bias by reshaping the institutional logic of capital allocation. In China, green finance policies increasingly integrate measurable environmental performance indicators, such as the quantity and quality of green patents, into lending and investment decisions. The enforcement of these policies varies regionally and is closely aligned with local industrial advancement and integration (Irfan et al., 2022), particularly between core sectors such as finance and innovation. In regions with higher FD-TI coupling coordination, reinforced by rigorous green financial regulations and specialised instruments, capital allocation is contingent on verifiable environmental outcomes rather than symbolic disclosures. This institutional framework imposes short-term profitability pressures on firms (Dogah et al., 2025), which can be alleviated by reorienting towards sustained green innovation to credibly signal environmental performance (Deng et al., 2025). In doing so, FD-TI coupling coordination constrains managerial tendencies toward symbolic compliance and reduces greenwashing.

Third, stronger FD-TI coupling coordination strengthens external governance mechanisms, such as audit quality, credit rating efficiency, and consumer oversight, which collectively constrain the space for greenwashing. High information asymmetry hinders stakeholders' ability to detect greenwashing (Li et al., 2023b), which can be substantially mitigated through technological applications, such as blockchain, in financing and marketing contexts. These technologies provide stakeholders with reliable, transparent, traceable, and tamperproof information (Nygaard and Silkoset, 2023), thereby improving auditing and credit evaluation and constraining managerial opportunism (Lobo et al., 2018). This increases the difficulty of engaging in deceptive practices like greenwashing, incentivising managers to adopt substantive, environmentally responsible strategies to credibly signal their environmental and social capabilities (Yousaf et al., 2024).

Finally, reducing financial mismatches through stronger FD-TI coupling coordination enhances the stability of returns from genuine green initiatives, thereby weakening firms'

incentives to engage in greenwashing. Financial mismatches arise when the efficiency of financial resource allocation deteriorates and the flow of production factors is impeded, leading to a significant decline in regional green total factor energy efficiency (Li et al., 2022). Strong FD-TI coupling coordination fosters closer communication between the financial and technological sectors, enabling local markets to better evaluate the intrinsic values of firms' green achievements and develop more effective channels for their commercialisation (Song and Du, 2024). As a result, greenwashing, once a "low-cost alternative" for signalling environmental responsibility, has become less attractive than the sustained profitability from substantive green practices.

Collectively, these discussions lead to the following hypothesis:

H2: A higher degree of coupling coordination between financial development (FD) and technological innovation (TI) significantly reduces corporate greenwashing behaviour.

1.2.3. The Moderating Role of Government Guarantees

Despite their significant social and economic value, many projects, particularly those involving technological innovations, face severe resource shortages due to substantial capital requirements and high risk profiles. As a complementary form of public intervention, government guarantees have become an important tool for alleviating such financing constraints (Kuo et al., 2011). These guarantees typically take the form of loan guarantee schemes, guarantee fee reductions, and credit interest subsidies. Loan guarantee schemes can be classified into direct and indirect types. In direct schemes, the government shares credit risk directly with banks by reimbursing a portion of unrecovered loans in the event of loan default (Bachas et al., 2021). Indirect schemes operate through counter-guarantees and co-guarantees, whereby third-party guarantors assume the initial risk and the government commits to covering part of the bank's losses if the guarantor defaults. Collectively, these measures aim to bridge the risk gap between firms and financial institutions, thereby alleviating financing constraints for firms undertaking substantive green transformation under increasingly stringent environmental compliance requirements. Given the deepening interaction between FD and TI across regions, government guarantees can reinforce the

market-driven effects of FD-TI coupling coordination, further constraining corporate greenwashing.

Specifically, government guarantees strengthen the mitigating effect of FD-TI coupling coordination on greenwashing by expanding firms' access to green finance through risk sharing and reduced financing costs. In regions with higher FD-TI coupling coordination, financial institutions have stronger screening and monitoring capabilities due to greater information transparency regarding the technological attributes and environmental outcomes of green projects. Firms with well-commercialised green projects are more likely to obtain financing on favourable terms, as demonstrable environmental benefits prompt investors to accept lower financial returns in exchange for sustainable outcomes (Dorfleitner et al., 2022). However, this market-based selection process may systematically exclude firms with strong long-term green potential but low current profitability. Introducing government guarantees in this context operates as a complementary institutional mechanism that reduces downside risks for both firms and financial institutions (Jin et al., 2022). By providing credit enhancement and risk-sharing, these guarantees increase lenders' willingness to finance previously excluded but environmentally promising firms, while also encouraging firms to seek loans to improve their environmental performance (Huang et al., 2019). This dual mechanism, combining the market-based selection generated by FD-TI coupling coordination with targeted institutional support through government guarantees, significantly alleviates the financing constraints of green projects and, in turn, reduces firms' reliance on greenwashing.

Moreover, government guarantees function as implicit state endorsements, reducing firms' risk aversion and enhancing their willingness to undertake genuine green transformations. Under increasingly stringent environmental regulations, some firms may otherwise adopt greenwashing as a cost-saving means of meeting environmental compliance requirements with minimal substantive effort. Government guarantees, however, provide a financial "safety cushion" by mitigating the downside risks associated with capital-intensive and high-risk green projects, ultimately supporting improved financial performance (Hu et al., 2021). This risk-sharing mechanism incentivises substantive engagement in environmentally beneficial projects, thereby increasing the likelihood that firms meet the eligibility criteria for green finance through substantive transformation rather than symbolic practices. As a result, the

effectiveness of regional FD-TI coupling coordination in reducing symbolic or deceptive environmental claims is enhanced under the reduced financial risk exposure afforded by government guarantees.

Finally, when government guarantees are contingent on firms' verifiable environmental performance, they operate as an effective external governance mechanism that supervises and promotes substantive green practices, thereby reinforcing the disciplining effect of FD-TI coupling coordination in reducing greenwashing. In practice, governments allocate guarantee endorsements by evaluating firms' comprehensive development capabilities within a transparent information environment, in which green-oriented productivity is a key evaluation criterion. This supervision function, combined with credit rating from financing institutions, ensures that only firms demonstrating substantive environmental achievements receive continued financial support from both financial markets and government programmes (Gidage and Bhide, 2025). Conversely, firms relying on opportunistic or deceptive environmental disclosures are penalised through credit rationing and restricted access to government guarantees. This supervisory effect is particularly pronounced in regions with stronger FD-TI coupling coordination, where enhanced information transparency and inter-institutional monitoring capacity improve detection of inconsistencies between disclosed and actual practices. For firms with a history of greenwashing, such misalignments expose them to substantial reputational and financial risks. To mitigate these risks and secure future access to guarantees, firms are incentivised to prioritise substantive green transformation, ensuring compliance with government supervision and maintaining social legitimacy (Lu et al., 2025). Consequently, this institutional arrangement establishes a clear incentive structure that rewards genuine environmental engagement while mitigating symbolic or fraudulent behaviour.

Consequently, the following hypothesis is proposed:

H3: A higher level of government guarantees allocated to firms significantly strengthens the mitigating effect of the coupling coordination between FD and TI on corporate greenwashing.

1.2.4. The Interactive Moderating role of Government Guarantees and Corporate Ownership Structure

Compared with most Western economies, China is characterised by stronger political intervention in the allocation of government resources due to its unique institutional environment. Firms in China can be broadly categorised by ownership structure into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs), which differ substantially in their access to economic, social and political resources (Geng and Pan, 2024). SOEs, characterised by their close political ties, consistently enjoy privileged access to external information and government-backed support, including government guarantees (Armanios et al., 2017). Such preferential treatment often weakens their sensitivity to external governance mechanisms, including financial discipline and market-based innovation incentives intended to promote sustainable development. In some cases, it may even allow SOEs to circumvent environmental supervision from regulators (Deng et al., 2020), thereby reducing their incentive to undertake risky initiatives such as green transformations. By contrast, non-SOEs are generally more responsive to external governance pressures. Constrained by limited resources and lacking institutional privileges, they depend more heavily on policy signals, credible performance records and government endorsements to secure financing and build reputational capital. Consequently, the moderating role of government guarantees in the relationship between FD-TI coupling coordination and corporate greenwashing is expected to vary by ownership type, weakening the mitigating effect in SOEs while strengthening it in non-SOEs.

Differences in resource utilisation efficiency further lead to distinct responses of SOEs and non-SOEs to government guarantees in the context of increasing marketisation fostered by FD-TI coupling coordination. Executives in SOEs, often appointed through political channels, tend to operate within less flexible and more hierarchical organisational structures, resulting in lower efficiency in resource allocation and utilisation (Genin et al., 2021). In contrast, non-SOEs typically encourage knowledge sharing and cross-departmental collaboration, directly enhancing their organisational intellectual capital accumulation and strengthening operational monitoring, which ultimately translates into superior resource utilisation efficiency (Ren et al., 2022). Regions with lower political interference generally exhibit more balanced

development (Li and Zhang, 2010), aligning closely with the objectives of FD-TI coupling coordination. However, this coordination can be distorted when government guarantees are disproportionately allocated to politically connected SOEs, particularly when these enterprises demonstrate weaker resource utilisation capabilities than non-SOEs. In such cases, government guarantees may become idle resources diverted towards managerial interests, such as political advancement or promotional green advertising, rather than being deployed for substantive environmental efforts. In contrast, in non-SOEs, government guarantees are more likely to function as intended, facilitating genuine green transformation by improving access to both financial and reputational capital. This alignment between resource efficiency, institutional incentives, and market discipline reinforces the effectiveness of FD-TI coupling coordination in mitigating greenwashing within non-SOEs.

Finally, preferential access to government guarantees may also generate adverse selection among SOEs (Cowan et al., 2015), fostering symbolic compliance driven by risk aversion and undermining the disciplining role of FD-TI coupling coordination. SOEs with weak green performance but strong administrative affiliations often maintain privileged access to government resources, insulating them from the financing constraints under green financial policies and shielding them from reputational penalties. This weakened the link between financial accessibility and actual green performance in SOEs (Wei et al., 2023b). In contrast, non-SOEs operate under stronger external governance pressures and must enhance substantive green performance to meet market and policy expectations with the aim of securing external financing. The market-driven FD-TI coupling coordination, characterised by improved information flow and performance-based competition, strengthens these accountability mechanisms. With the additional support of government guarantees, non-SOEs are better positioned to obtain financing for genuine green initiatives and credibly demonstrate their green transformations.

Collectively, these arguments lead to the following hypothesis:

H4: The moderating effect of corporate government guarantees on the relationship between FD-TI coupling coordination and corporate greenwashing varies by ownership structure. Government guarantees weaken the mitigating effect of FD-TI coupling

coordination in state-owned enterprises (SOEs) but strengthen it in non-state-owned enterprises (non-SOEs).

1.3. Methods

1.3.1. Sample and Data Collection

This study examines the symbiotic co-evolutionary relationship between financial development (FD) and technological innovation (TI), and measures their coupling coordination degree at the provincial level in China, using a sample of 30 provinces[1] from 2012 to 2020. Provincial-level data were obtained from the National Bureau of Statistics of China, the China Regional Financial Operation Report, the China Electronic Local Government Bond Market Access (CELMA), and the China Statistical Yearbook on Science and Technology.

Based on this, all Chinese A-share listed firms from 2012 to 2020 are selected as the initial sample for analysing the impact of the FD-TI coupling coordination degree on corporate greenwashing, and the moderating role of corporate government guarantees. Firm-level financial data are sourced from the China Stock Market and Accounting Research (CSMAR) database, corporate ESG disclosure data from the Bloomberg ESG database, and ESG rating information from Sino-Securities Index Information Service. To ensure data reliability and consistency, the following screening criteria were applied: (1) excluding firms in the financial sector; (2) excluding firms subject to special treatment (i.e., ST, ST*, or PT[2]) by the China Securities Regulatory Commission; and (3) excluding firms with missing values in key financial variables. The final firm-level sample consists of 6471 firm-year observations from 1203 A-share listed firms in China. All continuous firm-level variables are winsorised at the 1% and 99% quantile levels to mitigate the influence of extreme values.

[1] Hong Kong, Macao, Taiwan, and Tibet are excluded due to substantial missing data.

[2] ST (Special Treatment) refers to firms in abnormal financial situations, including two consecutive years of losses or a net asset value per share below the book value of equity per share. ST* denotes three consecutive years of losses with the risk of delisting. PT (Particular Transfer) refers to companies whose shares are subject to non-standard trading rules, such as being allowed to trade only on Fridays.

1.3.2. Variables and Model Specifications

1.3.2.1. Measurement of Biological Population Density FD and TI in Evolution

This study employs the annual value added of the financial industry and the annual value added of the high-tech industry in each year during 2012 - 2020 as proxies for the biological population density of financial development (Bio_FD) and technological innovation (Bio_TI), respectively, to examine their interactive co-evolutionary relationship. All data are normalised to address the potential estimation bias arising from differences in measurement units and scales.

1.3.2.2. Measurement of the Coupling Coordination Degree between FD and TI

An evaluation index system for financial development (FD) and technological innovation (TI) is constructed to measure their respective comprehensive levels (U_1 and U_2), which serve as the basis for calculating the coupling coordination (CCD) between them at the provincial level. The estimated provincial CCD values are then assigned to firms according to their registered locations, enabling firm-level analysis. Based on covariance theory in physics, 15 representative indicators covering three dimensions are selected to measure U_1 (Svirydzenka, 2016; Wang and Tan, 2021), while 12 indicators across two dimensions are used to measure U_2 (Chen et al., 2018; Haschka and Herwartz, 2020). Detailed definitions for all indicators are provided in **Appendix A1.** To determine indicator weights, the entropy method is applied within each system of FD and TI. This approach derives objective weights from variation in the observed data, thereby reducing potential bias from subjective judgment (e.g., Cui et al., 2019; Tan et al., 2022). In information theory, the entropy of information measures the degree of disorder of the information in a system. Accordingly, indicators with higher variation provide more information and are therefore assigned greater weights.

Formally, two original indicator data matrices for FD and TI are constructed as: $X = \{x_{\alpha kj}\}_{h*l*n_1}$ and $X = \{x_{\alpha kj}\}_{h*l*n_2}$, where $x_{\alpha kj}$ is the observed value of indicator j for province k in the year α. Here, h *(h=9)* denoted the length of the sample years between 2012 and 2020, l *(l=30)* represents the number of provinces, and n_1 ($n_1 = 15$), n_2 ($n_2 = 12$) are the number of indicators for FD and TI, respectively. Accordingly, the degree of variation

between observed values for each indicator can be obtained by calculating the entropy value. Specifically, the lower the entropy value of an indicator, the more information the indicator provides, and thus the greater its assigned weight (Xing et al., 2019). Based on above, the steps for calculating indicator weights in FD and TI systems using the entropy method are as follows:

(1) Data Standardisation Processing and Non-negative Processing.

All observed values for each indicator are standardised using the Min-Max normalisation method and transformed to ensure non-negativity, thereby eliminating differences in measurement scales (e.g., Zameer et al., 2020; Zhou et al., 2022). Given that all indicators in the FD and TI systems are positively oriented, i.e., higher values indicate better performance, the standardisation formula is expressed as:

$$u_{\alpha kj} = \frac{x_{\alpha kj} - min(x_{\alpha kj})}{max(x_{\alpha kj}) - min(x_{\alpha kj})} + 0.0001 \quad (1.1)$$

Where $max(x_{\alpha kj})$ and $min(x_{\alpha kj})$ represent the maximum and minimum values of the indicator j in system FD or TI, calculated over 30 provinces and 9 years, respectively.

(2) Construction of the Proportional Weight Matrix.

The normalised values are used to construct a weighting matrix for each system ($\left(P_{\alpha kj}\right)_{h*l*n}$):

$$\left(P_{\alpha kj}\right)_{h*l*n} = \frac{u_{\alpha kj}}{\sum_{\alpha=1}^{h}\sum_{k=1}^{l} u_{\alpha kj}} \; ; \; n = n_1 \; or \; n_2 \quad (1.2)$$

Where $P_{\alpha kj}$ represents the proportion of indicator j for province k in the year α, and n_1 (n_1=15) , n_2 ($n_2 = 12$) denote the number of indicators for FD and TI, respectively.

(3) Calculation of the Information Entropy value (e_j).

The information entropy of each indicator j is calculated as:

$$e_j = -\delta \sum_{\alpha=1}^{h}\sum_{k=1}^{l} P_{\alpha kj} ln(P_{\alpha kj}),\ \delta = \frac{1}{ln(h*l)} \quad (1.3)$$

where δ is the entropy normalisation constant. A lower e_j implies more variation between observed values and richer information.

(4) Determination of Variation Coefficient and Final Weight for Each Indicator.

The variation coefficient for each indicator j is calculated as $g_j = 1 - e_j$, representing the information contribution of indicator j. Finally, the weight of each indicator j within each system (λ_j)can be obtained using $\lambda_j = \frac{g_j}{\sum_{j=1}^{n} g_j}$, $where\ \sum_{j=1}^{n} \lambda_j = 1, n = n_1\ or\ n_2$.

Finally, the comprehensive level of FD and TI for each provinces and year, denoted as $U_{\alpha ki}$, are calculated using a linear weighting approach: $U_{\alpha ki} = \sum_{j=1}^{n} \lambda_{ij} u_{\alpha kj}$, $\lambda_j \geq 0$, where i represents FD (i=1) and TI (i=2), respectively. Following the original capacity coupling model in physics, the coupling deviation coefficient (C_d) is defined as: $C_d = \frac{S}{\left(\frac{U_1+U_2}{2}\right)} = \sqrt{1 - \frac{U_1 \times U_2}{\left(\frac{U_1+U_2}{2}\right)^2}}$, where $\boldsymbol{S}$ represents the standard deviation between the two systems, and C_d measures their average deviation. A smaller C_d indicates a higher degree of coupling. The minimum value of C_d can be obtained when $\frac{U_1 \times U_2}{\left(\frac{U_1+U_2}{2}\right)^2}$ reaches its maximum. Accordingly, the coupling degree **(CD)** ($CD \in [0, 1]$) between FD and TI is calculated as:

$$CD = \left[\frac{U_1 \times U_2}{\left(\frac{U_1+U_2}{2}\right)^2}\right]^{\frac{1}{2}} \tag{1.4}$$

However, the estimated ***CD*** may appear higher when U_1 and U_2 are both low but similar in value, which contradicts economic reality. To address this limitation, we adopt a coupling coordination degree model defined as:

$$\begin{cases} CCD = \sqrt{CD \times D} \\ D = \alpha \times U_1 + \beta \times U_2 \end{cases} \tag{1.5}$$

where $D \in [0, 1]$) measures the degree of coordination between FD and TI, α and β are weight coefficients. We set $\alpha = \beta = 0.5$ to reflect the equal importance of FD and TI in the socioeconomic development process. The ***CCD*** thus represents the coupling coordination degree of FD and TI.

1.3.2.3. Measurement of Corporate Greenwashing

Greenwashing refers to a corporate strategy whereby firms overstate their environmental efforts by engaging in symbolic communications and disclosing large volumes of ESG-related information with the aim of demonstrating their sustainable corporate images, without making corresponding substantive efforts to improve their actual ESG performance to the disclosed standards (Walker and Wan, 2012). Following the existing studies (e.g., Wang et al., 2024; Long et al., 2025), this study measures the degree of corporate greenwashing (***GW***) as the disparity between a firm's ESG disclosure score relative to its industry peers and its ESG real performance score, also measured by ESG rating score relative to its industry peers. A larger disparity indicates a higher degree of greenwashing. The specific calculation is as follows:

$$GW_{it} = \left[\left(ESG_{dis,it} - \overline{ESG_{dis,it}}\right)/\sigma_{ESG_{dis,it}}\right] - \left[\left(ESG_{rating,it} - \overline{ESG_{rating,it}}\right)/\sigma_{ESG_{rating,it}}\right] \quad (1.6)$$

where GW_{it} denotes the greenwashing level of firm *i* in year *t*. $ESG_{dis,it}$ and $\overline{ESG_{dis,it}}$ represent the ESG disclosure score of firm *i* in year *t* and the mean ESG disclosure score of all firms in the same industry that firm *i* operates, respectively. Similarly, $ESG_{rating,it}$ and $\overline{ESG_{rating,it}}$ denote the ESG rating score of firm *i* in year *t* and the mean ESG rating score of firms in the same industry where the firm operate in, respectively. $\sigma_{ESG_{dis,it}}$ and $\sigma_{ESG_{rating,it}}$ are standard deviations of the ESG disclosure and ESG rating score within the same industry-year, respectively, used to normalise the greenwashing scores and ensure cross-firm comparability.

1.3.2.4. Measurement for Corporate Government Guarantees

Corporate Government Guarantees (**CGG**) are measured as a form of government contingent liability. Following the methodology proposed by the International Monetary Fund (IMF) (IMF, 2009, 2014), and adopting the contingent claims analysis (CCA) framework, we construct a continuous proxy for **CGG**. This proxy is computed as the difference between the expected stock market-based losses of firms in year *t* ($ELV_E(t)$), derived from stock market

data, and the expected debt market-based losses in year t ($ELV_D(t)$), estimated from observable corporate bond credit spreads in year t ($spread(t)$). Referring to Ding et al. (2022), we measure the bond credit spread of China's A-share listed companies (CS) as the difference between the yield to maturity of a corporate bond and the yield of a treasury bond (i.e., the risk-free rate) with the same remaining maturity. Specifically, CS = the yield to maturity in year t of a treasury bond with the same issuance time and maturity period as the corporate bond - the yield to maturity in year t of that corporate bond. Additionally, in cases where the yield to maturity of the Chinese treasury bond is missing for a given year, it is derived using interpolation. The specific calculation proceeds as follows: first, $ELV_D(t)$ is calculated using $spread(t) = -\frac{1}{T} ln\left(1 - \frac{ELV_D(t)}{B(t)e^{-rT}}\right)$, where T = 9 denotes the total time horizon from the end of 2012 to the end of 2020. *t* is the *t.th* year within this period. $B(t)$ represents the face value of corporate debt, defined as the critical threshold for corporate default, calculated as *B(t)=current liabilities + 0.5*non-current liabilities.* *r* denotes the risk-free interest rate.

Second, $ELV_E(t)$ is estimated using a put option approach on an individual risk-adjusted (economic) balance sheet, constructed within the CCA framework (Jobst and Gray, 2013): $P_E(t) = Be^{-r(T-t)}\Phi\left(-d - \sigma_A\sqrt{T-t}\right) - A(t)\Phi(-d)$, where $P_E(t)$ represents the implicit (European) put option price, indicating the present value of market-implied expected losses linked with outstanding liabilities, which aligns with the put option formula in the traditional Black-Scholes-Merton (BSM) model. $\Phi(\cdot)$ denotes the cumulative standard normal distribution function. The term *d*, i.e., $ELV_E(t)$, is modelled as option price-based expected losses in the put option formula: $d = \frac{ln\left(\frac{A(t)}{B(t)}\right) + \left(r + 0.5 * \sigma_A^2\right)(T-t)}{\sigma_A\sqrt{T-t}}$, where A(t) is the market value of firm's assets, σ_A is the volatility of the asset's returns, which are jointly determined by solving the simultaneous equations from the option pricing model (Merton, 1974): $E(t) = A(t)\Phi(d) - B(t)e^{-r(T-t)}\Phi(d - \sigma_A * \sqrt{T-t})$, and the formula that follows Ito's lemma and Merton's assumptions: $\sigma_E = \left(\frac{A(t)}{E(t)}\right)\frac{\partial E}{\partial A}\sigma_A$ (Jones et al., 1984), in which σ_E and $E(t)$ are observable corporate equity return volatility and corporate equity market value at time t, respectively. We completed solving the equations using MATLAB R2024a, acquiring data for σ_A and A(t), supplemented by data from the CSMAR database.

Finally, $CGG_t = ELV_E(t) - ELV_D(t)$ provides the value of government guarantees received by A-share listed firms in China from 2012 to 2020. The resulting data were logarithmically transformed after adding one for subsequent analysis.

1.3.2.5. Control Variables

We include additional firm-level control variables that may influence corporate greenwashing behaviour, following existing studies (e.g., Khan et al., 2024; Hao et al., 2025b; Li et al., 2025b). These variables are defined as follows: (1) **Firm size (*Size*):** the natural logarithm of firm's total assets; (2) **Return on assets (*ROA*):** net income divided by total assets; (3) **Corporate leverage ratio (*Lev*):** the firm's total long-term debts divided by total assets; (4) **Cash flow Ratio (*CF*)**: the ratio of the net cash flows from operating activities in the total assets; (5) **Tobin's Q (TobinQ):** market value of the firm divided by total assets; (6) **Executive shareholding ratio (*ExecS*):** Percentage of shares held by executives.

The detailed definitions of all variables and their corresponding data processing methods are summarised in **Appendix D1**.

1.3.3. Model Specification

1.3.3.1. The Period-superimposed Logistic Co-evolution Model of FD and TI

Industries typically progress through stages of emergence, growth, and maturity, and in some cases, decline or extinction, showing distinctive evolutionary characteristics observed in natural species (Saviotti and Pyka, 2013). The development trajectories of financial development (FD) and technological innovation (TI) are deeply and significantly interrelated, with integration in terms of elements and interdependence in terms of external environment for the development, reflecting distinctive characteristics of symbiotic evolution.

Drawing on population symbiosis theory from biology, which describes a mutually beneficial relationship between species (Sapp, 1994), this study empirically examines whether FD and TI exhibit interactive co-evolution. This provides the foundation for analysing their coupling coordination. We conceptualise FD and TI as two biological populations whose growth

patterns follow the basic Logistic function, a widely adopted model for describing the evolution of natural populations. The individual dynamic evolution of FD and TI is represented by:

$$\begin{cases} \frac{dN_1(t)}{dt} = r_1\left(1 - \frac{N_1(t)}{N_{m1}}\right)N_1(t), & N_1(t_0) = N_{10} \\ \frac{dN_2(t)}{dt} = r_2\left(1 - \frac{N_2(t)}{N_{m2}}\right)N_2(t), & N_2(t_0) = N_{20} \end{cases} \tag{1.7}$$

Where N_{10} and N_{20} denote the initial population densities of FD and TI, respectively. $N_1(t)$ and $N_2(t)$ are their population densities in year t. Their natural growth rates are denoted by r_1 and r_2, and the maximum environmental carrying capacities are N_{m1} and N_{m2}, respectively.

To capture the dynamic interactions between FD and TI, we extend the **Model (1.7)** by introducing symbiotic influence coefficients α_{12} and α_{21} , which represent the symbiotic influence of TI on FD and of FD on TI, respectively. The mutually beneficial symbiosis, which is the most optimal interaction pattern between two industries, occurs only when both $\alpha_{12} > 0$ and $\alpha_{21} > 0$. This interaction can be symmetric or asymmetric, depending on whether these two coefficients are equal. Accordingly, the dynamic co-evolution is expressed as:

$$\begin{cases} \frac{dN_1(t)}{dt} = r_1\left(1 - \frac{N_1(t)}{N_{m1}} + \alpha_{12}N_2(t)\right)N_1(t) \\ \frac{dN_2(t)}{dt} = r_2\left(1 - \frac{N_2(t)}{N_{m2}} + \alpha_{21}N_1(t)\right)N_2(t) \end{cases} \equiv \begin{cases} \frac{dN_1(t)}{dt} = \lambda_1\left(1 - \frac{N_1(t)}{M_1}\right)N_1(t) \\ \frac{dN_2(t)}{dt} = \lambda_2\left(1 - \frac{N_2(t)}{M_2}\right)N_2(t) \end{cases} \tag{1.8}$$

where $\lambda_1 = r_1[1 + \alpha_{12}N_2(t)]$ and $\lambda_2 = r_2[1 + \alpha_{21}N_1(t)]$ are symbiotic natural growth rates of FD and TI, respectively, while $M_1 = N_{m1}[1 + \alpha_{12}N_2(t)]$ and $M_2 = N_{m2}[1 + \alpha_{21}N_1(t)]$ are maximum environmental carrying capacities of FD and TI during the symbiotic evolution process.

Based on this, to account for temporal changes, we develop a period-superimposed Logistic co-evolution model by dividing the study period (2012-2020) into yearly intervals $[t_i, t_{i+1}]$, with $\Delta t = t_{i+1} - t_i = 1$. This enables approximating the population evolution curves of

FD and TI as a series of connected logistic curve segments for each year, thereby allowing us to test their symbiotic co-evolution relationship. Since the curvature of the Logistic changes only slightly over small time intervals, it can be approximated by the slope of a straight line connecting two endpoints. In this context, the incremental changes in the population densities of FD and TI within an interval are denoted by $\Delta N_1(t_i, t_{i+1})$ and $\Delta N_2(t_i, t_{i+1})$, respectively. Consequently, the slopes of the lines connecting the two endpoints for FD and TI are given by $\frac{\Delta N_1(t_i,t_{i+1})}{\Delta t} = \Delta N_1(t_i, t_{i+1})$, and $\frac{\Delta N_2(t_i,t_{i+1})}{\Delta t} = \Delta N_2(t_i, t_{i+1})$, respectively, since $\Delta t = t_{i+1} - t_i = 1$. The population densities of FD and TI within each small interval are approximated by their mean values within each interval, i.e., $N_1(t_i) = \overline{N_1}(t_i, t_{i+1})$, $N_2(t_i) = \overline{N_2}(t_i, t_{i+1})$. The symbiotic natural growth rates for the interval of FD and TI are expressed as $\lambda_1^{i+1} = r_1\left[1 + \alpha_{12}\overline{N_2}(t_i, t_{i+1})\right]$ and $\lambda_2^{i+1} = r_2\left[1 + \alpha_{21}\overline{N_1}(t_i, t_{i+1})\right]$, respectively, and the maximum carrying capacities in the symbiotic environment are $M_1^{i+1} = N_{m1}[1 + \alpha_{12}\overline{N_2}(t_i, t_{i+1})]$ and $M_2^{i+1} = N_{m2}[1 + \alpha_{21}\overline{N_1}(t_i, t_{i+1})]$. Combining these with **Model (1.8)**, the population densities of FD and TI at time t can be solved as $N_1(t) = \frac{M_1^{i+1}}{1+\frac{M_1^{i+1}-N_1(t_i)}{N_1(t_i)}e^{-\lambda_1^{i+1}t}}$ and $N_2(t) = \frac{M_2^{i+1}}{1+\frac{M_2^{i+1}-N_2(t_i)}{N_2(t_i)}e^{-\lambda_2^{i+1}t}}$, respectively. Accordingly, a period-superimposed Logistic co-evolution model can be obtained by substituting correspond values into **Model (1.8)**, yielding:

$$\begin{cases} \frac{\Delta N_1(t_i,t_{i+1})}{\Delta t} = \lambda_1^{i+1}\left(1 - \frac{\overline{N_1}(t_i,t_{i+1})}{M_1^{i+1}}\right)\overline{N_1}(t_i, t_{i+1}) \\ \frac{\Delta N_2(t_i,t_{i+1})}{\Delta t} = \lambda_2^{i+1}\left(1 - \frac{\overline{N_2}(t_i,t_{i+1})}{M_2^{i+1}}\right)\overline{N_2}(t_i, t_{i+1}) \end{cases} \Rightarrow \begin{cases} M_1^{i+1} = \frac{\overline{N_1}(t_i,t_{i+1})}{1-\frac{\Delta N_1 t_i,t_{i+1})}{\lambda_1^{i+1}\overline{N_1}(t_i,t_{i+1})}} \\ M_2^{i+1} = \frac{\overline{N_2}(t_i,t_{i+1})}{1-\frac{\Delta N_2(t_i,t_{i+1})}{\lambda_2^{i+1}\overline{N_2}t_i,t_{i+1})}} \end{cases} \quad (1.9)$$

Since $M_1^{i+1} > 0$, it follows that $\lambda_1^{i+1} > \frac{\overline{N_1}(t_i,t_{i+1})}{\Delta N_1(t_i,t_{i+1})}$. Similarly, $\lambda_2^{i+1} > \frac{\overline{N_2}(t_i,t_{i+1})}{\Delta N_2(t_i,t_{i+1})}$. Based on this, $\overline{N_1}(t_i, t_{i+1})$, $\overline{N_2}(t_i, t_{i+1})$, $\Delta N_1(t_i, t_{i+1})$, and $\Delta N_2(t_i, t_{i+1})$ can be directly obtained from the collected FD and TI data. The natural growth rates of the population in each interval: $\hat{\lambda}_1^{i+1}$ and $\hat{\lambda}_2^{i+1}$, are then estimated accordingly. Using **Model (1.9)**, the maximum carrying capacities of the symbiotic environment, $\widehat{M}_1^{i+1}$ and $\widehat{M}_2^{i+1}$, are also calculated for each corresponding

interval. Subsequently, the estimated population densities ($\widehat{N}_1(t_{i+1})$ and $\widehat{N}_2(t_{i+1})$) can be computed.

The squared differences between the estimated and the observed values of population densities for FD and TI in each year are calculated as $\Delta e_1^2(k) = \sum_{i=0}^{n}[\widehat{N}_1(t_{i+1}) - N_1(t_{i+1})]^2$ and $\Delta e_2^2(k) = \sum_{i=0}^{n}[\widehat{N}_2(t_{i+1}) - N_2(t_{i+1})]^2$, respectively, where k denotes the *k-th* iteration. The parameter values λ_1^{i+1} , λ_2^{i+1}, M_1^{i+1} , and M_2^{i+1} for each year are estimated using the non-linear optimisation algorithm method, iterating until the variance no longer decreases[3] (Nelder and Mead, 1965).

1.3.3.2. The Impact of the Coupling Coordination Degree on Corporate Greenwashing

This study examines the impact of the estimated coupling coordination degree between financial development (FD) and technological innovation (TI) on firm's greenwashing behaviour using the following baseline model:

$$GW_{it} = \beta_0 + \beta_1 CCD_{it-1} + \beta_2 Controls_{it-1} + \lambda_i + \gamma_t + \varepsilon_{it} \quad (1.10)$$

Where subscripts i and t denote firm and year, respectively. GW_{it} is the degree of greenwashing behaviour for firm i in year t. CCD_{it-1} represents the degree of coupling coordination between FD and TI in the corresponding region, lagged by one year to reduce reverse causality risk. $Controls_{it-1}$ are set of the control variables, also lagged by one year to address potential synchronisation disturbances and to mitigate endogeneity concerns. λ_i and γ_t denote firm fixed effects and year fixed effects, respectively, to control for time-invariant firm-specific heterogeneity and macroeconomic yearly shocks. ε_{it} is the error term.

[3] All simulations, iterative computations, and parameter estimations for the period-superimposed Logistic co-evolution model were conducted in MATLAB R2024a.

1.3.3.3. The Moderating Role of Government Guarantees

To further investigate the moderating role of government guarantees received by firms in the process of the regional FD-TI coupling coordination mitigating firm's greenwashing behaviour, we extend **Model (1.10)** to the following specification:

$$GW_{it} = \alpha_0 + \alpha_1 CCD_{it-1} \times lnCGG_{it-1} + \alpha_2 CCD_{it-1} + \alpha_3 lnCGG_{it-1} + \alpha Controls_{it-1} + \lambda_i + \gamma_t + \varepsilon_{it} \quad (1.11)$$

where $CCD_{it-1} \times lnCGG_{it-1}$ is the interaction term between the regional CCD in the registered region of firm i and the logarithm of corporate government guarantees received by the firm, both lagged by one period. $lnCGG_{it-1}$ is normalised using the Min-Max Normalisation method to address potential multicollinearity concerns and to ensure a meaningful interpretation of the coefficient when interaction terms are included. The coefficients α_1 captures the moderating effect of government guarantees. If both α_2 and α_1 are negative and statistically significant, it indicates that the regional CCD effectively mitigates corporate greenwashing and that government guarantees provided to firms significantly strengthen this impact. All other variables, symbols and subscripts are as defined in the baseline **Model (1.10).**

Furthermore, within China's institutional context, state-owned enterprises (SOEs) have historically received preferential government support, such as debt maturity extensions and direct subsidies, due to their strategic importance for both economic growth and social welfare (Dong et al., 2021). To capture this heterogeneity, we further examine the interaction between corporate government guarantees and a firm's institutional ownership, assessing how these factors jointly influence the impact of regional CCD on corporate greenwashing behaviour.

1.3.4. Descriptive Analysis

Table 1.1 presents the descriptive statistics for the key variables. The minimum and maximum values of corporate greenwashing (***GW***) are -3.971 and 5.646, respectively, with the standard deviation of 0.944, which is comparable to those reported in previous studies (e.g., Long et al., 2025). Considerable variation is observed in greenwashing behaviour among Chinese A-

share listed companies. The average value of ***CCD*** is 0.354, indicating a moderate level of coupling coordination between FD and TI in the firms' registered regions. Similarly, the government guarantees received by firms (***lnCGG***) exhibit significant variability among sample firms, ranging from 0.002 to 5.641, with a standard deviation of 0.684. The descriptive statistics for the other control variables are generally consistent with those reported in existing studies (e.g., Zhang, 2023).

Table 1.1 Basic statistics of variables

Variable	N	Mean	SD	Min	Max
CCD	6471	0.354	0.117	0.104	0.659
lnCGG	6471	2.410	0.684	0.002	5.641
GW	6471	-0.040	0.944	-3.971	5.646
Size	6471	22.741	1.328	19.540	28.636
ROA	6471	0.028	0.073	-0.870	0.542
Lev	6471	0.088	0.092	0	0.741
CF	6471	0.053	0.087	-3.224	2.871
TobinQ	6471	1.809	1.058	0.674	27.338
ExecS	6471	0.112	0.172	0	0.815

Table 1.2 reports the Pearson correlation coefficient matrix among the variables. Most correlation coefficients are below 0.4, and the mean variance inflation factor (VIF) across all variables is 1.21, well below the threshold of 10, with the highest VIF found for ***Size***. These results collectively suggest no multicollinearity problem in the variable set used for subsequent regressions (Wooldridge, 2015).

Table 1.2 Pearson Correlation Matrix

* represent significance at the 10% levels.

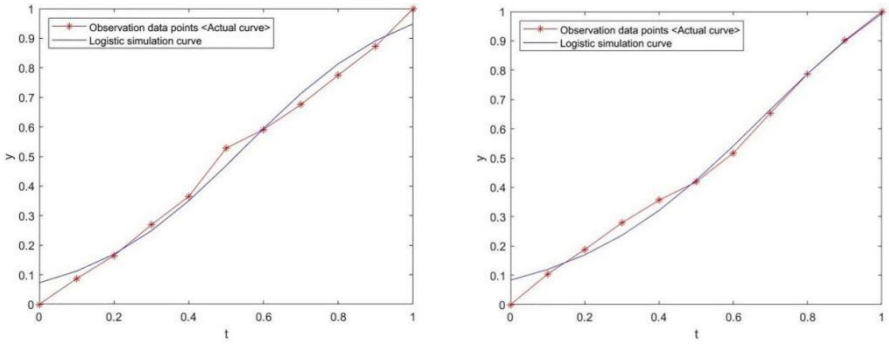
	CCD	***lnCGG***	***GW***	***Size***	***ROA***	***Lev***	***CF***	***TobinQ***	***ExecS***
CCD	1								
lnCGG	-0.3080*	1							
GW	-0.0616*	0.0198	1						
Size	0.0508*	-0.0833*	0.2365*	1					
ROA	0.0253	0.0409*	-0.0120	0.0476*	1				
Lev	-0.0846*	0.0074	0.0976*	0.3573*	-0.1238*	1			
CF	0.0434*	-0.0153	0.0265	0.0899*	0.2858*	-0.0064	1		
TobinQ	0.0520*	-0.0320	-0.0835*	-0.3566*	0.1148*	-0.2078*	0.0759*	1	
ExecS	0.1987*	-0.0670*	-0.1076*	-0.3513*	0.0957*	-0.1584*	-0.0407*	0.0859*	1

1.4. Results

1.4.1. Test of Symbiotic Co-evolution of FD and TI

First, under the assumption that financial development (FD) and technological innovation (TI) evolve independently, their dynamic evolution is simulated using **Model (1.7)** to obtain the corresponding biological population densities. The growth stages of FD and TI are then classified in this study according to the proportion of their respective population densities to their maximum carrying capacities. Specifically, when the proportion is between 0% and 20%, the system is in the *budding stage*, characterised by relatively low population density and a high growth rate. When the proportion ranges from 20% to 60%, it is in the *growing stage*, with moderate population density and a gradually declining growth rate. Finally, when the proportion exceeds 60%, the system is in the *maturity stage*, marked by relatively high population density and a low growth rate.

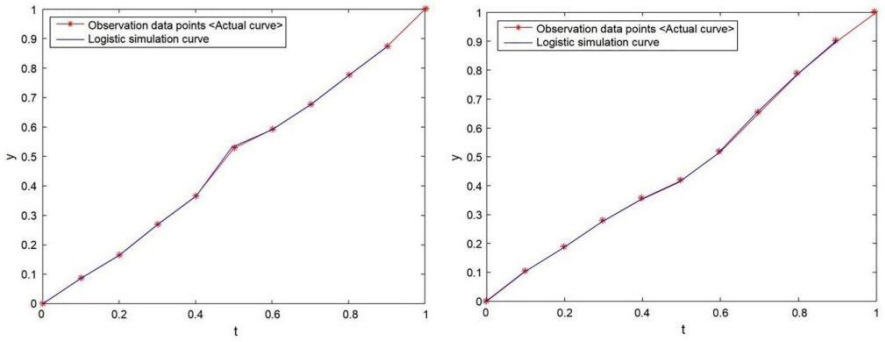
As shown in **Figure 1.1,** the estimated natural growth rates of FD and TI (r_1 and r_2) are 0.4760 and 0.3929, respectively, and their corresponding estimated maximum environmental carrying capacities (N_{m1} and $\mathrm{N_{m2}}$) are 375,511.9941 billion yuan and 270,875.1093 billion yuan, respectively. Under the assumption that FD and TI develop independently, the simulation curves for both variables deviate considerably from their actual curves, failing to capture their real-world development trajectories in China. In 2020, the annual value added of China's financial industry was 83617.7 billion yuan, representing 22.27% of its estimated maximum environmental carrying capacity, theoretically placing it in the early "*growing stage*". However, the observed growth rates of FD are generally low and volatile, suggesting that, in reality, FD in China is closer to the late "*budding stage*" or the "*maturity stage*". Similarly, for TI, the 2020 annual value added was 53,528.8 billion yuan, or 19.76% of its estimated maximum carrying capacity, implying a position in the "*growing stage*". However, the actual growth rates of TI are low and show a steady decline, indicating that TI in China should instead be classified as being in the early "*budding stage*" or the "*maturity stage*".



(a) FD Population (b) TI Population

Figure 1.1 Dynamic Evolution Curves of FD and TI in the Case of Independent Development

Subsequently, we investigate the mutual influence and symbiotic relationship between FD and TI by modelling their dynamic evolution using the period-superimposed Logistic co-evolution model specified in **Model (1.9).** The existence and nature of the symbiotic co-evolution between FD and TI are determined based on the estimated value of α_{12} and α_{21}.



(a) FD Population (b) TI Population

Figure 1.2 Dynamic Evolution Curves of FD and TI in the Case of Symbiotic Development

Figure 1.2 illustrates that the simulation curves for FD and TI closely align with their actual trajectories. Due to the symbiotic effect, the maximum carrying capacities of the symbiotic environments for FD and TI (M_1^{i+1} and M_2^{i+1}) demonstrate substantial growth potential, reaching 518,006.7935 billion yuan and 968,608.5271 billion yuan in 2019, respectively. In that year, FD in China amounted to 76,250.6 billion yuan, representing 14.72% of its estimated maximum carrying capacity, placing it in the late "*budding stage*" according to the logistic curve, consistent with the observed development pattern of FD in China. Similarly, TI in China reached 49,980.2 billion yuan, equivalent to 5.16% of its estimated maximum

carrying capacity, indicating an early "*budding stage*", which also aligns with its actual growth characteristics.

Moreover, the estimated coefficients of the symbiotic effects between FD and TI ($\alpha_{12} = 0.0087$ and $\alpha_{21} = 0.0694$)[4] indicate that the symbiotic effect of FD on TI is significantly greater than the reverse effect of TI on FD. The period-superimposed Logistic co-evolution model more effectively captures the actual dynamic evolution of FD and TI in China, thereby supporting **H1.** These results suggest that FD and TI in China are not independent but rather co-evolve, exhibiting an asymmetric, mutually beneficial symbiosis in which the symbiotic influence of FD on TI outweighs that of TI on FD. Over time, a coupling coordination relationship gradually emerges between the two systems.

1.4.2. Temporal and Spatial Characteristics of the CCD and its Spatial Autocorrelation

1.4.2.1. Basic Descriptive Statistics of the Coupling Coordination Degree

The estimated provincial coupling coordination degree of FD and TI (CCDs) from 2012 to 2020 in China, along with the corresponding comprehensive development levels of the FD and TI systems, are reported in **Appendix A2** based on their categorised regions. The 30 Chinese provinces are classified into four regions following the official classification standards in the China Statistical Yearbook on Science and Technology. **Table 1.3** summarises the basic descriptive statistics of the CCDs for the 30 provinces and their respective regions, reported annually from 2012 to 2020. To further examine the temporal and spatial characteristics of CCD across regions and provinces over time, this study classifies the stages of coupling coordination between FD and TI as follows: "extremely uncoordinated" stage when $0 \leq CCD < 0.1$; "low" stage when $0.1 \leq CCD < 0.3$; "moderate" stage when $0.3 \leq CCD < 0.7$; and "high" stage when $0.7 \leq CCD < 0.9$. Finally, "extreme coupling coordination" stage if $0.9 \leq CCD \leq 1.0$.

Overall, in Eastern China, the CCDs of all ten provinces exhibited an upward trend throughout the observation period, although some provinces experienced occasional fluctuations or declines. As shown in **Table 1.3,** the average CCD in Eastern China increased from 0.2814 to

[4] Newton's iteration for nonlinear least squares is used to estimate the coefficients of the symbiotic effect.

0.4141 over the nine years, remaining above the national average across the 30 provinces in China. Among them, Beijing consistently maintained the highest CCD level during the sample period. Eastern China is characterised by financial development (FD) outpacing technological innovation (TI), with the comprehensive levels of both FD and TI significantly higher than those in the other three regions.

In Central China, the CCDs generally followed a high growing trajectory, with only a few provinces experiencing declines in certain years. While the regional average CCD increased steadily, it did not reach the levels observed in Eastern China. From 2014 onwards, most central provinces rapidly approached the moderate stage of CCD, except for the CCD of Shanxi, which remained below the moderate stage by the end of 2020. Anhui and Hubei were the first to achieve moderate stage CCD in 2018 and have since jointly led the region. This may be mainly attributable to their geographical proximity to Eastern China, which facilitates access to advanced industrial development experience. Within the Central region, Hubei maintained the highest CCD in most years, although it was exceeded by Anhui in two years. This can be explained by the more frequent shifts between lagging FD and TI in Hubei, indicating a more balanced co-evolution between the two systems. Overall, Central China is characterised by TI lagging behind FD.

In Western China, the average CCD was the lowest among the four regions. Most provinces remained in the low-level stage throughout the nine years, with only two gradually advancing to the moderate stage. The region shows a significant lag in TI relative to FD, and overall FD comprehensive levels are lower than those of other regions. In Northeast China, CCDs remained in the low-level stage for the entire observation period, with a significant lag in TI relative to FD.

Table 1.3 Descriptive Statistics of the CCD across Chinese Provinces

CCD denotes the coupling coordination degree between financial development and technological innovation. The table reports the mean, maximum and minimum CCD values for each year during 2012 and 2020. Summary statistics are shown in **panel A** for all 30 provincial-level units and in **panel B** for the four macro-regions (Eastern, Central, Western, and Northeast).

Panel A: All 30 provinces: annual summary statistics									
Year	2012	2013	2014	2015	2016	2017	2018	2019	2020
Mean	0.2042	0.2152	0.2284	0.2536	0.2677	0.2706	0.2757	0.2884	0.3110
Max	0.4259	0.4315	0.4601	0.4833	0.5264	0.5146	0.5417	0.6203	0.6592
Min	0.1037	0.1139	0.1253	0.1504	0.1599	0.1558	0.1495	0.1441	0.1439

Panel B: Four major regions: annual summary statistics									
	Year	2012	2013	2014	2015	2016	2017	2018	2019	2020
Eastern region	Mean	0.2814	0.2936	0.3091	0.3311	0.3536	0.3521	0.3599	0.3840	0.4141
	Max	0.4259	0.4315	0.4601	0.4833	0.5264	0.5146	0.5417	0.6203	0.6592
	Min	0.1415	0.1495	0.1501	0.1559	0.1715	0.1558	0.1570	0.1753	0.1877
Central region	Mean	0.1777	0.1937	0.2100	0.2382	0.2498	0.2583	0.2679	0.2860	0.3130
	Max	0.2116	0.2179	0.2438	0.2777	0.2905	0.2897	0.3071	0.3302	0.3523
	Min	0.1568	0.1726	0.1755	0.1848	0.1868	0.1977	0.1986	0.2121	0.2330
Western region	Mean	0.1525	0.1589	0.1700	0.1976	0.2069	0.2113	0.2127	0.2145	0.2290
	Max	0.2203	0.2312	0.2453	0.2786	0.2890	0.3045	0.3080	0.3219	0.3417
	Min	0.1037	0.1139	0.1253	0.1504	0.1599	0.1562	0.1495	0.1441	0.1439
Northeast region	Mean	0.1895	0.2035	0.2100	0.2311	0.2402	0.2412	0.2415	0.2459	0.2641
	Max	0.2215	0.2361	0.2461	0.2619	0.2669	0.2684	0.2712	0.2696	0.2878
	Min	0.1691	0.1839	0.1847	0.2088	0.2154	0.2269	0.2238	0.2291	0.2468

Based on the above analysis, we further illustrate the spatial characteristics and evolutionary trend of provincial CCDs by mapping them across Chinese provinces for three representative years, 2012, 2015, and 2020, as shown in **Figure 1.3.** The results reveal a distinct spatial pattern of "high in the east and low in the west, high in the south and low in the north". Over the sample period, CCD values gradually increased nationwide and exhibited a spillover effect from coastal to inland provinces. This spatial diffusion pattern is similar to the distribution of total factor productivity and regional economic growth in China (e.g., Demurger, 2001; Bai et al., 2012; Zhou et al., 2021).



a. 2012 b. 2015



c. 2020

Figure 1.3 The Temporal and Spatial Pattern Evolution of the CCDs in 2012, 2015 and 2020

1.4.2.2. Spatial Autocorrelation Analysis of the Coupling Coordination Degree

Next, we perform a spatial autocorrelation analysis to investigate the relationship between the degree of FD-TI coupling coordination in a certain province and that of its neighbouring provinces. Specifically, we employ the Global Moran's I statistics and Moran Scatter plots to conduct global and local spatial autocorrelation analysis, respectively (H. Kelejian and Prucha, 2001). This approach not only allows us to determine whether spatial correlation exists among

provincial CCDs but also enables us to identify the characteristics and magnitude of such spatial correlation, including patterns of spatial clustering and the presence of spatial outliers.

(a) Global Spatial Autocorrelation Analysis

This study estimates the Global Moran's I statistic to assess the global spatial autocorrelation of provincial-level FD-TI coupling coordination degrees (CCD) from 2012 to 2020. First, a binary adjacency spatial weight matrix $\boldsymbol{W}$ is constructed for each province using the "queen contiguity" rule, in which the spatial weight element $\omega_{\alpha\beta}$ (i.e., the spatial weight between province α and β) equals 1 if the two provinces share a common boundary or point, and 0 otherwise. Following this, Moran's I index ($\boldsymbol{I}$) is calculated to test the presence of spatial autocorrelation in CCD values across provinces, as shown in equation: $I = \frac{n}{S_0} \times \frac{\sum_{\alpha=1}^{n}\sum_{\beta=1}^{n}\omega_{\alpha\beta}(CCD_\alpha - \overline{CCD})(CCD_\beta - \overline{CCD})}{\sum_{\alpha=1}^{n}(CCD_\alpha - \overline{CCD})^2}$, $I \in [-1, 1]$, where n=30 denotes the number of provinces in the sample. CCD_α and CCD_β represent the CCD values of the province α and β, respectively. $S_0 = \sum_{\alpha=1}^{n}\sum_{\beta=1}^{n}\omega_{\alpha\beta}$ is the sum of all spatial wrights, and $\overline{CCD} = \frac{1}{n}\sum_{\alpha=1}^{n} CCD_\alpha$ denotes the mean CCD value (Moran, 1950; Getis and Ord, 1992). A positive Moran's I ($\boldsymbol{I}$) indicates an overall positive spatial autocorrelation of CCD across provinces, suggesting spatial clustering from a global perspective.

Table 1.4 reports the Global Moran's I estimates for all 30 Chinese provinces from 2012 to 2020. The coefficients $\boldsymbol{I}$ are consistently positive and statistically significant at the 1% or 5% level, indicating a significant global spatial autocorrelation in CCD across provinces. This suggests that provinces with higher (lower) CCD values tend to be geographically clustered, respectively, supporting the observed spatial pattern of "high in the east and low in the west, high in the south and low in the north" as a systematic, rather than random, phenomenon. Furthermore, since a larger Moran's I value implies a more pronounced clustering of high- and low-CCD provinces, the fluctuating yet downward trend of the Global Moran's I estimate over the nine years, as shown in **Table 1.4**, suggests that the degree of global spatial autocorrelation in CCD has gradually weakened. This indicates increasing spatial spillovers, whereby provinces with higher CCD levels progressively influence neighbouring provinces

with lower CCD levels. Consequently, the regional gap in FD-TI coupling coordination has been slowly narrowing over time.

Table 1.4 Global Moran's I Estimates of the CCDs among 30 Chinese Provinces

ccd2012 to *ccd2020* denotes the CCDs of all 30 Chinese provinces from 2012 to 2020, respectively. The weight matrix was row-standardised before estimating Global Moran's I. A two-tail Z test was performed in estimating Global Moran's I. *, **, *** denote significance at the 10%, 5% and 1% levels respectively.

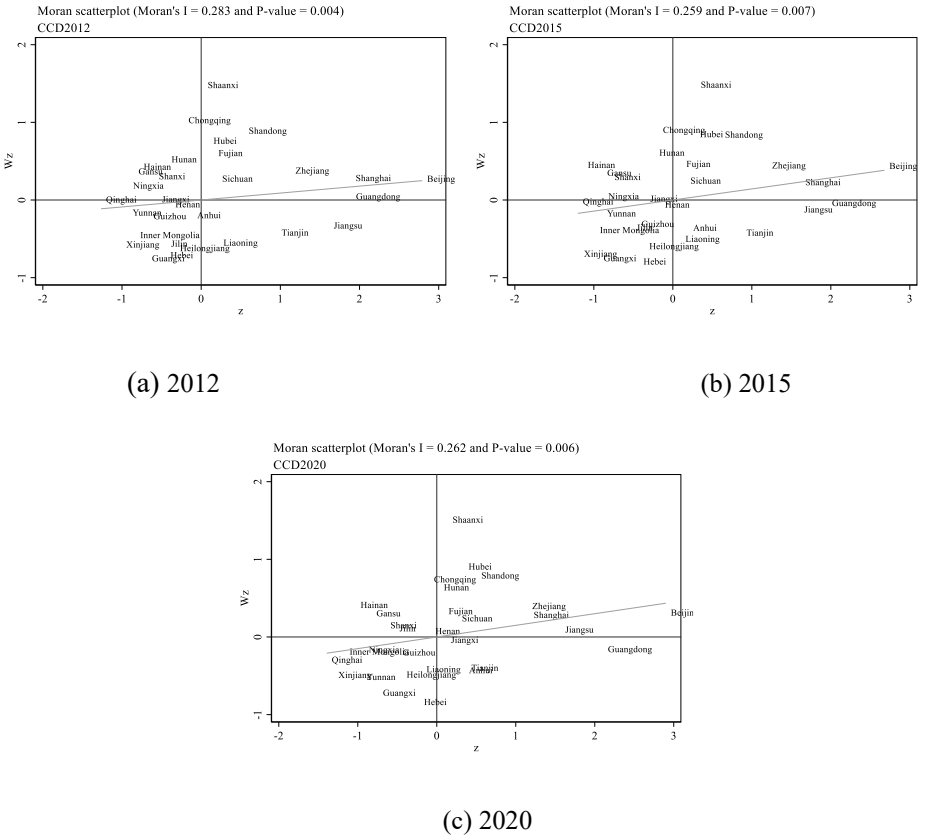
Variables	I	E(I)	sd(I)	z	p-value
ccd2012	0.283	-0.034	0.119	2.660	0.004***
ccd2013	0.283	-0.034	0.120	2.650	0.004***
ccd2014	0.291	-0.034	0.120	2.716	0.003***
ccd2015	0.259	-0.034	0.120	2.443	0.007***
ccd2016	0.256	-0.034	0.119	2.429	0.008***
ccd2017	0.236	-0.034	0.120	2.259	0.012**
ccd2018	0.227	-0.034	0.119	2.194	0.014**
ccd2019	0.240	-0.034	0.118	2.332	0.010**
ccd2020	0.262	-0.034	0.119	2.503	0.006***

(b) Local Spatial Autocorrelation Analysis

Subsequently, we conduct a local spatial autocorrelation analysis using Moran's I scatter plots to identify the precise spatial clustering patterns of CCDs across Chinese provinces, building on the evidence of global spatial autocorrelation analysis. Three representative years, 2012, 2015 and 2020, were selected to examine provincial-level clustering characteristics and to determine which provinces belong to high- or low-clustering regions.

As illustrated in **Figure 1.4**, Moran's I scatter plots categorise the clustering patterns of provincial CCDs into four types, corresponding to the four quadrants of the coordinate plane, where each point represents the FD-TI coupling coordination degree of a province. The coordinate points distributed in Quadrant I (H-H quadrant) mean that these provinces with relatively high CCD values are surrounded by neighbouring provinces exhibiting high CCD values. The coordinate points distributed in Quadrant II (L-H quadrant) imply that these provinces with relatively low CCD values are located near provinces with high CCD values. The coordinate points distributed in Quadrant III (L-L quadrant) represent that these provinces with relatively low CCD values are surrounded by neighbouring provinces with similarly low CCD values. Finally, the coordinate points distributed in Quadrant IV (H-L quadrant) reflect that these provinces with relatively high CCD values are located near provinces with low

CCD values. This classification enables the identification of both spatial clusters (H-H and L-L) and spatial outliers (L-H and H-L), providing more understanding of the spatial distribution of FD-TI coupling coordination across China.



(a) 2012 (b) 2015

(c) 2020

Figure 1.4 Moran's I Scatter Plots of the CCDs for 30 Chinese Provinces in 2012, 2015 and 2020

Figure 1.4 shows that, in all three representative years, most provincial CCD observations fall within *Quadrant I* (H-H quadrant) and *Quadrant III* (L-L quadrant), indicating that provinces with higher or lower FD-TI coupling coordination are typically adjacent to provinces with similar high or low values, respectively. This finding further supports the significant positive global spatial autocorrelation identified through the Global Moran's I analysis.

Provinces in *Quadrant I* are concentrated mainly in the eastern region, suggesting that the high-value CCD clusters occur predominantly in the east. The relatively scattered distribution of points within *Quadrant I* indicates significant variation in CCD levels among these eastern provinces, implying that their FD-TI coupling coordination is developing relatively independently. Beijing consistently appears at the far right of *Quadrant I*, reflecting its

exceptionally high FD-TI coupling coordination and strong clustering with neighbouring provinces exhibiting high CCD levels.

However, most provinces outside the eastern region remained in *Quadrant III* throughout the nine years. The dense clustering of their coordinate points indicates both slight variation in CCD values and mutual constraints in achieving higher FD-TI coupling coordination. From a dynamic perspective, the points in *Quadrant I* moved gradually closer together, reflecting gradually stronger spatial autocorrelation among provinces with higher FD-TI coupling coordination and the formation of a linkage development pattern.

In contrast, most low-CCD provinces showed little movement across quadrants during the sample period. For instance, Guizhou and Guangxi remained in *Quadrant III*, primarily due to the absence of neighbouring provinces with higher CCDs. Notably, Anhui shifted from *Quadrant III to Quadrant IV,* significantly illustrating a spillover effect of FD-TI coupling coordination. Its proximity to high-CCD coastal provinces such as Shanghai and Zhejiang facilitated significant improvements in Anhui's CCD, enabling it to escape the low-CCD clustering (L-L quadrant) and enter the H-L quadrant, despite there are still inland central provinces with lower CCD in their vicinity.

Similarly, Jiangxi moved from the boundary between *Quadrant II* (L-H quadrant) and *III* (L-L quadrant) to *Quadrant IV* (H-L quadrant)*,* benefiting from spillovers from high-CCD provinces such as Guangdong and Zhejiang. Furthermore, other central provinces, such as Henan and Hunan, shifted from *Quadrant III* and *II* to *Quadrant I*, respectively, further validating that the CCD growth in Anhui and Jiangxi had further spilt over to their neighbouring provinces.

Collectively, the FD-TI coupling coordination degrees across the 30 Chinese provinces show an upward trajectory, accompanied by significant positive global spatial autocorrelation and spatial heterogeneity, with a clear gradual decrease from east to west. Provinces in the eastern region have exhibited high-value clustering in CCDs since 2012, which has gradually spilt over to neighbouring central provinces and, subsequently, to the western region. As a result, the characteristic spatial pattern of "high in the east and low in the west, high in the south and low in the north" is expected to gradually diminish, with the inter-regional gap in CCD

narrowing over time. The geographical distribution of the CCDs has been evolving towards a more "balanced" spatial structure.

1.4.3. Impact of Coupling Coordination Degree on Corporate Greenwashing

1.4.3.1. Baseline Regression

Table 1.5 reports the baseline results on the impact of the FD-TI coupling coordination on greenwashing behaviours among A-share listed firms in China. The estimations are conducted using standard ordinary least squares (OLS) regressions, with or without firm-level fixed effects, while controlling for year-level fixed effects. Standard errors are clustered at the firm level. Both the CCD and greenwashing variables are standardised.

Columns (1) and (2) present results without and with control variables, respectively, including only year fixed effects. Columns (3) and (4) incorporate firm fixed effects to further control for unobservable, time-variant firm-specific heterogeneity. Across all specifications, the coefficients on CCD_{it-1} remain negative and statistically significant at the 1% level, regardless of whether control variables are included. As shown in column (4), after controlling for unobservable firm characteristics, time-varying factors, and key firm-level controls, a one standard deviation increase in the previous period's FD-TI coupling coordination degree is associated with a 1.663 standard deviation reduction in the firm's current greenwashing behaviour. This finding indicates a strong disciplinary effect of FD-TI coupling coordination on corporate greenwashing tendencies.

To further test the robustness of our baseline results, we incorporate alternative fixed effects specifications. Specifically, columns (5) and (6) include Industry×Year and Province×Year fixed effects, respectively, in addition to firm fixed effects, to absorb any time-variant industry-specific or region-specific shocks, and ESG-related policy changes. The coefficients on CCD_{it-1} remain negative and statistically significant at the 1% or 5% level, indicating that the baseline findings are not driven by omitted variables at the industry or regional level.

Table 1.5 The FD-TI Coupling Coordination and Corporate Greenwashing

Values of t-statistics are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	GW_{it}	GW_{it}	GW_{it}	GW_{it}	GW_{it}	GW_{it}
$\boldsymbol{CCD_{it-1}}$	**-0.425*****	**-0.366*****	**-1.626*****	**-1.663*****	**-1.784*****	**-0.935****
	(-3.211)	**(-2.732)**	**(-2.616)**	**(-2.704)**	**(-2.813)**	**(-2.037)**
$Size_{it-1}$		0.163***		-0.006	0.025	0.014
		(11.139)		(-0.115)	(0.524)	(0.310)
ROA_{it-1}		-0.064***		-0.014	-0.016	-0.008
		(-4.223)		(-0.913)	(-1.045)	(-0.515)
Lev_{it-1}		0.007		0.005	0.006	0.004
		(0.933)		(0.464)	(0.530)	(0.392)
CF_{it-1}		0.609***		-0.028	-0.310	0.004
		(2.752)		(-0.133)	(-1.408)	(0.017)
$TobinQ_{it-1}$		0.018		0.033*	0.038**	0.025
		(0.957)		(1.771)	(2.026)	(1.613)
$ExecS_{it-1}$		0.043		-0.205	-0.244	-0.247
		(0.553)		(-1.209)	(-1.502)	(-1.397)
Constant	0.131**	-3.816***	0.517**	0.590	-0.063	-0.079
	(2.342)	(-10.801)	(2.447)	(0.503)	(-0.056)	(-0.079)
Year FE	Yes	Yes	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	Yes	Yes
Industry×Year FE	No	No	No	No	Yes	No
Province×Year FE	No	No	No	No	No	Yes
N	6471	6471	6471	6471	6471	6471
Adj. R^2	0.003	0.060	0.624	0.624	0.642	0.605

1.4.3.2. Robustness Checks

We further conducted robustness checks to complement the alternative fixed-effects specifications reported in Columns (5) and (6) of **Table 1.5**, thereby reinforcing the validity of the baseline results. Since the baseline OLS regressions in **Table 1.5** primarily capture the conditional average effect (e.g., Li et al., 2023a; Li et al., 2025b), we additionally employ quantile regressions at the 25th, 50th, 75th and 90th percentiles. This approach mitigates potential estimation bias arising from outliers, skewed distributions, or heterogeneous effects across the distributions of greenwashing degrees. As shown in **Table 1.6**, the mitigating effect of regional FD-TI coupling coordination on corporate greenwashing remains statistically significant at the 5% or 1% levels across all quantiles. Moreover, the effect is stronger at the upper quantiles (q90) relative to the lower quantiles, suggesting that improvements in regional FD-TI coupling coordination are particularly effective in reducing greenwashing behaviours

among firms with the highest propensity for such practices. This finding emphasises the critical role of FD-TI coupling coordination in disciplining the most opportunistic firms.

Table 1.6 Quantile Regressions

Values of robust t-statistics are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)
	q25	q50	q75	q90
	GW_{it}	GW_{it}	GW_{it}	GW_{it}
$\boldsymbol{CCD_{it-1}}$	**-1.971****	**-0.294*****	**-1.419****	**-4.268*****
	(-1.993)	**(-10.387)**	**(-2.151)**	**(-3.794)**
Control	Yes	Yes	Yes	Yes
N	6471	6471	6471	6471
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Psedu R^2	0.005	0.001	0.003	0.010

1.4.3.3. Addressing Endogeneity Concerns

Building on the series of robustness checks, potential endogeneity concerns may still persist, particularly if firms' internal control mechanisms influence their greenwashing behaviours. To address this, we employ the *Pilot Policy Promoting the Integration of Technology and Finance (PPPITF)*, implemented in 2016 in China, which aims at fostering collaborations and integration between financial institutions and technological enterprises (Li et al., 2025a). This policy programme is expected to substantially enhance regional FD-TI coupling coordination, and thus serves as an alternative measure for the estimated CCD in our analysis. Given the staggered rollout of the PPPITF across different pilot locations in China, the policy provides a natural quasi-experiment setting. Accordingly, we employ a Difference-in-Differences (DID) model, as specified below, which is well-suited for estimating the causal effect of an exogenous policy intervention and for mitigating potential endogeneity concerns:

$$GW_{it} = \theta_0 + \theta_1 PPPITF_{it} + \beta_2 Controls_{it-1} + \lambda_i + \gamma_t + \varepsilon_{it} \quad (1.9)$$

where $PPPITF_{it}$ denotes the policy effect. Since the PPPITF policy was implemented in two batches, both in 2011 and 2016. In 2011, the PPPITF programme was jointly issued by five

Chinese government departments, designating Zhongguancun National Innovation Demonstration Zone, Tianjin, Shanghai, Shenzhen, and Jiangsu Province as the first batch of pilot zones for promoting the integration of technology and finance. In 2016, the PPPITF expanded to include a second batch of 10 pilot cities, including Zhengzhou, Xiamen, Ningbo, Jinan, Nanchang, Guiyang, Yinchuan, Baotou, and Shenyang, aimed at promoting the continuous integration of financial capital and the technology industry in these regions, with a focus on products, organisational structures, and service models. Given that the sample period in this study is 2012 to 2020, we used the second batch of PPPITF pilot cities set in 2016 as our treatment case. Specifically, $PPPITF_{it}$ is a binary indicator capturing the interactive terms of $Treat_i \times Post_t$, where $Treat_i$ equals 1 if firm i is registered in a city designed as part of the second batch of pilot zone, and 0 otherwise. $Post_t$ is another binary variable indicating the implementation period of the PPPITF, and equals 1 for the post-policy period (2016−2020), and 0 otherwise. All other symbols and subscripts are consistent with the definitions in the baseline **Model (1.7)**.

Table 1.7 reports the DID regression results. The coefficients of $PPPITF_{it}$ are consistently negative and statistically significant at the 1% or 5% level across all specifications, regardless of whether control variables or alternative fixed effects are included. These results indicate that the PPPTF policy, designed to promote the integration of the financial industry and technological enterprises, significantly reduces corporate greenwashing behaviours. This evidence further reinforces our baseline finding that stronger regional FD-TI coupling coordination has a significant mitigating effect on greenwashing, while alleviating potential endogeneity concerns.

Table 1.7 Difference-in-differences (DID) Regressions Results

Values of robust t-statistics are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)
	GW_{it}	GW_{it}	GW_{it}	GW_{it}
$\boldsymbol{PPPITF_{it}}$	**-0.138*****	**-0.109****	**-0.179*****	**-0.139*****
	(-2.839)	**(-1.977)**	**(-2.805)**	**(-3.441)**
Controls	No	Yes	Yes	Yes
Constant	-0.038	-3.717***	-1.954***	-3.972***
	(-1.355)	(-5.685)	(-3.183)	(-4.989)
Year FE	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes
Industry×Year FE	No	No	Yes	No
Province×Year FE	No	No	No	Yes
N	6471	6471	6471	6471
Adj. R^2	0.001	0.061	0.275	0.146

1.4.3.4. Moderating Effect Analysis

Table 1.8 presents the results of moderating effect regressions based on **Model (1.8)**, where the interaction term $CCD_{it-1} \times lnCGG_{it-1}$ captures whether government guarantees provided to firms, in the context of increasing FD-TI coupling coordination, strengthen its impact on corporate greenwashing behaviours.

Column (1) reports the OLS regression results, including control variables and year fixed effects only. Columns (2) and (3) incorporate firm-level fixed effects, with Column (3) additionally including control variables. Columns (4) and (5) replace the year dummies with alternative interactive fixed effects, Industry×Year and Province×Year, respectively, to test the robustness of the moderating effect while accounting for industry- or region-specific annual variations.

Across all specifications, the coefficients of $CCD_{it-1} \times lnCGG_{it-1}$ are consistently negative and statistically significant at the 1% level, indicating that higher levels of government guarantees significantly strengthen the negative relationship between FD-TI coupling coordination and subsequent greenwashing, consistent with **H3.** Moreover, the coefficients of CCD_{it-1} remain negative and statistically significant, reconfirming the baseline finding that stronger FD-TI coupling coordination effectively mitigates greenwashing. The statistically significant negative coefficients of $lnCGG_{it-1}$ further suggest that larger government guarantees directly curb firms' propensity to engage in symbolic or misleading environmental disclosure.

Collectively, government guarantees and FD-TI coupling coordination act as complementary governance mechanisms for enhancing corporate environmental performance. While government guarantees independently reduce corporate greenwashing, they also amplify the disciplining effect of market-driven FD-TI coupling coordination on firms' environmental commitments.

Table 1.8 The Moderating Role of Government Guarantees

Values of t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
	GW_{it}	GW_{it}	GW_{it}	GW_{it}	GW_{it}
$\boldsymbol{CCD_{it-1} \times lnCGG_{it-1}}$	**-1.767*****	**-2.228*****	**-2.370*****	**-2.324*****	**-1.902*****
	(-2.581)	**(-3.464)**	**(-3.647)**	**(-3.191)**	**(-3.326)**
$\boldsymbol{CCD_{it-1}}$	**-1.371*****	**-2.152*****	**-2.259*****	**-2.412*****	**-2.279*****
	(-3.392)	**(-3.271)**	**(-3.475)**	**(-3.498)**	**(-3.809)**
$\boldsymbol{lnCGG_{it-1}}$	**-0.844*****	**-0.991*****	**-1.053*****	**-0.995*****	**-0.774*****
	(-3.251)	**(-3.869)**	**(-4.053)**	**(-3.366)**	**(-3.243)**
$Size_{it-1}$	0.163***		0.013	0.035	-0.006
	(11.167)		(0.262)	(0.790)	(-0.119)
ROA_{it-1}	-0.066***		-0.018	-0.020	-0.016
	(-4.406)		(-1.182)	(-1.334)	(-0.867)
Lev_{it-1}	0.007		0.007	0.005	0.008
	(0.920)		(0.681)	(0.507)	(0.716)
CF_{it-1}	0.620***		-0.043	-0.260	-0.051
	(2.796)		(-0.205)	(-1.198)	(-0.239)
$TobinQ_{it-1}$	0.017		0.035*	0.037**	0.015
	(0.925)		(1.882)	(1.963)	(0.966)
$ExecS_{it-1}$	0.023		-0.302*	-0.318**	-0.271
	(0.300)		(-1.767)	(-2.036)	(-1.377)
Constant	-3.227***	0.857***	0.536	0.048	0.934
	(-8.307)	(3.583)	(0.462)	(0.045)	(0.849)
Year FE	Yes	Yes	Yes	No	No
Firm FE	No	Yes	Yes	Yes	Yes
Industry×Year FE	No	No	No	Yes	No
Province×Year FE	No	No	No	No	Yes
N	6471	6471	6471	6471	6471
Adj. R^2	0.062	0.628	0.628	0.650	0.607

Subsequently, to account for ownership characteristics, specifically, state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs), we further examine the heterogeneity in the moderating effect of government guarantees between these two types of firms. As shown in **Table 1.9**, Columns (1) and (2) present subgroup regressions alongside inter-group coefficient difference tests using Fisher's permutation method. Column (3) reports regressions incorporating triple interaction terms $CCD_{it-1} \times lnCGG_{it-1} \times SOE_{it-1}$ to capture the overall

moderating effect of government guarantees and its interaction with firm ownership structure within a single specification. Unlike subgroup regressions, the significance of the triple interactive terms directly indicates whether the moderating effects of government guarantees differ significantly between ownership types. Moreover, Column (3) uses the full sample, thereby avoiding estimation bias from sample variation and further validating the robustness of the interactive moderating effect analysis. All regressions control for firm- and year-level fixed effects, with standard errors clustered at the firm level.

Specifically, as shown in Columns (1) and (2), first, the coefficients of CCD_{it-1} are negative and statistically significant at 1% level for SOEs, with a higher magnitude than for non-SOEs, where the coefficient is smaller and only statistically significant at the 10% level. This suggests that regional FD-TI coupling coordination is more effective in constraining corporate greenwashing among SOEs than among non-SOEs. Furthermore, the coefficients of $lnCGG_{it-1}$ are negative and statistically significant at the 1% level for both SOEs and Non-SOEs, indicating that standalone government guarantees effectively mitigate corporate greenwashing.

However, when jointly considering the coefficients of $CCD_{it-1} \times lnCGG_{it-1}$, the estimates remain negative and statistically significant at the 1% level for the non-SOE groups, but become positive and statistically significant at the 5% level for the SOE groups. It suggests that, in the context of evolving market-driven FD-TI coupling coordination, government guarantees may weaken the mitigating effect of such coordination on greenwashing among SOEs, possibly due to adverse selection arising from long-term preferential treatment by the government. In contrast, government guarantees strengthen the disciplining effect in non-SOEs, likely because these firms tend to gain more competitive advantages within their industries through additional resources from the government. To formally assess the statistical significance of these inter-group differences, we employ Fisher's permutation test with 2,000 bootstrap replications. The results confirm the heterogeneity, with an empirical p-value of 0.037, indicating statistical significance at the 5% level.

Column (3) further validates the robustness of these findings. The triple interactive term $CCD_{it-1} \times lnCGG_{it-1} \times SOE_{it-1}$ demonstrates statistically significant positive coefficients, indicating a clear difference in the direction of the moderating effect of government

guarantees between SOEs and non-SOEs. Collectively, both regional FD-TI coupling coordination and standalone government guarantees effectively mitigate firms' greenwashing tendencies. However, as FD-TI coupling coordination continues to evolve, the influence of government guarantees varies across corporate ownership types in this context: for SOEs, such guarantees may reduce environmental compliance pressure, thereby weakening the disciplining effect of FD-TI coupling coordination; in contrast, for non-SOEs, they may encourage stronger environmental commitments aimed at achieving genuine market competitiveness. Therefore, **H4** is supported.

Table 1.9 The Interactive Moderating Role of Government Guarantees and Corporate State Ownership
Values of t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Non-SOEs	SOEs	
	(1)	(2)	(3)
	GW_{it}	GW_{it}	GW_{it}
$\boldsymbol{CCD_{it-1} \times lnCGG_{it-1} \times SOE_{it-1}}$			**0.390****
			(2.063)
$\boldsymbol{CCD_{it-1} \times lnCGG_{it-1}}$	**-2.588*****	**2.270****	**-0.353*****
	(-2.831)	**(2.448)**	**(-2.947)**
CCD_{it-1}	-1.518*	-3.008***	-0.341***
	(-1.767)	(-3.276)	(-4.676)
$lnCGG_{it-1}$	-1.100***	-1.064***	-0.159***
	(-2.953)	(-3.003)	(-3.148)
$CCD_{it-1} \times SOE_{it-1}$			0.363***
			(3.071)
$lnCGG_{it-1} \times SOE_{it-1}$			0.104*
			(1.670)
SOE_{it-1}			-0.124***
			(-2.963)
Controls	Yes	Yes	Yes
Constant	-0.839	1.814	-0.829***
	(-0.649)	(0.836)	(-13.677)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	4324	2147	6471
Adj. R^2	0.632	0.625	0.080
Fisher's permutation test Empirical p-value	0.037**		

1.5. Conclusions and Implications

China's rapid economic growth has long been accompanied by high energy consumption and severe environmental pollution. In response to growing environmental challenges, the

Chinese government has implemented increasingly stringent environmental regulations and market standards, directly linking environmental performance to firms' access to key productive resources. Consequently, many firms have resorted to greenwashing as a superficial strategy to signal environmental responsibility for compliance purposes and to secure external resources. Against this backdrop, the effectiveness of market forces in fostering genuine corporate environmental commitment has attracted growing attention from policymakers and scholars.

The rapid development of the market economic growth has also led to the accelerated integration of the two pillar industries of the financial sector and the technological sectors across regions, intensifying market dynamics by enhancing information transparency and resource flows. Simultaneously, given the substantial costs associated with green transformation, government guarantees have been introduced as supplementary resources to incentivise corporate substantive environmental actions. Therefore, it becomes essential to evaluate the effectiveness of both market-driven interactions between industries and government interventions in shaping corporate environmental strategies while also accounting for potential heterogeneity across firms.

To address these questions, this study develops a period-superimposed Logistic co-evolution model and a coupling coordination degree model, drawing on concepts from biology and physics, to examine the dynamic co-evolution of financial development (FD) and technological innovation (TI) at the provincial level in China. The degree of coupling coordination between FD and TI (CCD) is measured across 30 Chinese provinces from 2012 to 2020. Furthermore, fixed-effect OLS regressions, supplemented by robustness checks and interaction effect analyses, are employed to explore how market forces arising from FD-TI coupling coordination influence corporate greenwashing behaviour. The analysis also investigates the role of government guarantees and their interaction with state ownership. Based on these findings, recommendations are proposed for relevant stakeholders.

First, FD and TI in China are co-evolving, exhibiting an asymmetric, mutually beneficial symbiotic relationship, with the symbiotic effect of FD on TI significantly exceeding that of TI on FD. A coupling coordination relationship is gradually taking shape between FD and TI. Provincial estimates of the coupling coordination degree between FD and TI (CCD) in 30

Chinese provinces from 2012 to 2020 show that, while CCD across provinces has increased, it generally remains low. It displays significant temporal and spatial disparities across provinces, with TI lagging behind FD in most provinces. To address this imbalance, policymakers could prioritise measures that enhance the contribution of TI to FD. Targeted initiatives include increasing R&D investment in both traditional financial institutions and Fintech firms, fostering collaboration with higher education and research institutes, and accelerating the integration of innovative technologies into the financial sector to improve its efficiency, security and service diversity.

Second, regional CCD estimates reveal the pattern of East > Central > Northeast > West, reflecting the spatial characteristic of "high in the east and low in the west, high in the south and low in the north." Global and local spatial autocorrelation analyses confirm significant positive spatial autocorrelation of CCD across provinces, where provinces with similar CCD levels cluster together, respectively, and the considerable spillover effect from coastal eastern provinces to central and western inland provinces. This indicates a potential long-term trend towards a more balanced spatial distribution of CCD. To narrow regional disparities and foster more balanced national development, local governments could promote cross-regional flows and sharing of resources and talent in FD and TI, facilitate inter-regional knowledge and technology transfer, and encourage the establishment of inter-regional financial institution alliances, joint platforms for FD and TI enterprises, and collaborative R&D projects between more and less developed provinces. Policies fostering international cooperation and learning from global best practices can further accelerate the catch-up process in lagging regions (Amankwah-Amoah et al., 2018).

Third, higher provincial FD-TI coupling coordination significantly reduces corporate greenwashing behaviour, and this disciplining effect is further enhanced by government guarantees. This highlights the joint importance of market-driven integration and government intervention in promoting genuine corporate environmental commitment. Both central and local governments could expand the scale and improve the review mechanisms of government guarantees, with transparent, data-driven criteria enabled by FD-TI coupling coordination to ensure that guarantees are allocated to firms demonstrating substantive green performance. Developing integrated digital platforms for environmental and financial disclosure can

enhance monitoring, reduce resource misallocation by financial institutions and regulators, and support real green transformation.

Finally, the moderating effect of government guarantees differs by ownership structure: guarantees weaken the mitigating impact of FD-TI coupling coordination in state-owned enterprises (SOEs) but strengthen it in non-state-owned enterprises (non-SOEs). This suggests the need for market-oriented evaluation standards in assessing SOE environmental performance, with government guarantees allocated strictly based on verifiable green outcomes rather than administrative preferences. To avoid moral hazard and adverse selection, government guarantees allocation could follow transparent and merit-based criteria for all firms, with regular public disclosure of environmental results and guarantee utilisation. Strengthened monitoring and accountability mechanisms for SOEs can incentivise genuine green transformation and discourage symbolic compliance.

CHAPTER TWO

Can Green Financial Policies Shield Firms from Stock Price Crashes? The Role of Government Guarantees and Green Innovation Efficiency

Abstract

This chapter examines the effectiveness of green financial policies in promoting corporate green transformation for environmental objectives while simultaneously mitigating stock price crash risk, thereby contributing to economic stability. Focusing on China's Green Finance Reform and Innovation Pilot Zone (GFRIPZ) policy, we examine the mediating role of green innovation efficiency, which captures firms' capacity to undertake green transformation as intended by the policy. We also explore the moderating effect of government guarantees allocated to firms within the GFRIPZ framework, particularly in relation to their high-tech certification status. Employing a staggered difference-in-differences (DID) methodology, we find that the GFRIPZ policy, initiated in 2017, significantly reduces corporate stock price crash risk. However, this risk-mitigating effect is substantially weakened in the presence of higher levels of government guarantees, especially among high-tech certified firms. To measure firm-level green innovation efficiency for Chinese A-share listed companies across industries from 2012 to 2021, we construct a two-stage multiple input-output Stochastic Frontier Analysis (SFA) model that distinguishes between the R&D and commercialisation stages. We find that improvements in green innovation efficiency, particularly at the commercialisation stage, serve as a critical channel through which the GFRIPZ policy reduces stock price crash risk. These findings provide valuable policy insights into integrating environmental sustainability with corporate risk management practices.

Keywords

Green Financial Policy; Stock Price Crash Risk; Government Guarantees; Green Innovation Efficiency; SFA model.

2.1. Introduction

The rapid economic growth in China has relied on a scale-oriented development model characterised by intensive resource consumption and substantial pollutant emissions, posing significant challenges to sustainable development. Given the negative externalities of environmental protection, private sector production, while a key engine of economic growth, has also become a major source of environmental degradation. Directly shutting down these firms or imposing severe penalties for polluting behaviours undermines market stability and economic development. The primary challenge for the government is therefore to balance long-term corporate operational stability with environmental protection. Promoting firms' green transformation through regulatory tools has emerged as a promising strategy to achieve this balance (Kunapatarawong and Martínez-Ros, 2016).

As a form of market-based environmental regulation, green financial policies aim to internalise environmental protection costs by directly linking firms' access to external financing with their environmental performance. On 26th June 2017, China implemented a policy program titled "*Establishing Pilot Zones for Green Finance Reform and Innovations*", commonly known as the Green Finance Reform and Innovation Pilot Zone (GFRIPZ) policy. This initiative initially designated eight states or cities as the first batch of pilot zones to implement differentiated green finance practices. In late 2019, the policy expanded to a second batch of pilot zones, further promoting green finance innovation across regions. The GFRIPZ policy imposes tighter financing constraints on high-polluting and energy-intensive firms, while offering preferential terms to environmentally responsible firms. In this context, polluting firms will likely face heightened environmental compliance pressures when securing adequate capital at affordable costs. Government guarantees, another key form of financial support provided by the government, can alleviate the resource constraints induced by green financial regulations. However, government guarantees are also associated with moral hazard, potentially amplifying firms operational risks. Within the broader goal of coordinating the often conflicting objectives of economic stability and environmental protection, it is essential to examine the relationship between the GFRIPZ policy and stock price crash risk, an important indicator of firm-level operational stability with macroeconomic implications. This study specifically investigates the underlying mechanism role of green

transformation and also examines how government guarantees influence this process. Furthermore, given the strategic importance and inherent innovation capacity of high-tech firms, exploring how government guarantees interact with firms' high-tech certification status offers deeper insights into the effectiveness of the GFRIPZ policy.

This chapter contributes to the literature in three main aspects: (1) Using the phased implementation of China's GFRIPZ policy as an exogenous shock, we conduct a quasi-natural experiment using staggered difference-in-differences (DID) models combined with propensity score matching (PSM) to demonstrate the policy's effectiveness in mitigating firms' stock price crash risk. Unlike earlier green finance initiatives, the GFRIPZ policy represents a more comprehensive and dynamic approach, incorporating diverse green finance instruments and a gradual implementation strategy; (2) We calculate the level of government guarantees received by A-share listed firms in China from 2012 to 2021 and examine their moderating effect on the GFRIPZ policy's impact. Further, we explore how these guarantees interact with firms' high-tech certification status. To the best of our knowledge, few studies have analysed government guarantees as government contingent liabilities at the firm level in China within the context of stringent environmental regulations, nor does it consider how government guarantees interact with high-tech certifications in this context; (3) we employ a two-stage multiple input-output Stochastic Frontier Analysis (SFA) model to estimate firm-level green innovation efficiency (GIE), capturing efficiencies separately at the R&D and commercialisation stages across industries, which is a key intended outcome of the GFRIPZ policy. This approach offers a more nuanced measure of corporate green transformation than conventional proxies such as green patent counts. We further investigate their mediating role in the relationship between the GFRIPZ policy and stock price crash risk.

The remaining structure of this chapter is as follows: section 2.2 reviews the relevant literature and develops hypotheses accordingly. Section 2.3 describes the data and the methodology. Section 2.4 presents the empirical results and provides a corresponding interpretation. Section 2.5 concludes the chapter and offers policy recommendations.

2.2. Literature Review and Hypotheses Development

2.2.1. GFRIPZ Policy and Stock Price Crash Risk

As profit-maximising entities, firms typically lack the motivation to engage in environmental protection. Similarly, creditors such as banks tend to prioritise profitability and solvency over firms' ecological practices in loan-pricing decisions (Karaman et al., 2025). These environmental externalities have led to continuous government intervention. In this context, green finance, an extension of traditional environmental regulations, has emerged as an effective tool (Xu et al., 2023). By linking environmental performance to firms' access to and costs of external capital, green finance helps redirect capital flows towards environmental friendly projects, while constraining funds for polluting production activities. Given the critical role of external finance in corporate operations, green financial instruments such as green credit policies (e.g., Wen et al., 2021), green bond issuance (e.g., Flammer, 2021), and (carbon) emissions trading system (e.g., Compernolle et al., 2022) collectively impose a "penalty effect" on firms' polluting behaviours. These mechanisms incentivise investment in low-carbon technologies, enabling firms to adopt cleaner production methods and secure more favourable financing conditions.

The green financial policy framework in China was formally launched in 2012 with the introduction of the "*Green Credit Guidelines*", which mandated that banks incorporate firms' environmental performance into loan pricing and credit allocation. This regulatory approach linked green finance performance to banks' supervisory ratings, thereby avoiding banking institutions' undesirable lending behaviours driven solely by profitability. However, considering the significant regional disparities in financial development across China (Hu et al., 2019), a more targeted and region-specific approach to green finance implementation would be more appropriate than a uniform national strategy. In response, the Green Finance Reform and Innovation Pilot Zone (GFRIPZ) policy was implemented since 2017, progressively designating selected cities and regions as pilot zones for targeted experimentation with green financial instruments. These pilot zones promote the coordinated development of financial institutions, green financial products, information platforms, government support mechanisms, and risk prevention systems. A core feature is the application of differentiated interest rates and capital requirements based on firms'

environmental performance. This encourages firms to practically signal their green commitment to secure adequate and cost-effective financing. This signalling, often described as a "reputation insurance effect" (Bazillier et al., 2017), improves corporate information transparency and facilitates access to more favourable external capital.

Managerial career concerns and equity-based compensation have long incentivised executives to inflate corporate financial performance and conceal negative news (Jin and Myers, 2006; Kim and Zhang, 2016). The accumulation of undisclosed negative news hinders investors' timely expectation updates and delays the termination of underperforming projects (Ben-Nasr et al., 2021). Once the volume of concealed negative news exceeds a critical threshold beyond which continued concealment becomes too costly, it will be suddenly released to the market. This often triggers large-scale sell-offs, resulting in a sharp decline in stock prices and an overall crisis of stock market stability. Such unexpected stock price decline significantly damages corporate financial performance and shareholder value (Chen et al., 2023).

Within the frameworks of agency theory, information asymmetry theory, and signalling theory, the GFRIPZ policy is expected to reduce stock price crash risk. Firstly, by enhancing corporate information transparency, the GFRIPZ policy mitigates stock price crash risk driven by investor sentiment (Kim and Zhang, 2014; Firth et al., 2015). It mandates that financial institutions evaluate firms' environmental performance both pre- and post-lending. Accordingly, firms are mandated to disclose accurate and detailed information regarding their environmental protection efforts when applying for funding and maintain continuous environmental disclosures for ongoing supervision (Chen et al., 2023). In this context, the GFRIPZ policy facilitates the continuous optimisation of formal green credit rating systems jointly administered by government authorities, financial institutions, and third-party agencies. Unlike voluntary corporate social responsibility disclosures, which may reflect firms' desire to obtain the investor preference, these systems mitigate investor concerns around "greenwashing" through credible external monitoring (Yin et al., 2025). Consequently, by incentivising more comprehensive and consistent disclosure by firms to obtain external financing at lower costs, the GFRIPZ policy effectively addresses agency problems and information asymmetries (DeFond et al., 2015), thereby mitigating the risk of stock price crashes.

Secondly, the GFRIPZ policy effectively alleviates long-standing financing constraints by incentivising banking institutions to increase capital allocation to environmentally friendly firms that align with environmental compliance standards. The expansion of green credit and lower financing costs enhances firms' access to external capital, strengthens their risk management capacity, and reduces their incentives to conceal adverse information due to financing pressure, thereby decreasing stock price crash risk.

Thirdly, the GFRIPZ policy facilitates accurate assessments of firms' fundamental value by providing complementary information. Without credible disclosures, managers may selectively highlight positive information, causing investor over-optimism about the firm's growth prospects and speculative bubbles in stock prices (D'Arcangelis and Rotundo, 2021). The mandatory environmental and financial disclosures required by the GFRIPZ policy provide an information channel (Dhaliwal et al., 2012). This mitigates the impact of market noise on investors' decision-making, reducing the likelihood of stock price crashes.

Finally, the GFRIPZ policy enables firms to enhance their public image and build reputational capital by signalling their commitment to environmental responsibility. This not only improves stock price resilience that emerged from the insurance-like effect of strong environmental performance (Jia et al., 2020) but also aligns with investors' growing environmental concerns, thereby attracting long-term investor support (Zhang et al., 2022).

Collectively, the first hypothesis can be proposed as follows.

H1: The implementation of the GFRIPZ policy in China significantly reduces the stock price crash risk for firms in the pilot zones.

2.2.2. The Moderating Role of Government Guarantees

Some projects, despite generating significant social welfare benefits, often face severe financial constraints due to high risk profiles, limited collateral, and volatile returns. These challenges are further exacerbated under the GFRIPZ policy, which links firms' environmental performance to financing accessibility and cost. As a form of public intervention, government guarantees have emerged as an important mechanism to alleviate the resource constraints imposed by such green financial regulations (Kuo et al., 2011). These

guarantees typically take the form of loan guarantee schemes, guarantee fee reductions, and credit interest subsidies. Loan guarantee schemes can be categorised into direct and indirect types: under direct guarantees, the government shares credit risk directly with designated banks by reimbursing a portion of the unrecovered loan in the event of borrower default (Bachas et al., 2021); indirect guarantees operate through counter-guarantees and co-guarantees which involve third-party guarantors, with the government committing to covering part of the bank's losses if the guarantor defaults. Additionally, guarantee fee reductions and credit interest subsidies directly reduce the cost of external finance for firms (Luo et al., 2024). Collectively, these guarantee schemes help bridge the risk gap between firms and financial institutions, thereby alleviating firms' financing constraints in the context of increasingly stringent environmental policies.

However, the risk exposure bridge function of government guarantees may reduce investors' sensitivity to firm-specific risks. Firstly, such guarantees can be perceived as a form of political endorsement strategically acquired by firms, potentially distorting investors' assessment of firms' fundamental growth prospects. While the GFRIPZ policy enhances corporate information transparency and improves investors' monitoring and pricing accuracy, government guarantees may send a strong positive signal regarding a firm's development potential, which is highly valued by both banks and external investors (Söderblom et al., 2015). Consequently, firms receiving such guarantees may be viewed as enjoying implicit insurance protection, thereby weakening investors' sensitivity to the potential operational risk and exacerbating information asymmetry. As a result, the reduction in stock price crash risk initially achieved through the GFRIPZ policy may be partially offset, or even reversed, due to the unintended consequences of more government guarantees.

Second, government guarantees may increase firms' propensity toward moral hazard. The primary objective of the GFRIPZ policy is to make corporate environmental performance a key criterion for financial resource allocation, thereby forcing firms to undertake green initiatives and mitigating the tendency of firms' short-term or excessive risk-taking behaviours. However, when firms can access government guarantees typically awarded based on profitability and perceived growth potential, they receive both reputational endorsements and additional financial resources. This can incentivise firms to construct operational risk

shelters, prioritising access to government guarantees over compliance with the environmental standards mandated by the GFRIPZ framework. Consequently, these firms may divert resources from government guarantees towards high-risk projects with potentially higher returns, rather than towards substantial environmental investments. This misalignment weakens the disciplining effect of the GFRIPZ policy on corporate risk-taking, increases the likelihood of concealing negative news, and exacerbates misleading disclosures regarding green practices, ultimately elevating the risk of stock price crashes.

Third, while the GFRIPZ policy effectively attracts more investors with long-term scope and strong green concerns who make influential investments in greener projects, the allocation of government guarantees may serve as short-term signals about a firm's development prospects. Firms benefiting from government guarantees are often perceived as having strong short-term growth potential, which attracts more speculative investors with shorter investment horizons. This shift in investor composition can lead to higher volatility of stock prices, as speculative investors are more prone to herding behaviour and sentiment-driven trading (D'Arcangelis and Rotundo, 2021). Consequently, the likelihood of large-scale sell-offs driven by market overreactions or irrational sentiment is heightened, thereby increasing the risk of stock price crashes.

Collectively, the effectiveness of the GFRIPZ policy in mitigating stock price crash risk may be undermined by the involvement of government guarantees. These government guarantees may weaken the policy's intended governance mechanisms by introducing adverse selection and moral hazard, thereby undermining the transparency and discipline fostered through the GFRIPZ policy. Accordingly, the second hypothesis is proposed as follows:

H2a: A higher level of government guarantees allocated to firms significantly weakens the mitigating effect of the GFRIPZ policy on corporate stock price crash risk.

2.2.3. The Interactive Moderating Role of Government Guarantees and High-tech Certification

High-tech firms are typically distinguished from various production sectors by their significant R&D investments, a high proportion of intangible assets such as patents

(Chabakauri and Han, 2020; Wu and Lai, 2020), the significant share of scientific research personnel in their workforce, and the production with advanced technologies (An et al., 2020). In China, firms can apply for official high-tech enterprise verification under the criteria outlined in the official document implemented by Chinese authorities in 2016, "*Management Measures for the Recognition of High-tech Enterprises*[5]". Firms certified as high-tech enterprises in China are eligible for a range of preferential government supports, including access to government guarantees, income tax reductions, and assistance in talent recruitment. Managers are thus incentivised to aggressively increase R&D expenditures and exploratory innovation projects to obtain high-tech certification, even when the expected net present value of such projects is negative. Managers may conceal the financial risks or poor prospects of these projects during the certification process to meet the eligibility thresholds (Bai et al., 2022). However, once certification is secured, this bad news will be strategically released, resulting in a heightened stock price crash risk for firms with high-tech certification.

Under the GFRIPZ policy framework, enhanced environmental performance can act as a substitute for traditional tangible assets in serving as collateral (Nandy and Lodh, 2012). This substitution effect is particularly relevant for firms in the high-tech industry, which are typically characterised by a high intensity of intangible assets and limited tangible collateral. Ideally, these high-tech firms would be more responsive to the GFRIPZ policy, leveraging their environmental performance to alleviate financing constraints. However, firms with high-tech certification in China benefit from various preferential treatments such as government guarantees, which may serve as a financial "safety cushion". This external support may weaken the firm's incentive to actively engage in environmental information disclosure as mandated by the GFRIPZ policy. Instead of leveraging environmental performance to gain access to green finance, high-tech certified firms may strategically rely on the financial support brought by government guarantees. Consequently, the negative moderating effect of government guarantees on the relationship between the GFRIPZ policy and stock price crash risk is expected to be more pronounced among firms with high-tech certifications.

[5] This document specifies that high-tech enterprises must engage in continuous R&D and technology transformation in government-classified high-tech industries. These firms must develop core independent intellectual property rights and conduct business activities based on these innovations. To qualify as high-tech enterprises, firms must meet specific criteria, such as allocating a particular proportion of revenue to R&D and making substantial investments in technical human capital.

Additionally, high-tech firms are inherently subject to greater uncertainty and risk in their return profiles. These characteristics result in more severe financing constraints, making them more likely to discontinue or suspend R&D projects due to funding shortages (Hall and Lerner, 2010; Li, 2011). As a result, investor sensitivity to negative signals is heightened, increasing the likelihood of sell-offs and thereby amplifying stock price crash risk in high-tech firms. Within this context, high-tech certified firms in China are more willing to leverage government guarantees as the "insurance-like" mechanism to shield their risky investment behaviours. Compared to non-high-tech firms, they are more likely to engage in aggressive information manipulation, earnings management, and selective disclosure to maintain high-tech certification for long-term government benefits. Consequently, more government guarantees allocated to high-tech certified firms can exacerbate the risk of stock price crashes in high-tech certified firms by distorting the effectiveness of the governance mechanism of information transparency by the GFRIPZ policy.

Collectively, firms with incentives to pursue and maintain high-tech certifications are more inclined to engage in policy arbitrage from government resources such as guarantee schemes, thereby weakening the effectiveness of the GFRIPZ policy, which is designed to promote corporate environmental commitment. Rent-seeking behaviours are particularly pronounced among high-tech certified firms, making them more likely to obtain financing through greenwashing strategies rather than genuine improvements in environmental performance. As a result, the effectiveness of the GFRIPZ policy in mitigating stock price crash risk by encouraging real enhancements in environmental performance that are valued by investors is substantially weakened in these cases. This ultimately leads to a more pronounced stock price crash risk among high-tech certified firms.

Therefore, the following hypothesis can be proposed:

H2b: Compared to non-high-tech certified firms, high-tech certified firms exhibit greater sensitivity to government guarantees weakening the mitigating effect of the GFRIPZ policy on the corporate stock price crash risk.

2.2.4. The Channel Role of Green Innovation Efficiency

Porter's hypothesis demonstrates that well-designed environmental regulations, even when stringent, can significantly enhance firms' long-term profitability by incentivising the development and adoption of green innovations (Porter and Vanderlinde, 1995; Chemmanur and Fulghieri, 2014; Sun et al., 2020; Fu et al., 2023). Although such regulations may initially impose substantial compliance costs on firms and cause short-term productivity losses during the green transformation process, these costs can be offset by improvements in green productivity, primarily through higher efficiency of green innovation (Acemoglu et al., 2016). Specifically, green innovation encompasses both environmental protection and technology advancement, referring to innovations aimed at mitigating the adverse environmental impacts of polluting and energy-intensive sectors (Chen et al., 2006). While indicators such as the number of green patents and their associated ratios are widely used as proxies for green innovation capacity at the regional or firm level (e.g., Irfan et al., 2022; Liu and Wang, 2023), the efficiency of green innovation has emerged as a more critical metric for financial institutions and investors to assess how effectively firms transform inputs into environmentally beneficial outcomes, thus serving as an essential indicator of the effectiveness of stringent environmental regulations (Xing et al., 2021).

The continuous development of green finance plays a critical role in improving environmental quality by promoting green innovation (Su and Lee, 2025). As one of the most influential green finance initiatives in China, the GFRIPZ policy regulates corporate environmental behaviours by mandating financial institutions to allocate credit based on specific environmental performance indicators, such as green innovation. However, green innovation is a long-term, resource-intensive process. The GFRIPZ policy addresses these challenges by offering below-market interest rates to support green innovation efforts. Amid the broader adoption of environmental regulations, external investors have become increasingly favouring greener projects (Yang et al., 2017). Consequently, firms are incentivised to proactively maximise the outputs and outcomes of green innovation with minimal inputs, thereby enhancing green innovation efficiency, as a way to signal environmental commitment to stakeholders. Under the GFRIPZ policy's governance mechanism, which operates on the principle that "the greener the firm, the cheaper and faster the financing," firms can improve

their access to green financing only by demonstrating high efficiency in green innovation and thus optimising their environmental credentials (Xu et al., 2023). This dynamic encourages firms to more effectively allocate internal resources toward high-potential green innovations in the R&D stage and to expedite the commercialisation of green technologies as a prerequisite for securing external financing (An et al., 2021). Financial institutions, in turn, are more inclined to provide timely and sustained financial support on favourable terms to firms with higher efficiency in green innovation (Degryse et al., 2023). Following the systematic development and investments of green innovation efficiencies in both R&D and commercialisation stages, firms accumulate greater intangible assets, which yield marginal value and generate additional stock returns (Duong et al., 2025). These developments help alleviate investor concerns regarding uncertain returns, thereby reducing idiosyncratic risks in stock prices arising from fluctuations in investor sentiment (Xue et al., 2020).

Specifically, the green innovation process can be divided into two key stages: the research and development (R&D) and commercialisation. The R&D stage primarily involves the accumulation of technological knowledge and technology reserves. However, due to the significant information asymmetry existed in advanced technological development, the outcomes of the R&D stage are often difficult for external stakeholders to evaluate. These achievements typically require a high level of technical expertise to assess and they can only be seen over extended time horizons. As such, the R&D stage does not produce immediately observable results, making it challenging for firms to receive timely recognition from external investors for their green innovation performance during this stage,. Nevertheless, effective resource utilisation in the R&D stage contributes significantly to a firm's internal efficiency and serves as a positive signal of its long-term development potential. By demonstrating a commitment to forward-looking environmental strategies, firms can partially address growing investor green concerns. This thus attract favourable investor attention, thereby helping to reduce stock sell-off risks (Grimmer and Bingham, 2013).

Subsequently, the GFRIPZ policy incentivises firms to accelerate the transformation of advanced green technologies accumulated during the R&D stage into commercially viable products and services. This process not only enhances the firm's profitability prospects but also encourages the disclosure of environmental responsibility inherent in their production

and sales activities. By doing so, firms increase the transparency of their operations, effectively sending a credible green signal to external stakeholders and capital markets. This enhanced information disclosure reduces operational and financial risks by improving investor confidence, and it aligns firms with growing environmental expectations through more efficient green innovation (Benlemlih et al., 2018). As a result, the risk of stock price crashes due to the concealment or delayed release of negative news is significantly mitigated.

Moreover, the inherent significant information asymmetry between firms, government agencies, and financial institutions leads the GFRIPZ policy to primarily rely on quantity-based indicators, such as the number of green patents, the diffusion rate, and the market share of green products, as metrics to evaluate corporate environmental performance. Consequently, firms are incentivised to pursue the efficient commercialisation of green innovations, enabling them to quickly meet these compliance thresholds and secure eligibility for preferential green financing. Higher efficiency in the commercialisation stage of green innovation reflects both greater profit potential and more visible environmental responsibility. This, in turn, generates reputational assets and fosters improvements in both the frequency and quality of corporate information disclosure (Cui et al., 2018), thereby reducing the managers' incentives to conceal operational risks. Additionally, since the risk of future stock price crashes often originates from investors' difficulty in accurately assessing the true value of the firm, the greater transparency surrounding a firm's real green innovation capacity allows investors to form more accurate price expectations that are closely aligned with fundamental value (Guan and Wen, 2025). Consequently, the risk of future stock price crashes is significantly mitigated.

Collectively, the two-stage green innovation process under the GFRIPZ policy framework enables firms to accumulate technology reserves and intellectual capital during the R&D stage, which are then effectively transformed into commercialised products through marketisation capabilities (Jia et al., 2024). By improving efficiency in both R&D and commercialisation, the GFRIPZ policy enhances investors' expectations and understanding of firms' long-term prospects. This improved transparency and positive signalling strengthen firms' resilience to negative price movements and help maintain investor confidence, thereby significantly reducing stock price crash risk driven by investor panic.

Overall, the following hypothesis can be proposed:

H3: The GFRIPZ policy mitigates the corporate stock price crash risk through the channel of enhancing firms' two-stage green innovation efficiency, especially the commercialisation-stage efficiency.

2.3. Methods

2.3.1. Sample and Data Collection

This study selects all Chinese A-share listed firms as the initial sample, focusing on a five-year period before and a four-year period after the release of the GFRIPZ policy to examine its impact on firm performance. This timeframe, spanning from 2012 to 2021, minimises the interference of extraneous policy noise over a longer horizon (Shi et al., 2022). To ensure the reliability and consistency of the data, the following firms are excluded from the sample: (1) firms in the financial sector; (2) firms subject to special treatment (i.e., ST, ST*, or PT), as designated by the China Securities Regulatory Commission; (3) firms with missing information in key financial data; and (4) firms with fewer than 30 trading weeks of stock return data in a given fiscal year. Ultimately, the final sample consists of 15823 firm-year annual observations from 3447 unique firms. All continuous firm-level variables are winsorised at the 1% and 99% percentiles to mitigate the influence of extreme values. The primary data source is the China Stock Market and Accounting Research (CSMAR) database, supplemented by data from the National Bureau of Statistics of China and the Statistical Communiqué of the National Economic and Social Development. Information on firms' high-tech certifications is obtained from the Chinese Research Data Services (CNRDS) Platform[6].

[6] In China, high-tech enterprise certification criteria are outlined in the government working program "*Management Measures for the Recognition of High-tech Enterprises*," issued by three central administration departments of China on 29 January 2016. This document specifies that the qualification of an enterprise certified as a high-tech enterprise in a particular year is valid for three years from when the certificate is issued. Based on this document, the Torch High Technology Industry Development Centre of the Ministry of Science and Technology of China publishes updated lists of high-tech enterprises in China annually.

2.3.2. Variable Selection and Measurement

2.3.2.1. Dependent Variables

Two indicators are employed to measure the stock price crash risk of firms: (1) the negative conditional skewness of firm-specific weekly returns over the fiscal year (***NCSKEW***), and (2) the down-to-up volatility (***DUVOL***), namely the logarithm of the variance of weekly returns in "down weeks" relative to "up weeks." (Chen et al., 2001; Xu et al., 2024). Both measures are calculated based on firm-specific weekly returns, which are derived from the residuals of a regression of market-weighted average returns. Specifically, the following regression, shown in **Equation (2.1)**, is initially conducted to obtain the residuals used in calculating ***NCSKEW*** and ***DUVOL*** for the sample firms:

$$r_{i,j} = \alpha_i + \beta_{1,i} r_{m,j-2} + \beta_{2,i} r_{m,j-1} + \beta_{3,i} r_{m,j} + \beta_{4,i} r_{m,j+1} + \beta_{5,i} r_{m,j+2} + \varepsilon_{i,j} \quad (2.1)$$

where $r_{i,j}$ denotes the weekly return of firm ***i*** in week ***j***, adjusted for the reinvestment of cash dividends; $r_{m,j}$ is the average return of all stocks of A-share listed firms in China weighted by their outstanding market capitalisation at week *j*. The model also incorporates two-period lead and lag terms of the value-weighted market return to account for the effect of non-synchronous trading (Kim et al., 2011). The residual term ($\varepsilon_{i,j}$) captures the firm-specific component of returns that cannot be explained by fluctuations in the value-weighted market return. Subsequently, the firm-specific weekly return for firm ***i*** adjusted by the value-weighted market return for week j, denoted as $W_{i,j}$, is calculated using $W_{i,j} = ln(1 + \varepsilon_{i,j})$ (Hutton et al., 2009). Based on this, *NCSKEW* and *DUVOL* are calculated using **Equations (2.2)** and **Equation (2.3)**, respectively**:**

$$NCSKEW_{i,t} = -\left[n(n-1)^{\frac{3}{2}} \sum W_{i,j}^3\right] / \left[(n-1)(n-2)\left(\sum W_{i,j}^2\right)^{\frac{3}{2}}\right] \quad (2.2)$$

$$DUVOL_{i,t} = log\{[(n_u - 1)\sum_{Down} W_{i,j}^2] / [(n_d - 1)\sum_{Up} W_{i,j}^2]\} \quad (2.3)$$

where $\boldsymbol{n}$ denotes the total number of trading weeks for firm $\boldsymbol{i}$ in year $\boldsymbol{t}$; n_d and n_u represent the number of weeks in which the firm-specific weekly return of firm $\boldsymbol{i}$ is below and above the annual average of its firm-specific weekly returns, respectively.

2.3.2.2. Moderating Variable

Corporate Government Guarantees (CGG_t) are conceptualised as a form of government contingent liability. Following the methodology proposed by the International Monetary Fund (IMF) (2009, 2014), and based on the Contingent Claims Analysis (CCA) framework, this study constructs a continuous proxy for CGG. Specifically, the CGG is defined as the disparity between the expected stock market-based losses of firm $\boldsymbol{i}$ in year $\boldsymbol{t}$ ($ELV_E(t)$), derived from stock market data, and the expected debt market-based losses ($ELV_D(t)$), estimated from corporate bond spreads. It is calculated as $CGG_t = ELV_E(t) - ELV_D(t)$ and subsequently logarithmically transformed for empirical analysis. The detailed calculation process for the parameters is presented in **Section 1.3.2.4** of **Chapter One.** The key difference here lies in the sample period: while chapter one covers 2012-2020, this chapter extends the horizon to 2012-2021. Accordingly, the parameter **T** in the calculation reflects this revised period, namely **T=10.** The resulting dataset provides annual firm-level estimates of government guarantees received by China's A-share listed firms from 2012 to 2021.

2.3.2.3. Control Variables

This study also includes a range of firm-level and regional-level control variables: **(1) Firm size (*Size*):** measured as the natural logarithm of a firm's total assets; **(2) Corporate leverage ratio (*Lev*)**: defined as the logarithm of a firm's total long-term debts divided by its total assets; **(3) Return on assets (*ROA*):** calculated as the firm's net income divided by its total assets; **(4) Stock volatility (*Sigma*):** measured as the standard deviation of firm-specific weekly returns derived based on $W_{i,j} = ln(1 + \varepsilon_{i,j})$ within a fiscal year (Kim and Zhang, 2016); **(5) Detrended stock turnover ratio fluctuation during the year (*Dturnover*)**: measures the heterogeneity of investor opinions that leads to changes in stock trading volume and liquidity (Ji et al., 2021). Given the typically high turnover ratios in China's A-share market, detrended

stock turnover ratio fluctuation is defined as the average monthly stock turnover ratio of a firm in year t minus that in year t-1; **(6) lagged stock price crash risk (*NCSKEW* and *DUVOL*)**: The one-period lagged values of the firm's stock price crash risk indicators are included to capture the potential serial correlation effects (Kim et al., 2014); (7) **Industrial structure (*lnIndus*):** measured as the logarithm of the proportion of the total output value of the secondary sector[7] to GDP in firm's registered city; and **(8) Urban financial development (*lnCityFin*):** proxied by the natural logarithm of the total amount of deposits and loans held by financial institutions in the city.

The detailed definitions of all variables and their corresponding data processing methods are summarised in **Appendix D1**.

2.3.3. Model Specification

2.3.3.1. The GFRIPZ Policy Effect on Stock Price Crash Risk

The GFRIPZ policy, first introduced in 2017 and subsequently expanded in 2019, represents an exogenous policy shock with respect to corporate stock price crash risk and thus provides a suitable setting for a quasi-natural experiment. Given that the policy was implemented in multiple phases across different regions over the period from 2012 to 2021[8], a staggered difference-in-differences (DID) approach is adopted to evaluate the policy's effect on firms' stock price crash risk, as shown in Model (2.4). The staggered DID framework offers important advantages in this policy context, as it captures both temporal and regional variation in treatment timing and allows all treated firms and not-yet-treated firms to jointly contribute to identification, an aspect that cannot be captured using a static DID approach. However, recent literature has also highlighted important limitations of the conventional two-way fixed effects estimator in staggered adoption settings. In particular, conventional two-way fixed-effects estimates may be biased when treatment effects vary across cohorts or over time, and

[7] The secondary sector in China includes mining (excluding mining specialities and auxiliary activities), manufacturing (excluding metal products, machinery and equipment repair), electricity, heat, gas and water production and supply, and construction.

[8] The first batch of pilot zones was designated in June 2017, covering eight regions: Huzhou and Quzhou in Zhejiang Province; Ganjiang New District in Jiangxi Province; Guangzhou in Guangdong Province; Gui'an New District in Guizhou Province; and Hami City, Changji Prefecture, and Karamay in the Xinjiang Autonomous Region. The second batch was introduced in December 2019, with Lanzhou in Gansu Province included as a new pilot zone.

they may lead to risks of implicit comparisons between already-treated and later-treated groups. Moreover, sharply segmenting policy implementation periods may introduce additional bias (Baker et al., 2022). To address these concerns, this chapter interprets the staggered DID results using the estimator developed by Callaway and Sant'Anna (2021), which is particularly suitable for settings with variation in treatment timing across units. This framework requires several assumptions that are satisfied in the context of the GFRIPZ policy. First, the treatment is irreversible, as once a city enters the pilot zone, it remains treated thereafter. Second, both the untreated group and the not-yet-treated group can serve as credible comparison units, as they satisfy the conditional parallel trends assumption before treatment. Third, the estimator assumes that treatment assignment is independent across units, conditional on observable covariates, which is consistent with the staggered and policy-driven nature of the GFRIPZ implementation. Beyond this estimator setting, the baseline staggered DID findings are further complemented by several robustness tests to ensure the credibility of the estimation, including propensity score matching (PSM) to reduce potential self-selection bias, a dynamic trend test to examine the pre-trend effect, and placebo tests using alternative treatment timing specifications. These complementary analyses ensure that the estimated policy effects are not driven by biases related to the estimator or timing.

$$CrashRisk_{it+1} = \beta_0 + \beta_1 GFRIPZ_{it} + \beta Controls_{it} + \lambda_i + \gamma_{jt} + \varepsilon_{ijt} \quad (2.4)$$

where the subscripts ***i***, ***j*** and ***t*** represent firm, industry and year, respectively. $CrashRisk_{it+1}$ represents the one-period-ahead stock price crash risk of firm ***i*** in year ***t+1***. $GFRIPZ_{it}$ is a binary indicator variable equal to 1 if firm *i* is located in a city designated as a pilot zone under the GFRIPZ policy in year ***t***, and 0 otherwise. $Controls_{it}$ denotes a set of control variables. λ_i represent the firm-fixed effects to account for unobserved time-invariant differences across firms (Liu and Wang, 2023). γ_{jt} represents the industry-by-year (*Year*Industry*) fixed effects (Maksimovic and Phillips, 2008), to control for the interference of industry cycle impacts over different years on stock price crash risk. ε_{ijt} is the error term.

Considering the potential self-selection bias from the non-random designation of pilot zones under the GFRIPZ policy due to both observable and unobservable regional characteristics such as industrial structure, economic endowments, and the level of financial development, which cannot be not fully captured, we employ propensity score matching (PSM) method to address this concern (Al Guindy, 2021). PSM allows us to identify the observable factors influencing a firm's probability of being assigned to the treated group, thereby mitigating the endogeneity issues that arise when such factors are included in the error terms otherwise. A Logistic regression (Xiao et al., 2023), as presented in **Model (2.5)**, is employed to estimate the propensity scores and proceed with the matching process.

$$\rho(Covariates_i) = Pr[Treat_i = 1|Covariates_i] = E(Treat_i|Covariates_i) \quad (2.5)$$

Where $Treat_i$ is a binary variable indicating whether a firm is registered in a city designated as a pilot zone under the GFRIPZ policy during the sample period. $Covariates_i$ denotes a set of observable firm- and region-level characteristics that influence the likelihood of a firm being located in a pilot zone by the GFRIPZ policy. $\rho(Covariates_t) = Pr[Treat_i = 1|Covariates_t]$ represents the probability that a firm is assigned to the treatment group, conditional on these covariates. We include all firm-level and city-level control variables from **Model (2.4),** excluding the current period dependent variable, as covariates in the propensity score estimation. Besides, two firm-level variables are incorporated as additional covariates: Capital expenditure as a percentage of total assets (***Capex***); and the executive shareholding ratio (***ExecS***), both of which capture key dimensions of corporate investment and governance structure. Among the total 15,823 firm-year observations, 843 are identified as treated ($Treat_i = 1$), we apply a 1:5 k-nearest neighbour matching strategy to enhance matching efficiency and ensure balance, allowing each treated observation to be matched with up to five untreated firms exhibiting similar characteristics in terms of key influencing factors. A tolerance level of 0.05 is incorporated into the caliper matching estimator to limit the maximum allowable distance in propensity scores between matched pairs, thereby mitigating

the risk of poor matches. This approach enables us to construct a comparable control group for the robustness of the policy evaluation (Rosenbaum and Rubin, 1983).

2.3.3.2. The Moderating Effect of Government Guarantees and Its Interaction with High-tech Certification

Building upon the baseline estimation of the GFRIPZ policy's impact on corporate stock price crash risk, we further explore the moderating role of market-implied government guarantees and their interaction with firms' high-tech certification status (**H2** and **H2a**) using **Models (2.6)** and Model **(2.7)** as specified below:

$$Crashrisk_{it+1} = \alpha_0 + \alpha_1 GFRIPZ_{it} \times lnCGG_{it} + \alpha_2 GFRIPZ_{it} + \alpha_3 lnCGG_{it} + \alpha Controls_{it} + \lambda_i + \gamma_{jt} + \varepsilon_{ijt} \quad (2.6)$$

$$Crashrisk_{it+1} = \alpha_0 + \alpha_1 GFRIPZ_{it} \times lnCGG_{it} \times Hightech_{it} + \alpha_2 GFRIPZ_{it} \times lnCGG_{it} + \alpha_3 GFRIPZ_{it} \times Hightech_{it} + \alpha_4 lnCGG_{it} \times Hightech_{it} + \alpha_5 GFRIPZ_{it} + \alpha_6 lnCGG_{it} + \alpha_7 Hightech_{it} + \alpha Controls_{it} + \lambda_i + \gamma_{jt} + \varepsilon_{ijt} \quad (2.7)$$

In **Model (2.6)**, $GFRIPZ_{it} \times lnCGG_{it}$ denotes the interaction between the GFRIPZ policy and the level of government guarantees received by firms. A consistently negative α_2, accompanied by a statistically significant positive α_1, would indicate that the the GFRIPZ policy significantly mitigates corporate stock price crash risk, but this mitigating effect is weakened when firms receive more government guarantees.

To address potential multicollinearity and ensure a meaningful interpretation of the coefficients when interaction terms are included, the normalisation treatment is applied to the $lnCGG_{it}$. Given that the raw values of government guarantees in the sample are highly skewed and contain extreme values, we use mean-value normalisation, calculated by subtracting the sample mean from each observation and dividing by the range (i.e., the difference between the maximum and minimum values). Subsequently, **Model (2.7)** explores the interaction of

the moderating role of corporate government guarantees with firms' high-tech certification status. We employ a difference in difference in difference (DDD) estimation technique (Olden and Møen, 2022), in which $Hightech_{it}$ is a dummy variable equal to 1 if firm i obtained high-tech certification in year t, and 0 otherwise. All other symbols and subscripts follow the definitions established in the baseline **Model (2.4)**.

2.3.3.3. The Mechanism Role of Green Innovation Efficiency

The verification steps for exploring the mechanism through which the GFRIPZ policy mitigates corporate stock price crash risk via the two-stage green innovation efficiencies are outlined as follows (e.g., Irfan et al., 2022; Zeng et al., 2022):

$$GIE_{it} = \theta_0 + \theta_1 GFRIPZ_{it} + \theta Controls_{it-1} + \lambda_i + \gamma_{jt} + \varepsilon_{ijt} \quad (2.8)$$

$$Crashrisk_{it+1} = \delta_0 + \delta_1 GFRIPZ_{it} + \delta_2 GIE_{it} + \delta Controls_{it} + \lambda_i + \gamma_{jt} + \varepsilon_{ijt} \quad (2.9)$$

where GIE_{it} denotes the two-stage corporate green innovation efficiency, including both the R&D stage efficiency (GIE_RD_{it}) and commercialisation stage efficiency (GIE_COM_{it}), with the effects of each stage analysed separately. The mechanism analysis is conducted in two steps, conditional on the statistical significance of the coefficient β_1 in **Model (2.4).** Specifically, **Model (2.8)** examines the impact of the GFRIPZ policy on the two-stage corporate green innovation efficiency, while **Model (2.9)** investigates the mediating role of green innovation efficiency in the relationship between the GFRIPZ policy and corporate stock price crash risk**.** Following the causal step approach (Baron and Kenny, 1986; Kenny et al., 1998) and building on existing studies (e.g., Wan et al., 2022), the validity of the statistically significant negative coefficient β_1 in the baseline regressions confirms the primary effect of the GFRIPZ policy in reducing stock price crash risk. A statistically significant positive coefficient θ_1 in **Model (2.8)** indicates that the GFRIPZ policy significantly enhances corporate green innovation efficiency. Subsequently, the statistical significance of both δ_1 and δ_2 in **Model (2.9)** suggests that green innovation efficiency serves as a partial mediator in the relationship between the GFRIPZ policy and stock price crash risk,

where $\beta_1 = \delta_1 + \theta_1\delta_2$. If the sign of $\theta_1\delta_2$ is the consistent with that of δ_1(expected to be negative), the partial mediation effect of the two-stage green innovation efficiency is further supported, with the magnitude of the mediating effect calculated as $\theta_1\delta_2$.

2.3.4. The Evaluation of Corporate Green Innovation Efficiency

Green-oriented innovation has become a primary strategy for firms seeking to meet rising environmental expectations from investors, thereby gaining competitive advantages and securing above-average industry returns (Yu et al., 2021a). Evaluating the efficiency of green innovation offers critical insights into a firm's actual capability to optimise green innovation outputs relative to the resources invested (Cruz-Cázares et al., 2013), reflecting its proficiency in implementing sustainable practices. However, few studies have focused on green-oriented innovation efficiency at the firm level, with most evaluations conducted at the regional or national level (Zeng et al., 2021). Some studies have examined overall innovation efficiency at the firm level (Avilés-Sacoto et al., 2020) or broader industry and regional levels (Guan and Chen, 2012; Wan et al., 2022). These analyses commonly employ both non-parametric and parametric methods for efficiency estimation, such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA).

Given that our sample comprises annual observations for over 3000 firms, exhibiting significant firm-level heterogeneity, the DEA approach may fail to account for random factors and is highly sensitive to outliers. Therefore, we use the SFA method to measure firm-level green innovation efficiency using dynamic panel data (Aigner et al., 1977; Schmidt and Sickles, 1984; Kumbhakar, 1990; Battese and Coelli, 1995; Greene, 2005). The SFA framework facilitates the separation of traditional random noise from the "compound disturbance term," thereby quantifying technical efficiency through the remaining technical inefficiency term. This approach reduces the influence of outliers and simplifies the data processing requirements (Wan et al., 2022). Specifically, we employ the technical inefficiency effects model proposed by Battese and Coelli (1995), which is particularly suitable for panel data analysis. This BC-SFA framework models the inefficiency term, interpreted here as losses in green innovation efficiency, as a function of firm-specific exogenous variables, allowing the exploration of how these factors influence green innovation efficiency across

both the R&D and commercialisation stages. A Cobb-Douglas production function is adopted in conjunction with a two-stage correlation model for the estimation process (Afrifa et al., 2022).

In this study, the corporate green innovation process is divided into two distinct stages: the R&D stage and the commercialisation stage. The R&D stage represents the initial phase of green innovation, including inputs such as human, financial investment, and material resources, and generating outputs in the form of green innovation achievements (Min et al., 2020). The commercialisation stage reflects a firm's ability to transform these R&D achievements into economic returns and market value. We construct two-stage multiple input-output SFA models, specified in **Model (2.10)** and **Model (2.11),** aimed at evaluating green innovation efficiency from the perspective of achieving maximum output for a given level of input.

$$y_{R\&D,it} = \beta_{R\&D,0} + \sum_{K=1}^{K} \beta_{R\&D,k}\, x_{R\&D,k,it} + \varepsilon_{R\&D,it}\,,\ \varepsilon_{R\&D,it} = v_{R\&D,it} - \mu_{R\&D,it} \tag{2.10}$$

$$y_{Commercial,it} = \beta_{commercial,0} + \beta_{commercial,1}\, y_{R\&D,it} + \sum_{K=1}^{K} \beta_{commercial,k}\, x_{commercial,k,it} + \varepsilon_{commercial,it}\,,\varepsilon_{commercial,it} = v_{commercial,it} - \mu_{commercial,it} \tag{2.11}$$

where $y_{R\&D,it}$ and $y_{Commercial,it}$ represent the R&D-stage output and commercialisation-stage output of firm ***i*** in year ***t***, respectively. The error terms $\varepsilon_{R\&D,it}$ and $\varepsilon_{commercial,it}$ denote the "compound disturbance terms", which comprise a conventional random noise component ($v_{R\&D,it}$ and $v_{commercial,it}$) capturing stochastic variation beyond the control of firm ***i,*** and a technical inefficiency component ($\mu_{R\&D,it}$ and $\mu_{commercial,it}$) measuring the extent to which practical productivity output of firm ***i*** deviates from the theoretical output possibility frontier. The two-stage green innovation efficiency (GIE_{it}), comprising R&D-stage efficiency (GIE_RD_{it}) and commercialisation-stage efficiency (GIE_COM_{it}), is estimated by computing the expectation value of the conditional distribution of the technical inefficiency terms, given

the compound disturbance terms, following the Battese and Coelli (1995) estimator, i.e., $GIE_{it} = E(e^{\mu_{it}} | \varepsilon_{it})$.

Specifically, $y_{R\&D,it}$ is measured by the natural logarithm of the number of granted green patents. The green patent data is obtained by matching the IPC classification numbers of each firm's granted patents issued by the China National Intellectual Property Administration (CNIPA) and the IPC Green Inventory[9] issued by the World Intellectual Property Organisation (WIPO). If a corporate patent's IPC number appears in the IPC Green Inventory, it is classified as a green patent (Wang and Li, 2022). The R&D stage input vector, denoted as $\sum_{K=1}^{K} \beta_{R\&D,k}\, x_{R\&D,it}$ include four indicators (***k=4***) for firm *i* in year *t*: the proportion of R&D personnel (*lnRDperson*) (Avilés-Sacoto et al., 2020), total R&D expenditure (*lnRDexpense*) (Wang et al., 2016), the R&D government subsidies directed at supporting green innovation (*lnRDsubsidy*) (Huergo and Moreno, 2017; Branstetter et al., 2023), and annual net fixed assets (*lnRDfixedasset*), which serve as a proxy for the material R&D input into R&D activities.

The commercialisation stage output, denoted as $y_{Commercial,it}$, is measured by the natural logarithm of a firm's main business income. All granted green patents from the R&D stage are assumed to have "double identities", which are potential inputs for commercialisation stage (Guan and Chen, 2010). Free intermediate outputs are not accounted for. $\beta_{commercial,1}\, y_{R\&D,it}$ denotes the logarithmic number of granted green patents (*lnGreengrant*), which captures the linkage between the two stages in the green innovation (Lee et al., 2019). The input vector for the commercialisation stage, denoted as $\sum_{K=1}^{K} \beta_{commercial,k}\, x_{commercial,k,it}$, includes three variables (***k=3***): the proportion of non-R&D employees (*lnNonRDperson*), the natural logarithm of firm carbon dioxide emissions (*lnFirmCO2*), and the firm's annual total energy consumption (*lnEnergyconsume*). Based on the annual total energy consumption for each industry[10], the firm-level annual total energy consumption is calculated using the ratio

[9] The "IPC Green Inventory" facilitates searches for patent information related to Environmentally Sound Technologies (ESTs), as identified by the United Nations Framework Convention on Climate Change (UNFCCC). (https://www.wipo.int/classifications/ipc/green-inventory/home).

[10] Since direct firm-level energy consumption is typically unavailable, it is estimated through industrial-level energy consumption data. Specifically, total industrial energy consumption includes usage of raw coal, crude oil and derivatives, natural gas and electricity. Given that coal constitutes over 70% of industrial energy consumption in China, all types of energy are converted to standard coal equivalents for aggregation and comparison purposes.

of the firm's annual operating cost to those of its corresponding industry, following the approach of Ding et al. (2023)[11].

The production frontier is estimated using the technical inefficiency effects BC-SFA model under maximum likelihood estimation (MLE) and random-effects time-varying settings, based on the common characteristics of all firms (Battese and Coelli, 1995). However, industry-level heterogeneity in production technologies need to be considered, as some sectors rely more on fixed asset investments and energy consumption, whereas others depend heavily on R&D inputs. Following the *Guidance for Industry Classification of Listed Companies* (2012 revision) issued by the China Securities Regulatory Commission (CSRC) in 2012[12], our sample firms are distributed across eight of the nineteen broad industries. Accordingly, we estimate two-stage green innovation efficiency by grouping firms into these eight industries. The full set of nineteen industry categories, and the specific eight industries covered by the sample in this Chapter, are listed in **Appendix B2**.

This approach enhances the comparability of estimated green innovation efficiencies across industries with varying structural characteristics. To address the issue of significant heteroskedasticity inherent in the SFA process, particularly when using unbalanced panel data, we adopt a heterogeneity-adjusted specification (Afrifa et al., 2022). This adjustment helps to mitigate potential bias in the green innovation efficiency measurement by accounting for firm-level and industry-specific heterogeneity in the inefficiency distribution, especially differences in technological capabilities and pollution intensity. Specifically, a key influencing factor, z_{1i}, is introduced to capture the variation in technical inefficiency and its uncertainty using model $\varpi_i = \gamma_0 + \gamma_1 z_{1i}$, where ϖ_i represents the deviation of firm i from the stochastic frontier. In this context, z_{1i} comprises two industry-level dummy variables: one indicating whether the firm operates in a high-tech industry (*Hightech*), and another indicating whether the firm is classified as the high-polluting sectors[13] (*Pollut*) (Kumbhakar et al., 2012).

[11] Corporate Energy consumption = (Corporate Annual Operating Cost / Industrial Annual Operating Costs) * Industrial Energy Consumption.

[12] This document classifies A-share listed companies in China into 90 different sectors under 19 broad industries.

[13] In China, the identification of high-polluting firms primarily follows the criteria outlined in the "*Directory of Industry Classification Management of Listed Companies for Environmental Verification (2008)*" and the "*Guidelines for Disclosure of Environmental Information of Listed Companies (2010)*", both issued by the Ministry of Ecology and Environment of China. These documents classify 14 sectors as highly polluting, which correspond to 19 sectors outlined in the Guidance for Industry Classification of Listed Companies (2012 revised edition) released by the China Securities Regulatory Commission (See **Appendix C1**). We cross-reference these classifications with industry codes of China's A-share listed firms to accurately

2.3.5. Descriptive Analysis

Descriptive statistics for the key variables are reported in **Table 2.1**. The mean and standard deviation values of the one-period forward dependent variables ($NCSKEW_{it+1}$ and $DUVOL_{it+1}$) are broadly consistent with those found in existing research using Chinese firm-level data (e.g., Ji et al., 2021; Xu et al., 2024). The logarithmic value of corporate government guarantees (***lnCGG***) exhibits substantial variability, as evidenced by the wide range between the minimum (0.440) and maximum (3.678) values. The mean value of ***GFRIPZ*** is 0.036, indicating that 3.6% of firm-year observations in the sample were categorised as affected by the GFRIPZ policy during the observation period. Both R&D-stage and commercialisation-stage green innovation efficiencies (***GIE_RD*** and ***GIE_COM***) exhibit significant variation across firms, with the commercialisation stage broadly showing higher efficiency levels. The two-stage frontier estimation results from the two technical inefficiency effects BC-SFA models, specified in **Model (2.9)** and **Model (2.10)**, are presented in **Appendix B1.** The descriptive statistics of the remaining control variables are largely consistent with those reported in the existing studies.

Table 2.1 Descriptive Statistics of Variables

Variable	N	Mean	SD	Min	Max
NCSKEW	15823	-0.343	0.715	-2.492	1.636
DUVOL	15823	-0.228	0.468	-1.346	0.987
Size	15823	22.558	1.257	20.257	26.412
Lev	15823	0.085	0.092	0	0.424
ROA	15823	0.033	0.059	-0.245	0.183
Sigma	15823	0.049	0.019	0.017	0.109
Dturnover	15823	-0.095	0.449	-2.006	0.960
Capex	15823	5.189	4.608	0.065	22.309
Execs	15823	11.569	17.650	0	64.809
lnCGG	15823	2.455	0.499	0.440	3.678
lnCityFin	15823	10.142	1.520	6.468	12.573
lnIndus	15823	3.649	0.332	2.760	4.167
GFRIPZ	15823	0.036	0.187	0	1
GIE_RD	15823	0.402	0.281	0.136	0.699
GIE_COM	15823	0.634	0.203	0.083	0.884

identify those operating in high-polluting sectors.

As shown in **Table 2.2**, the correlation coefficient matrix reveals a strong and statistically significant correlation of 0.8750 between the two proxies of stock price crash risk. This finding aligns with most studies (Callen and Fang, 2015; Jia, 2018), ensuring the comparability and robustness of regression results using either dependent variable. All other pairwise correlation coefficients are below 0.5. The complementary variance inflation factor (VIF) test reports a maximum VIF of 1.75 and a mean VIF of 1.31 (VIF<10), further indicating that there are no multicollinearity problems among the variables (Wooldridge, 2015).

Table 2.2 Correlation Matrix of Variables

* represents significance at the 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) $NCSKEW_{it+1}$	1														
(2) $DUVOL_{it+1}$	0.8750*	1													
(3) $Size_{it}$	0.0017	-0.0161	1												
(4) Lev_{it}	-0.0114	-0.0187	0.3233*	1											
(5) ROA_{it}	0.0425*	0.0369*	-0.1052*	-0.0784*	1										
(6) $Sigma_{it}$	0.0168	-0.0041	-0.2630*	-0.1017*	0.1001*	1									
(7) $Dturnover_{it}$	-0.0396*	-0.0508*	0.1569*	0.0800*	0.0010	0.2461*	1								
(8) $Capex_{it}$	0.0299*	0.0092	-0.0608*	0.1383*	0.0153	0.0239	-0.1219*	1							
(9) $Execs_{it}$	0.0101	0.0099	-0.3441*	-0.1360*	0.0609*	0.1715*	-0.1703*	0.1526*	1						
(10) $lnCGG_{it}$	-0.0064	-0.0114	-0.0794*	-0.0469*	-0.0041	-0.1718*	-0.0114	0.0785*	-0.0406*	1					
(11) $lnCityFin_{it}$	0.0023	0.0065	0.0756*	-0.0273*	0.0371*	0.0478*	-0.0518*	-0.0784*	0.0780*	-0.1692*	1				
(12) $lnIndus_{it}$	-0.0066	-0.0124	-0.0996*	0.0080	-0.0256	-0.0212	0.0155	0.0895*	0.0061	0.1380*	-0.4319*	1			
(13) $GFRIPZ_{it}$	0.0042	0.0010	-0.0105	-0.0072	0.0200	-0.0092	-0.0107	0.0156	0.0272*	-0.0479*	0.0724*	-0.0741*	1		
(14) GIE_RD_{it}	0.0143	0.0253	-0.2058*	-0.1359*	0.0397*	0.1442*	-0.1107*	0.0386*	0.2518*	-0.1802*	0.1025*	-0.0568*	0.0579*	1	
(15) GIE_COM_{it}	0.0144	0.0067	0.2795*	-0.0918*	0.0001	0.0136	-0.0170	-0.0630*	0.0549*	-0.1024*	0.2163*	-0.1386*	0.0404*	0.3237*	1

2.4. Results

2.4.1. Baseline Regression

The baseline estimation of the impact of the GFRIPZ policy on corporate stock price crash risk was conducted using fixed effects difference-in-differences (FE-DID) regressions, applied to samples both before and after propensity score matching. Given that the GFRIPZ policy specifically targets the designation and development of selected cities as pilot zones, standard errors were clustered at the firm's registered city level. This approach helps mitigate the potential bias from cross-sectional dependence (Xu et al., 2024), such as the correlations within different cities' economic development (Bruhn and Love, 2014).

Table 2.3 summarises the results of the propensity score matching process. After applying the k-nearest neighbour matching, the Average Treatment Effect on the treated group (ATT) increased to 0.0561 and 0.0578, with corresponding t-statistics of 2.09 and 2.04 when using NCSKEW and DUVOL as the dependent variable, respectively, both statistically significant at the 5% level. Only 80 observations from the untreated group, out of 15823, fell outside the common support. This suggests that, in addition to mitigating self-selection bias, the matching process effectively addressed potential bias arising from the significant imbalance in the number of treated and control group observations.

Table 2.3 Propensity Score Matching Analysis

ATT denotes Average Treatment Effect on the Treated; ATE denotes Average Treatment Effect (on all); ATU denotes Average Treatment Effect on the Untreated.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
NCSKEW	Unmatched	-0.3196	-0.3446	0.0250	0.0253	0.99
	ATT	-0.3196	-0.3757	0.0561	0.0268	2.09
	ATU	-0.3447	-0.3146	0.0300	.	.
	ATE			0.0314	.	.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
DUVOL	Unmatched	-0.3066	-0.3340	0.0275	0.0263	1.05
	ATT	-0.3066	-0.3643	0.0578	0.0283	2.04
	ATU	-0.3340	-0.3115	0.0224	.	.
	ATE			0.0243	.	.

Treatment	Common Support		
Assignment	**Off support**	**On support**	**Total**
Untreated	80	14900	14980
Treated	0	843	843
Total	80	15743	15823

The balance test results in **Table 2.4** indicate that the *p*-values for all covariates are higher than 10% after matching, suggesting the robust matching quality given the set of covariates in constructing a treated and control group without systematic differences post-matching.

Table 2.4 Balance Test of Propensity Score Matching Process

* if variance ratio outside [0.87; 1.14] for U and [0.87; 1.14] for M, U represents Unmatched and M represents Matched.

Variable	Unmatched	Mean		%reduct		t-test		V(T)/V(C)
	Matched	Treated	Control	%bias	|bias|	t	p>|t|	
Size	U	22.49	22.562	-6.0		-1.62	0.106	0.82*
	M	22.49	22.529	-3.2	46.5	-0.66	0.512	0.82*
Lev	U	-3.5214	-3.4396	-4.1		-1.20	0.229	1.21*
	M	-3.5214	-3.499	-1.1	72.6	-0.23	0.820	1.17*
ROA	U	-2.9998	-3.0543	3.9		1.06	0.289	0.84*
	M	-2.9998	-2.9889	-0.8	79.9	-0.16	0.873	0.84*
Sigma	U	0.04799	0.04957	-8.1		-2.23	0.026	0.86*
	M	0.04799	0.04785	0.7	91.0	0.16	0.875	0.99
Dturnover	U	-0.10314	-0.09469	-1.9		-0.53	0.595	0.97
	M	-0.10314	-0.10521	0.5	75.5	0.10	0.923	1.04
Capex	U	5.4895	5.1724	7.1		1.94	0.052	0.88
	M	5.4895	5.4506	0.9	87.7	0.17	0.862	0.80*
Execs	U	11.969	11.547	2.4		0.68	0.499	1.07
	M	11.969	11.551	2.3	1.1	0.48	0.632	1.08
lnCityFin	U	10.486	10.122	26.9		6.76	0.000	0.54*
	M	10.486	10.537	-3.8	85.9	-0.83	0.409	0.64*
lnIndus	U	3.5806	3.6531	-23.9		-6.17	0.000	0.63*
	M	3.5806	3.5916	-3.6	84.8	-0.74	0.460	0.61*

Figure 2.1, together with **Table 2.4**, demonstrates a substantial reduction in the absolute percentage bias across covariates after matching, with reductions ranging from 1.1% to 91.0% compared to the unmatched case. **Figure 2.1** illustrates a pronounced deviation in the kernel density function distribution between the two groups before matching, which is significantly mitigated following the matching process.

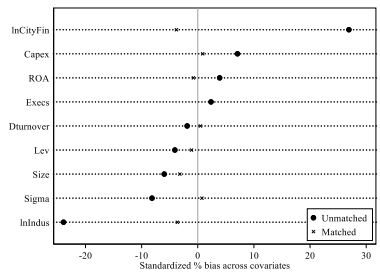


Figure 2.1 The Bias of the Treated and Control Groups before and after Propensity Score Matching

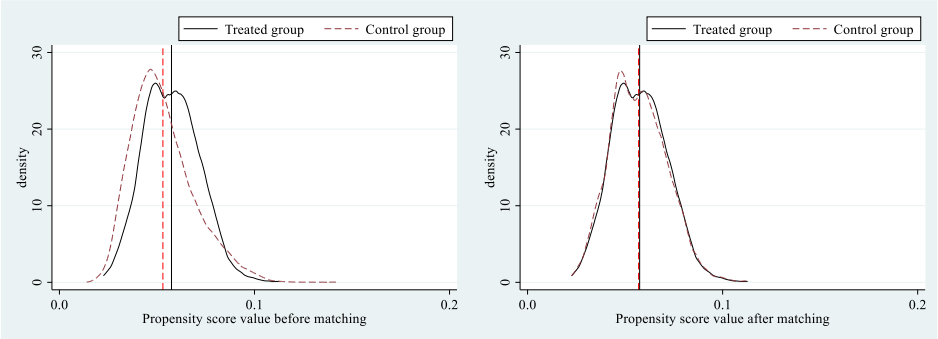


Figure 2.2 Kernel Density Function Distributions before and after Propensity Score Matching

As shown in **Table 2.5**, columns (1) and (2) report the baseline results with only firm-level fixed effects, while the remaining columns incorporate additional *Year*Industry* interactive fixed effects. Specifically, columns (1) to (4) report baseline results using the full samples before PSM, whereas Columns (5) to (8) present results based on the sample after PSM. Columns (5) and (6) show the results using the sample of firms engaged in PSM[14], and columns (7) and (8) present the results using firms that satisfy the Common Support Hypothesis[15] for testing the robustness of PSM results.

Firstly, the coefficients of $GFRIPZ_{it}$ across all specifications in **Table 2.5** remain consistently negative and stable in magnitude. The use of two alternative proxies, NCSKEW and DUVOL, further validates the robustness of baseline analysis for **H1.** Specifically, the GFRIPZ policy led to a reduction in the stock price crash risk of approximately 8.3% to 8.7% when measured by NCSKEW, with the coefficients statistically significant at the 1% level. Similar statistical significance is observed when using DUVOL as the dependent variable, indicating a reduction in corporate stock price crash risk ranging from 7.6% to 9.1%. Additionally, the coefficients of the control variables are consistent with those reported in prior studies (e.g., Xu et al., 2021).

[14] **_weight** indicates whether a sample firm participates in matching and its relative importance in the process. Thus, ***_weight!=.*** denotes firms involved in PSM, which helps mitigate potential self-selection bias present in pre-PSM regressions to some extent.

[15] The Common Support Hypothesis (CSH) ensures substantial overlap in the distribution of propensity scores between treated and control groups, meaning each treated observation has comparable counterparts in the control group. Accordingly, ***On_Support*** denotes firms that satisfy CSH.

Table 2.5 The GFRIPZ Policy and Corporate Stock Price Crash Risk

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM				After PSM			
					(*Weight!=.*)		(*On_Support*)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$NCSKEW_{it+1}$	$DUVOL_{it+1}$	$NCSKEW_{it+1}$	$DUVOL_{it+1}$	$NCSKEW_{it+1}$	$DUVOL_{it+1}$	$NCSKEW_{it+1}$	$DUVOL_{it+1}$
$\boldsymbol{GFRIPZ_{it}}$	**-0.086*****	**-0.076*****	**-0.087****	**-0.091*****	**-0.083****	**-0.088*****	**-0.085****	**-0.089*****
	(-2.797)	**(-2.932)**	**(-2.239)**	**(-2.739)**	**(-2.046)**	**(-2.774)**	**(-2.178)**	**(-2.695)**
$Size_{it}$	0.045**	0.021	0.060***	0.026*	0.062	0.053	0.064***	0.028**
	(2.138)	(1.227)	(3.099)	(1.794)	(1.282)	(1.324)	(3.554)	(2.080)
Lev_{it}	0.001	0.001	0.004	0.004	0.004	0.001	0.005	0.004
	(0.046)	(0.284)	(0.789)	(0.984)	(0.255)	(0.079)	(0.805)	(0.997)
ROA_{it}	0.009**	0.006*	0.012***	0.007**	0.016	0.015*	0.012***	0.007**
	(2.057)	(1.941)	(2.648)	(2.369)	(1.226)	(1.868)	(2.651)	(2.288)
$Sigma_{it}$	1.661***	0.687**	2.490***	1.256***	2.323***	1.808***	2.498***	1.254***
	(3.724)	(2.486)	(5.573)	(4.723)	(2.625)	(2.779)	(5.478)	(4.607)
$Dturnover_{it}$	0.126***	0.093***	0.044**	0.030*	0.196***	0.129***	0.045**	0.031*
	(6.392)	(6.697)	(2.171)	(1.899)	(5.073)	(4.362)	(2.190)	(1.936)
$NCSKEW_{it}$	-0.112***		-0.108***		-0.116***		-0.109***	
	(-10.155)		(-8.511)		(-4.817)		(-8.635)	
$DUVOL_{it}$		-0.102***		-0.096***		-0.107***		-0.097***
		(-11.664)		(-9.604)		(-3.976)		(-9.849)
$lnIndus_{it}$	-0.023	-0.011	-0.060	-0.025	-0.203	-0.012	-0.069	-0.030
	(-0.249)	(-0.164)	(-0.655)	(-0.384)	(-0.954)	(-0.078)	(-0.754)	(-0.466)
$lnCityFin_{it}$	0.039	0.039**	0.053	0.033	0.067	0.030	0.059*	0.032
	(1.396)	(2.078)	(1.541)	(1.169)	(0.774)	(0.450)	(1.722)	(1.139)
Constant	1.923***	-1.109**	-2.163***	-1.136**	-3.287**	1.858	-2.274***	-1.150**
	(2.900)	(-2.014)	(-3.088)	(-2.109)	(-2.180)	(1.571)	(-3.242)	(-2.153)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
N	15823	15823	15823	15823	3376	3376	14885	14885
Adj. R^2	0.054	0.046	0.097	0.092	0.059	0.058	0.098	0.092

2.4.2. Robustness Test

2.4.2.1. Parallel Trend Test

The event study approach is employed to test the parallel trend assumptions, which is a key prerequisite for the validity of the baseline staggered Difference-in-Differences (DID) models. This is implemented by incorporating a series of dummy variables that indicate whether the GFRIPZ policy was implemented in a firm's registered city in year t. Specifically, the event study framework is established in **Model (2.12)** as follows:

$$CrashRisk_{ijt+1} = \omega_0 + \omega_1 pre_5 + \omega_2 pre_4 + \omega_3 pre_3 + \omega_4 pre_2 + \omega_5 current + \omega_6 post_1 + \omega_7 post_2 + \omega_8 post_3 + \omega_9 post_4 + \beta Controls_{ijt} + \lambda_i + \gamma_{jt} + \varepsilon_{ijt} \quad (2.12)$$

Where *pre_** (* = 2,3,4,5) and *post_** (*=1,2,3,4) represent the years relative to the implementation of the GFRIPZ policy in the city where a firm is registered. For instance, *pre_2* and *post_3* denote two years before and three years after the policy implementation year, respectively. The implementation year itself, either 2017 or 2019, depending on the city where the firm is registered, is captured by the variable ***current. Pre_1*** (one year before the specific implementation year of the GFRIPZ policy) is chosen as the base year and excluded from the model to avoid multicollinearity. The coefficients of ***pre_**, **post_*,*** and ***Current***, along with their statistical significance, describe the difference in the stock price crash risk between firms in pilot and non-pilot cities across time relative to the policy's implementation. All other symbols and subscripts maintain the same definitions as in the baseline models.

Table 2.6 presents the regression results of the parallel trend test. Across all specifications, both before and after propensity score matching (PSM) and using the two alternative dependent variables, show no statistically significant relationship between *pre_** and the corporate stock price crash risk before the implementation year of the GFRIPZ policy. There was no significant difference in the stock price crash risk between the treated and control groups during the pre-policy period, supporting the parallel trends assumption. The coefficients of ***current*** are consistently negative and significantly negative at the 5% level,

suggesting that the mitigating effect of the GFRIPZ policy on stock price crash risk for firms in pilot zones significantly became evident in the year of implementation. Furthermore, the coefficients for *post_1* and *post_2* remain significantly negative in several specifications at the 5% or 10% level, confirming the persistence of the policy's impact in the subsequent years.

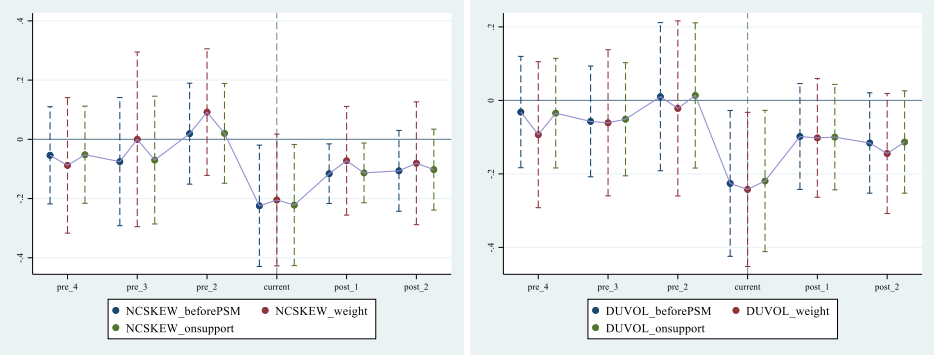
Table 2.6 Parallel Trends and Dynamic Analysis

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM		After PSM			
			(*Weight!=.*)		(*On_Support*)	
	(1)	(2)	(3)	(4)	(5)	(6)
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
pre_5	**-0.021**	**-0.093**	**-0.014**	**-0.102**	**-0.019**	**-0.090**
	(-0.233)	**(-1.633)**	**(-0.120)**	**(-1.427)**	**(-0.204)**	**(-1.588)**
pre_4	**-0.054**	**-0.032**	**-0.088**	**-0.093**	**-0.052**	**-0.035**
	(-0.646)	**(-0.412)**	**(-0.759)**	**(-0.928)**	**(-0.624)**	**(-0.459)**
pre_3	**-0.075**	**-0.057**	**-0.000**	**-0.061**	**-0.070**	**-0.051**
	(-0.685)	**(-0.747)**	**(-0.000)**	**(-0.605)**	**(-0.640)**	**(-0.655)**
pre_2	**0.019**	**0.010**	**0.092**	**-0.022**	**0.020**	**0.014**
	(0.221)	**(0.099)**	**(0.849)**	**(-0.181)**	**(0.235)**	**(0.135)**
current	-0.224**	-0.226**	-0.205*	-0.242**	-0.222**	-0.219**
	(-2.157)	(-2.241)	(-1.820)	(-2.283)	(-2.135)	(-2.246)
post_1	-0.116**	-0.098	-0.072	-0.102	-0.113**	-0.100
	(-2.268)	(-1.342)	(-0.780)	(-1.248)	(-2.213)	(-1.371)
post_2	-0.106	-0.116*	-0.081	-0.145*	-0.102	-0.113
	(-1.534)	(-1.669)	(-0.770)	(-1.749)	(-1.474)	(-1.601)
post_3	0.012	-0.017	0.065	-0.038	0.016	-0.013
	(0.108)	(-0.248)	(0.474)	(-0.475)	(0.146)	(-0.188)
post_4	-0.066	-0.061	-0.058	-0.101	-0.060	-0.054
	(-1.151)	(-0.891)	(-0.648)	(-1.219)	(-1.054)	(-0.812)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.877**	-0.913	-3.123*	-1.071	-1.872**	-0.848
	(-2.511)	(-1.613)	(-1.821)	(-0.826)	(-2.554)	(-1.497)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	15823	15823	3376	3376	14918	14918
Adj. R^2	0.078	0.070	0.082	0.086	0.079	0.072

Additionally, **Figure 2.3** illustrates that the estimated coefficients of *pre_** (* = 2,3,4,5) remain statistically insignificant and fluctuate closely around zero prior to the policy implementation. In contrast, following the implementation of the GFRIPZ policy, the

coefficients exhibit a sharp decline below zero, indicating a significant negative effect of the policy on the corporate stock price crash risk of firms in pilot zones. Overall, these results confirm that the baseline model's findings satisfy the parallel trend assumption.



(a) Dependent variable: $NCSKEW_{t+1}$ (b) Dependent variable: $DUVOL_{t+1}$

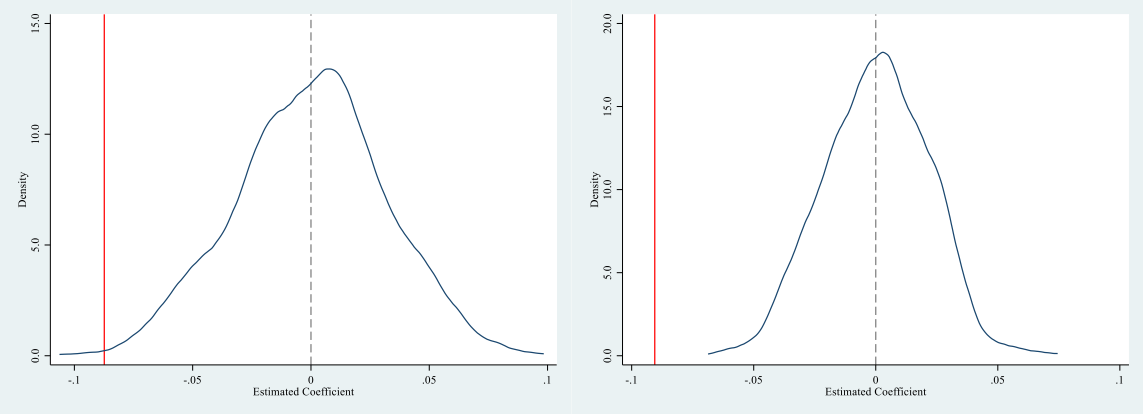
Figure 2.3 Dynamic Effect of the GFRIPZ Policy

2.4.2.2. Placebo Test

The core feature of the GFRIPZ policy is the designation of two batches of pilot zones, nine cities in total, introduced in 2017 and 2019. Firms registered in these cities constitute the treated group. To further ensure the robustness of our findings, we conducted placebo tests at both the regional and firm levels to examine potential interference from random region- or firm-specific factors. Specifically, since 187 firms in the sample are located in the nine official pilot zones affected by the GFRIPZ policy during the sample period, we randomly selected 187 firms and nine cities, respectively, from the full sample to construct fictitious treated groups. This random sampling process was repeated 1000 times. For each time, we conducted PSM-DID regressions consistent with the specifications in columns (7) and (8) of the baseline regression analysis shown in **Table 2.5.**

Figure 2.4 presents the probability distribution of the estimated coefficients of $\boldsymbol{GFRIPZ_{it}}$ from 1000 placebo regressions using the two dependent variables. The red vertical lines indicate the actual estimated coefficients from the baseline regressions in **Table 2.5**. These red lines stand out as outliers relative to the bootstrapped coefficients, which are approximately normally distributed and centred around zero. This contrast indicates that the baseline results are unlikely to occur when the treated group is randomly assigned. The observed reduction in

stock price crash risk is not driven by random regional or individual firms' factors, but rather by the setting of the two batches of pilot zones by the GFRIPZ policy in 2017 and 2019.



(a) Dependent variable: $NCSKEW_{t+1}$ (b) Dependent variable: $DUVOL_{t+1}$

Figure 2.4 Region-based placebo test

2.4.2.3. Addressing Reusing Natural Experiments

An expanding body of literature has employed natural experiment methods to assess the impact of state- or region-level regulatory changes. However, repeated testing of the same natural experiment can significantly increase the likelihood of false discoveries (Heath et al., 2023). To the best of our knowledge, existing articles examining the effects of the GFRIPZ policy using a DID framework have primarily relied on traditional DID models that adopt a single treatment year of 2017, without accounting for the second batch of pilot zones designated in 2019. In contrast, our study employs a staggered DID design, capturing the ongoing evolution of the policy's phased implementation. Additionally, the risk of false discovery remains negligible when the number of independent studies on a specific experiment is fewer than ten (Gao et al., 2021a). Prior research has primarily focused on the GFRIPZ policy's impact on outcomes such as on corporate (green) innovation (Liu and Wang, 2023; Xu et al., 2023), debt-financing cost (Shi et al., 2022), and investment efficiency, whereas our study contributes to the literature by investigating its effect on corporate stock price crash risk.

2.4.3. Moderating Effect Analysis

2.4.3.1. The Moderating Effect of Government Guarantees

Table 2.7 presents the results examining the moderating role of government guarantees received by firms. Columns (1) and (2) report FE-DID regressions using samples before propensity score matching (PSM), while Column (3) and (4) present the results using firms that satisfy the Common Support Hypothesis after PSM. Firm-level fixed effects and the year*industry interaction fixed effects are included in all regressions.

Table 2.7 Moderating Effect: Government Guarantees

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM		After PSM (*On_Support*)	
	(1)	(2)	(3)	(4)
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
$\boldsymbol{GFRIPZ_{it} \times lnCGG_{it}}$	**0.419*****	**0.240****	**0.418*****	**0.241****
	(2.682)	**(2.537)**	**(2.674)**	**(2.542)**
$\boldsymbol{GFRIPZ_{it}}$	**-0.058***	**-0.061****	**-0.058***	**-0.060****
	(-1.740)	**(-2.117)**	**(-1.749)**	**(-2.110)**
$lnCGG_{it}$	0.001	0.001	0.001	0.001
	(0.893)	(0.734)	(0.968)	(0.720)
$Size_{it}$	0.045**	0.022	0.045**	0.023
	(2.126)	(1.325)	(2.291)	(1.450)
Lev_{it}	-0.001	-0.001	-0.001	-0.001
	(-0.167)	(-0.363)	(-0.175)	(-0.394)
ROA_{it}	0.009**	0.006*	0.009*	0.006*
	(1.995)	(1.836)	(1.923)	(1.763)
$Sigma_{it}$	1.721***	0.718**	1.736***	0.725**
	(3.862)	(2.470)	(3.812)	(2.466)
$Dturnover_{it}$	-0.124***	-0.093***	-0.126***	-0.094***
	(-6.311)	(-6.663)	(-6.271)	(-6.650)
$NCSKEW_{it}$	-0.111***		-0.112***	
	(-9.631)		(-9.869)	
$DUVOL_{it}$		-0.101***		-0.102***
		(-11.150)		(-11.476)
$lnIndus_{it}$	0.023	-0.007	0.021	-0.009
	(0.241)	(-0.105)	(0.223)	(-0.134)
$lnCityFin_{it}$	0.042	0.044**	0.043	0.043**
	(1.472)	(2.153)	(1.483)	(2.070)
Constant	-1.988***	-1.214**	-1.994***	-1.205**
	(-2.869)	(-2.169)	(-2.928)	(-2.219)
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
N	15823	15823	14885	14885
Adj. R^2	0.052	0.045	0.053	0.045

All coefficients of $GFRIPZ_{it}$ remain negative, consistent with the baseline regression results, although both the magnitude and statistical significance levels decline slightly, with significance levels at the 10% and 5% thresholds, respectively. The mitigating effect of the GFRIPZ policy on corporate stock price crash risk persists even when government guarantees are taken into account. The coefficients of the interaction terms ($GFRIPZ_{it} \times lnCGG_{it}$) are all positive and statistically significant at the 1% and 5% level, respectively. This indicates that government guarantees allocated to firms after implementing the GFRIPZ policy significantly weaken its effectiveness in mitigating stock price crash risk.

As a form of external additional financial support from the government, government guarantees may alleviate corporate financing constraints but also induce moral hazard and opportunistic behaviour. This may reduce the firms' compliance with environmental regulations and responsiveness to green financial policy signals. Such behaviour could subsequently lead to an increase in sell-off risks, as firms fail to meet investors' growing green expectations on sustainable and environmentally responsible practices, thus weakening the GFRIPZ policy effectiveness in mitigating their stock price crash risk. Collectively, **H2a** is supported.

2.4.3.2. The Interactive Moderating Effect of Government Guarantees and High-tech Certification

Firstly, subgroup regressions are conducted to explore the heterogeneity between firms with and without high-tech certification regarding the moderating role of corporate government guarantees in the effectiveness of the GFRIPZ policy in mitigating stock price crash risk, as presented in **Table 2.8**. All regressions are based on the sample after PSM.

Table 2.8 Heterogeneity Analysis: High-tech and Non-High-tech Enterprises

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Non-high-tech	High-tech	Non-high-tech	High-tech
	(1)	(2)	(3)	(4)
	$NCSKEW_{it+1}$	$NCSKEW_{it+1}$	$DUVOL_{it+1}$	$DUVOL_{it+1}$
$\boldsymbol{GFRIPZ_{it} \times lnCGG_{it}}$	**0.154**	**0.333****	**0.082**	**0.228****
	(0.358)	**(2.419)**	**(0.388)**	**(2.096)**
$GFRIPZ_{it}$	-0.043	-0.098	-0.081	-0.104*
	(-0.419)	(-1.505)	(-1.101)	(-1.654)
$lnCGG_{it}$	0.001	0.001	0.001	-0.001
	(0.152)	(0.511)	(0.729)	(-0.022)
Controls	Yes	Yes	Yes	Yes
Constant	-1.945**	-2.689**	-1.141*	-2.042**
	(-2.007)	(-2.367)	(-1.681)	(-2.545)
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
N	7723	6722	7723	6722
Adj. R^2	0.054	0.065	0.053	0.049

The coefficients of the interaction term $GFRIPZ_{it} \times lnCGG_{it}$ are consistently positive across all subgroups, indicating the inhibiting effect of government guarantees on the policy's effectiveness. However, statistical significance is observed only in the subgroup of high-tech certified firms at the 5% level. This provides support for **H2b,** suggesting that the negative moderating effect of government guarantees is primarily concentrated among high-tech certified firms. These firms are more likely to regularly receive preferential support from the government, such as guarantees, to sustain their ongoing innovation activities (Howell, 2017). Such support may reduce the disciplining pressure imposed by market-oriented environmental regulations. Moreover, high-tech firms are often more sensitive to the risk of innovation-related information leakage, which may also incentivise the concealment of bad news. This tendency further exacerbates the negative impact of government guarantees on the effectiveness of the GFRIPZ policy in mitigating stock price crash risk.

Given that all baseline coefficients of GFRIPZ remain negative, while statistical significance is observed only in the regression where DUVOL is employed as the dependent variable at the 10% level (as shown in column (4) of **Table 2.8**), the subgroup regressions demonstrate certain limitations. Specifically, while they are useful for identifying within-group effects, they do not directly test whether the moderating effects differ significantly across subgroups. A triple interaction approach is employed to address this limitation and assess cross-group differences. By incorporating the triple interaction term ($GFRIPZ_{it} \times lnCGG_{it} \times Hightech_{it}$), we

can simultaneously capture the baseline effect of the GFRIPZ policy, the overall moderating effect of government guarantees, and the heterogeneity in this moderating effect attributable to high-tech certification within a single regression framework. This serves as a complementary robustness check to the subgroup analyses, enhancing the reliability of our inference regarding the differentiated moderating roles across firm types.

As shown in **Table 2.9**, regressions using samples both before and after PSM are conducted as an additional robustness check. The coefficients of $GFRIPZ_{it} \times lnCGG_{it} \times Hightech_{it}$, which capture the interaction between government guarantees and high-tech certification, are consistently negative and statistically significant across all specifications. This indicates that high-tech certified firms exhibit greater sensitivity to the negative moderating effect of government guarantees, which diminishes the governance function of the GFRIPZ policy in reducing stock price crash risk. These findings are consistent with those observed in **Table 2.8**, thereby providing further support for **H2b**.

Table 2.9 The Interactive Moderating Role of Government Guarantees and High-tech Certification.
Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Before PSM		After PSM (*On_Support*)	
	(1) $NCSKEW_{it+1}$	(2) $DUVOL_{it+1}$	(3) $NCSKEW_{it+1}$	(4) $DUVOL_{it+1}$
$\boldsymbol{GFRIPZ_{it} \times lnCGG_{it} \times Hightech_{it}}$	**0.518***	**0.317****	**0.511***	**0.311***
	(1.682)	**(1.992)**	**(1.664)**	**(1.957)**
$\boldsymbol{GFRIPZ_{it} \times Hightech_{it}}$	**-0.218*****	**-0.081****	**-0.213*****	**-0.078****
	(-2.848)	**(-2.305)**	**(-2.787)**	**(-2.217)**
$GFRIPZ_{it} \times lnCGG_{it}$	0.139	0.074	0.140	0.077
	(0.512)	(0.614)	(0.520)	(0.642)
$lnCGG_{it} \times Hightech_{it}$	0.009	0.036	0.017	0.029
	(0.152)	(0.893)	(0.296)	(0.723)
$\boldsymbol{GFRIPZ_{it}}$	**-0.092**	**-0.107*****	**-0.093**	**-0.108*****
	(-1.536)	**(-3.572)**	**(-1.573)**	**(-3.603)**
$lnCGG_{it}$	0.013	0.023	0.011	0.020
	(0.385)	(0.915)	(0.350)	(0.817)
$Hightech_{it}$	-0.030	-0.004	-0.037	-0.001
	(-0.877)	(-0.156)	(-1.055)	(-0.013)
Controls	Yes	Yes	Yes	Yes
Constant	-2.044***	-1.232**	-2.055***	-1.224**
	(-3.005)	(-2.245)	(-3.068)	(-2.295)
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
N	15823	15823	14885	14885
Adj. R^2	0.052	0.045	0.053	0.045

Additionally, coefficients of $GFRIPZ_{it} \times Hightech_{it}$ in **Table 2.9** are all negative and statistically significant at the 1% or 5% levels. This provides evidence that, when government guarantees are excluded from consideration, high-tech firms experience a more pronounced mitigating effect of the GFRIPZ policy on their stock price crash risk. Moreover, the coefficients of $GFRIPZ_{it} \times lnCGG_{it}$ are all positive but statistically insignificant in this specification. This further emphasises the importance of incorporating firm-specific characteristics, particularly high-tech certification, when evaluating the moderating effect of corporate government guarantees on the effectiveness of the GFRIPZ policy in mitigating stock price crash risk.

2.4.4. Mechanism Analysis

2.4.4.1. The Mechanism Role of Two-stage Green Innovation Efficiency

The mechanism through which the GFRIPZ policy mitigates corporate stock price crash risk via green innovation efficiency is analysed by decomposing the innovation process into two stages: the R&D stage and commercialisation stage, which are analysed separately. The corresponding regression results are presented in **Table 2.10**. All regressions are conducted using the sample that satisfies the Common Support Hypothesis after PSM.

Table 2.10 Underlying Mechanism: Two-stage Corporate Green Innovation Efficiency.

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Model (2.8)		**Model (2.9)**			
	(1)	(2)	(3)	(4)	(5)	(6)
	GIE_RD_{it}	GIE_COM_{it}	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
$\boldsymbol{GFRIPZ_{it}}$	**0.029***	**0.013****	**-0.085****	**-0.071****	**-0.082*****	**-0.073****
	(1.857)	**(2.028)**	**(-2.163)**	**(-2.453)**	**(-2.705)**	**(-2.150)**
$\boldsymbol{GIE_RD_{it}}$			**-0.037**	**-0.032**		
			(-1.093)	**(-1.235)**		
$\boldsymbol{GIE_COM_{it}}$					**-0.223****	**-0.121****
					(-2.442)	**(-2.172)**
$Size_{it-1}$	0.052***	0.067***				
	(10.170)	(32.557)				
$Size_{it}$			0.064***	0.014	0.064***	0.032***
			(3.581)	(0.927)	(3.090)	(2.678)
Lev_{it-1}	0.001	-0.003***				
	(0.587)	(-3.912)				
Lev_{it}			-0.004	-0.002	-0.001	-0.002
			(-0.775)	(-0.399)	(-0.225)	(-0.525)
ROA_{it-1}	-0.001	0.001*				
	(-0.703)	(1.729)				
ROA_{it}			0.012***	0.008**	0.009**	0.006**
			(2.652)	(2.346)	(2.011)	(2.155)
$Sigma_{it-1}$	0.211*	0.004				
	(1.724)	(0.089)				
$Sigma_{it}$			2.490***	1.204***	1.667***	0.692**
			(5.477)	(4.389)	(3.676)	(2.551)
$Dturnover_{it-1}$	0.002	-0.001				
	(0.347)	(-0.386)				
$Dturnover_{it}$			-0.044**	-0.033**	-0.126***	-0.094***
			(-2.185)	(-2.188)	(-6.344)	(-7.041)
$NCSKEW_{it}$			-0.109***		-0.113***	
			(-8.686)		(-10.399)	
$DUVOL_{it}$				-0.094***		-0.103***
				(-10.076)		(-11.642)
$lnIndus_{it-1}$	-0.095***	-0.103***				
	(-4.181)	(-11.246)				
$lnIndus_{it}$			-0.068	-0.036	0.000	-0.025
			(-0.746)	(-0.534)	(0.002)	(-0.501)
$lnCityFin_{it-1}$	0.077***	0.040***				
	(9.362)	(12.048)				
$lnCityFin_{it}$			0.059*	0.042*	0.047*	0.043**
			(1.724)	(1.836)	(1.769)	(2.485)
Constant	-1.206***	-0.894***	-2.268***	-0.902	-2.224***	-1.261***
	(-6.966)	(-12.817)	(-3.239)	(-1.613)	(-3.454)	(-3.368)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	14885	14885	14885	14885	14885	14885
Adj. R^2	0.693	0.891	0.098	0.072	0.055	0.047

Firstly, Columns (1) and (2) of **Table 2.10** present the impact of the GFRIPZ policy on green innovation efficiency at the R&D and commercialisation stages, respectively, as specified in **Model (2.8)**. The coefficients of $GFRIPZ_{it}$ are both positive and statistically significant, indicating that the GFRIPZ policy leads to an average increase of 2.9% in R&D-stage green innovation efficiency and 1.3% in commercialisation-stage green innovation efficiency. The effect on commercialisation-stage efficiency is more statistically significant, at the 5% level, compared to the 10% level for the R&D stage. Columns (3) to (6) report the results from **Model (2.9).** All coefficients of $GFRIPZ_{it}$ remain negative and statistically significant at or above the 5% level, consistent with the baseline regression results after PSM**.**

Regarding the mediating variables, the coefficients of both GIE_RD_{it} and GIE_COM_{it} are negative, while statistical significance is observed only for GIE_COM_{it}. This suggests that the commercialisation stage of green innovation plays a more prominent mediating role in the GFRIPZ policy's effect on reducing stock price crash risk. The negative coefficients of $GFRIPZ_{it}$ in column (1) multiplied by the positive coefficients of GIE_RD_{it} are negative, which jointly imply a negative indirect effect, consistent with the direction of $GFRIPZ_{it}$ in Columns (3) and (4). The estimated mediating effect of R&D-stage green innovation efficiency can be calculated as 0.029*0.037 and 0.029*0.032 when NCSKEW and DUVOL are used as proxies for stock price crash risk, respectively. However, given the lack of statistical significance for GIE_RD in these regressions, the mediating effect through the R&D stage appears limited.

In contrast, all coefficients of GIE_COM_{it} are statistically significant at the 5% level, highlighting the important mediating role of green innovation efficiency during the commercialisation stage. The coefficients of $GFRIPZ_{it}$ in Column (2), when multiplied by the positive coefficients of GIE_COM_{it} in Columns (5) to (6), are consistent in sign with those of GFRIPZ in Columns (5) to (6), thereby further supporting the existence of the channel. Specifically, the estimated indirect effects through commercialisation-stage green innovation efficiency are calculated as 0.013*0.223 and 0.013*0.121, respectively. These findings suggest that the GFRIPZ policy partly mitigates stock price crash risk by enhancing the efficiency of green innovation commercialisation, with R&D-stage green innovation efficiency only playing a limited mechanism role in the process. Collectively, **H3** is confirmed.

2.4.4.2. Sobel Test

While **Table 2.10** has provided intuitive evidence of a partial mediation effect, particularly for commercialisation-stage green innovation efficiency, the Sobel mediation test is employed to offer a more formal statistical assessment of the validity of this two-stage mediation mechanism. The Sobel test evaluates whether the indirect effect of the independent variable on the dependent variable through the mediating variable is statistically different from zero. Formally, the test is based on the product of the estimated coefficients θ_1 in **Model (2.8)** and δ_2 in **Model (2.9).** The null hypothesis states that the indirect mediation effect equals zero (H_0: $\theta_1\delta_2 = 0$), implying there is no mediation. The Sobel statistic is computed using the estimated standard error of $\theta_1\delta_2$ to determine whether the indirect effect is statistically significant (Sobel, 1982). As shown in **Table 2.11**, the test is conducted using the same post-PSM sample as that used in the mechanism analysis in **Table 2.10.** The results offer additional support for the partial mediation of green innovation efficiency, thereby confirming the robustness of the findings.

Table 2.11 Sobel-Aroian-Goodman Mediation Test

Values of *z*-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	$NCSKEW_{t+1}$				$DUVOL_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sobel	Aroian	Goodman	Proportion	Sobel	Aroian	Goodman	Proportion
GIE_RD_{it}	-0.002	-0.002	-0.002	0.022	-0.001	-0.001	-0.002	0.008
	(-1.432)	(-1.360)	(-1.515)		(-0.778)	(-0.727)	(-0.840)	
GIE_COM_{it}	-0.004**	-0.004*	-0.004*	0.041	-0.002*	-0.002*	-0.002*	0.026
	(-2.005)	(-1.946)	(-2.070)		(-1.737)	(-1.674)	(-1.807)	
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year*Industry FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	14885	14885	14885	14885	14885	14885	14885	14885

Columns (1) to (3) and (5) to (7) in **Table 2.11** report the coefficients representing the partial mediation effect of the mechanism variables, with standard errors calculated using the Sobel method, supplemented by Aroian and Goodman methods, respectively, for robustness (MacKinnon et al., 2002). The *Z*-statistics for the coefficients of GIE_RD_{it} indicate statistical

insignificance across all methods. In contrast, the Z-statistics for the coefficients of GIE_COM_{it} are statistically significant at or above the 10% level, confirming that commercialisation-stage green innovation efficiency serves as a significant partial mediator in the process of GFRIPZ policy mitigating stock price crash risk. Columns (4) and (8) show that the average magnitude of the mediation effect through commercialisation-stage green innovation efficiency is 4.1% and 2.6%, respectively.

Collectively, while the mediating role of two-stage green innovation efficiency, particularly that of the commercialisation stage, is confirmed, its overall effectiveness remains limited. This finding is consistent with existing studies, such as Xu et al. (2023), which suggests that in the short term, stringent environmental regulatory policies may incentivise firms to prioritise low-quality, strategic innovations to meet regulatory compliance quickly. Substantive and high-quality green innovations typically require longer time horizons and substantial resource investment. This delayed realisation of innovation outcomes may constrain the evaluation of the mediating effect of green innovation efficiency in mitigating stock price crash risk within the relatively short evaluation window, such as 3 to 5 years after implementing the GFRIPZ policy.

2.4.4.3. Alternative Tobit Approach

The values of two-stage green innovation efficiencies range between 0 and 1, exhibiting significant left and right truncation characteristics. Therefore, the Tobit regression model is employed to re-estimate the results of **Model (2.8)** as a robustness check for the mechanism analysis. As presented in **Table 2.12**, the coefficients of $GFRIPZ_{it}$ remain positive and statistically significant at the 1% level, showing the validity of the segmented promoting effects of the GFRIPZ policy on both R&D and commercialisation stage green innovation efficiencies.

Table 2.12 Tobit Regression Results.

Values of z-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)
	GIE_RD_{it}	GIE_COM_{it}
$\boldsymbol{GFRIPZ_{it}}$	**0.071*****	**0.024*****
	(5.978)	**(4.562)**
Controls	Yes	Yes
Constant	-0.095	-1.400***
	(-0.930)	(-27.553)
N	15823	15823
Presduo R^2	0.3598	0.3240

2.5. Conclusions and Implications

The implementation of the GFRIPZ policy, launched in batches of pilot zones across China from 2017 onwards, represents a crucial milestone in green finance practice in China. This policy aims to promote environmental protection through more efficient capital allocation mechanisms. However, given the presence of imperfect economic institutions during the transition period in China, questions have arisen about whether firms located in the pilot zones of the GFRIPZ policy genuinely benefit from their status as early adopters of green financial policies in terms of achieving sustainable development while maintaining operational stability that supports regional economic growth. Additionally, it is unclear whether corporate government guarantees, another form of government-backed financing support, play a significant role in the context of the stringent GFRIPZ policy. Furthermore, given that green innovations are central to firms' efforts to enhance green productivity for compliance with the GFRIPZ policy, it is also important to evaluate whether improvements in green innovation efficiency serve as the mechanism through which the GFRIPZ policy affects corporate operational stability.

To address these questions, we treat the GFRIPZ policy, which has been implemented in phased batches of pilot zones since 2017, as a quasi-natural experiment. A staggered Difference-in-Differences (DID) model is employed, supplemented by robustness checks, interaction effect analyses, and causal step approach verification methods. This allows us to assess the impact of the GFRIPZ policy on firms' operational stability, measured by stock price crash risk, in the designated pilot zones, and to investigate the mediating role of two-stage green innovation efficiencies (R&D and commercialisation stages) in this process.

Additionally, we explore the moderating role of government guarantees and evaluate whether high-tech certification amplifies this effect. Based on these findings, recommendations are made for relevant stakeholders.

Firstly, we demonstrate the effectiveness of the GFRIPZ policy in enhancing the operational stability of firms within the pilot zones, specifically by mitigating corporate stock price crash risk. Placebo tests, parallel trend tests, and propensity score matching (PSM) are conducted to ensure the robustness and validity of the results. However, providing government guarantees in the context of the GFRIPZ policy significantly weakens the policy's effectiveness in mitigating stock price crash risk. Consequently, in the context of stringent, market-based environmental regulations, where financial resource allocation serves as a tool to constrain corporate polluting behaviour, governments should exercise greater caution when granting government guarantees to firms. Specifically, as a form of additional financial support, these guarantees may induce moral hazards and short-termism among firms, thereby hindering the intended disciplinary effect of the GFRIPZ policy. To address this issue, incorporating environmental performance metrics as additional eligibility criteria for granting government guarantees may enhance policy effectiveness.

This chapter also reveals that firms with high-tech certifications in China are more sensitive to the negative moderating role of government guarantees. While many countries prioritise the development of high-tech firms due to their substantial contributions to economic growth, our findings suggest that preferential support for such firms with high-tech certifications should be contingent upon stringent environmental performance requirements, rather than being granted solely based on their capabilities of advanced technologies or perceived economic significance. Additionally, financial institutions should consider incorporating environmental criteria when extending credit to high-tech firms. Establishing evaluation systems tailored to firms with high-tech certification, focusing on firms' green innovation capacity and environmental commitment, would enable more effective credit allocation. In the context of the GFRIPZ policy, such targeted financial support not only enhances the efficiency of environmental protection efforts by leveraging the superior green innovation capabilities of high-tech firms but also inhibits their reliance on government guarantees as

alternative financing resources, particularly when they encounter challenges in complying with policy requirements.

Moreover, enhancing firms' two-stage green innovation efficiency (GIE), particularly at the commercialisation stage, serves as a key channel through which the GFRIPZ policy's mitigates stock price crash risk. The policy promotes improvements in GIE by encouraging financial institutions to adopt it as a critical metric when assessing firms' environmental performance and financial stability. In response to growing investor concern about firms' environmental performance, firms are incentivised to demonstrate stronger commitments to green practices, thereby improving their GIE. This improved efficiency in the green achievements realisation stage, specifically the commercialisation stage, serves as a tangible environmental performance, enhancing investor confidence and information transparency, ultimately reducing stock price crash risk (Zaman et al., 2021). Based on our findings, the governments should consider expanding the GFRIPZ policy by gradually designating additional pilot zones to deepen green financial practice. It is also advisable to establish more comprehensive institutional mechanisms, such as platforms for green technology transfer and trading operated by public agencies, to evaluate firms’ green innovation achievements. These systems should particularly address the current lack of effective evaluation for green innovation efficiency during the R&D stage, thereby reducing information asymmetries in investors’ evaluations of corporate environmental performance. Besides, Chinese firms should actively leverage the benefits of participating in the GFRIPZ framework to mitigate the stock price crash risk and enhance access to external capital through more efficient green innovation.

CHAPTER THREE

Light a Fire under Green Technological Innovation Quality: Stabilising the Effect of Environmental Fee-to-Tax Reform Policy through Government Guarantees

Abstract

China's rapid economic growth has come at the cost of high resource consumption and significant emissions, prompting the implementation of various environmental regulations. This study examines the impact of the Environmental Fee-to-Tax Reform (EFTR), introduced in 2018 as a market-based regulatory instrument, on corporate green technological innovation. It particularly explores the role of government guarantees within the EFTR context and their interaction with firm characteristics. Using data on A-share listed firms in China from 2012 to 2022, we find that while the EFTR promotes the quantity of green technological innovation, both the EFTR and standalone government guarantees individually hinder its quality, revealing both "compensation" and "crowding-out" effects. However, when government guarantees are provided in conjunction with the EFTR, they significantly mitigate the EFTR's adverse impact on green technological innovation quality, with their effectiveness varying by firm attributes. Government guarantees exacerbate the policy's adverse effects for state-owned enterprises but alleviate them for non-state-owned enterprises. High-tech certified firms benefit more from government guarantees in offsetting the policy's adverse impact than their non-high-tech counterparts. These findings provide valuable insights for policymakers seeking to optimise environmental regulations and enhance the efficiency of government guarantees, ensuring better alignment between corporate strategies and sustainability goals.

Keywords

Environmental Fee-to-Tax Reform; Green Technological Innovation Quality; Corporate Government Guarantees; State-owned Enterprises; High-tech Enterprises

3.1. Introduction

Given the "externalities" of environmental protection efforts by enterprises, addressing environmental degradation and resource depletion caused by corporate polluting activities has become a critical priority for governments worldwide. China, in particular, faces significant environmental challenges, as its long-term economic growth has largely relied on high resource consumption and emissions. Initially implemented as a command-and-control environmental measure, the emission fee system marked the beginning of environmental regulatory tools in China. However, it has demonstrated limited effectiveness in environmental governance due to bureaucrats' career ambitions to advance within the leadership hierarchy. Local officials frequently granted exemptions or imposed minimal environmental fees on firms that significantly contributed to GDP, even if they were major polluters. Market-based environmental regulatory tools internalise environmental costs by connecting corporate environmental governance with mechanisms such as taxes and credit interest rates. These tools provide firms with greater flexibility in choosing their environmental management strategies, and the positive impacts of green finance policies have been widely studied (e.g., An et al., 2021; Jin et al., 2024). However, these policies impose stringent financial constraints on high-polluting firms, potentially restricting their access to funding for green transformation and thus reinforcing their reliance on polluting practices (Zhang et al., 2025b). Tax-based measures have demonstrated greater effectiveness, especially in scenarios where initial emissions are exceptionally high (Dou and Choi, 2024; Bian and Zhao, 2020). The implementation of the ***Environmental Protection Tax Law*** on 1st January, 2018[16], also referred to as the **"Environmental Fee-to-Tax" Reform (EFTR)**, marked a significant milestone in China's environmental regulations. It introduces a precise classification of taxable pollutants and imposes differentiated tax rates based on pollution levels (Liu et al., 2022). It also restructured the allocation of tax revenues by directing all proceeds to local governments, replacing the previous emission fee system, under which 10% of collected emission fees were transferred to the central government.

[16] A brief introduction to this legislation is available on the website by UNEP's Law and Environment Assistance Platform (UNEP-LEAP): https://leap.unep.org/en/countries/cn/national-legislation/environmental-protection-tax-law [Accessed: 22nd August 2025]

Within the framework of these stringent environmental policies, the effective advancement and diffusion of green technological innovations are widely recognised as crucial for coordinating the often conflicting objectives of environmental protection and economic growth (Zhou et al., 2023). However, firms frequently lack sufficient motivation for innovation due to its substantial costs and the difficulty of fully capturing its benefits (Doran and Ryan, 2016). This highlights the need for government intervention to shape firms' incentives for innovation. Many research has examined the impact of environmental regulations on technological innovation, especially green-oriented innovation, at both firm and regional levels. However, findings remain inconsistent, largely divided between the "crowding-out effect" and the "compensation effect". These inconsistencies may arise not only from differences in regulatory frameworks but also from the oversight of disaggregating green technological innovation into two dimensions, quantity and quality. Firms often prioritise achieving rapid breakthroughs in the quantity to benefit from government subsidies based on quantity-based metrics. However, this approach may come at the expense of quality (Huang et al., 2023), which more accurately reflects firms' true innovative capacity.

As China’s first tax-based environmental regulation, the EFTR policy faced a slow start due to its inherent complexity, and its overall effects remain uncertain. Firms often face a trade-off between rapid compliance through quantity-focused projects and maintaining high-quality innovation, which has limited the environmental and economic benefits of green innovations. Acting as an additional financial resource for firms, government guarantees serve as another form of government intervention aimed at addressing this issue by alleviating resource constraints imposed by the heightened environmental taxes under the EFTR, aligning with the principles of the Double Dividend Hypothesis. However, standalone government guarantees may also create a “moral hazard”, making firms reluctant to invest in long-term advancements, such as improving the quality of green innovations. Therefore, it is valuable to explore the relationship between the EFTR policy and firms' green technological innovations from a quality perspective, while also providing new insights into the role of government guarantees when they operate alongside the EFTR policy. Given China's distinctive firm ownership structures−state-owned and non-state-owned firms−as well as the critical role of the high-tech industry for national economic growth, further investigation into

how government guarantees interact with these firm attributes would provide deeper insights into the effectiveness of both the EFTR and government guarantees.

This chapter contributes to the ongoing debate on the impact of environmental regulations and government guarantees in three key aspects: (1) Utilising China's EFTR policy as an exogenous shock, we conduct a quasi-natural experiment with Difference-in-Difference (DID) models combined with propensity score matching (PSM) to examine its effect on both the quantity and quality of corporate green technological innovation; (2) We calculate the level of government guarantees received by firms. By employing continuous measures rather than the binary indicators commonly used in previous research, this study highlights how varying levels of government guarantees moderate the EFTR's impact on the quality dimension of green technological innovation; (3) Using a triple-interaction estimation approach, we investigate the interactive moderating effects of government guarantees and firm characteristics, specifically ownership structure and high-tech certification. To the best of our knowledge, no existing study has estimated government guarantees as a form of government contingent liability at the firm level in China or explored their differentiated role in the presence of stringent environmental regulations, and research on how government guarantees affect firms with different characteristics in this context remains limited.

The research framework of this chapter is scheduled as follows: section 3.1 includes the research background, research questions and objectives, followed by the main contributions; section 3.2 reviews the key insights from related literature and develops the hypotheses accordingly; section 3.3 describes the data and methodology; section 3.4 provides the empirical results and their interpretation; section 3.5 summarises the conclusions and recommendations.

3.2. Literature Review and Hypotheses Development

3.2.1. Institutional Background

3.2.1.1. Environmental Tax and Environmental Fee-to-tax Reform in China

Environmental taxes have become effective regulatory tools that incentivise cleaner production and support broader socio-economic goals. Governments commonly use taxes to

regulate corporate behaviour (Zwick and Mahon, 2017). Environmental taxes, in particular, target energy-intensive and high-polluting industries to incentivise cleaner production. Under the "double dividend hypothesis", environmental taxes are no longer solely aimed at environmental objectives, but also provide fiscal revenues that can be reallocated to support other sectors, generating both environmental and economic benefits.

China's early emission fee system faced enforcement challenges, highlighting the need for a more robust environmental taxation regulation. The emission fee system introduced in 1979 marked the first penalty-based environmental regulation in China. However, its effectiveness was limited, as some local governments exploited policy loopholes to exempt high-polluting enterprises that contributed significantly to GDP.

China formally implemented the "Environmental Fee-to-Tax" Reform (EFTR) by enacting the Environmental Protection Tax Law in 2018, marking the country's first environmental tax directly targeting pollution-intensive sectors. This EFTR replaced the earlier emission fee system with a more dynamic and differentiated framework. Unlike the previous "one size fits all" approach, the EFTR allows local governments to adjust tax rates for various pollutants based on regional economic conditions and their respective pollution intensity, within the central government's guidelines. Studies have demonstrated that the EFTR effectively reduces environmental violations and improves regional air quality (e.g., Jin et al., 2024), though it may also crowd out labour share (Wei et al., 2023a). Despite its growing importance, research on the relationship between the EFTR policy and green technological innovation remains underexplored.

3.2.1.2. Government Guarantees and its Practice in China

Projects with high growth potential and social benefits often face financing barriers due to their high-risk characteristics, insufficient collateral, and information asymmetry. Government guarantees serve as a public intervention tool to bridge these financing gaps and to incentivise firms to engage in socially desirable activities, such as green production (Kuo et al., 2011; Jin et al., 2022a).

Government guarantees in China take both direct and indirect forms, with growing adoption of risk-sharing models to support firm financing. Government guarantees are generally classified as either institution-oriented or firm-oriented. Institution-oriented guarantees primarily operate through loan guarantee schemes, including direct and indirect forms (Beck et al., 2010). Direct guarantees involve the government sharing credit risk with designated banks by reimbursing a portion of the unrecovered loans in case of default (Lelarge et al., 2019; Bachas et al., 2021). Indirect guarantees, such as counter-guarantees and co-guarantees, operate through multiple intermediaries like foundations, guarantee companies or insurers, improving firms' access to financing by mitigating banks' risk exposure. In counter-guarantees, the government covers part of the bank's losses if the guarantor defaults. In China, local governments have provided direct credit guarantees for over three decades. Since 2015, the central government has promoted counter- and co-guarantees in collaboration with local authorities across different regions[17].

Firm-oriented government guarantees in China primarily operate through guarantee fee reductions and credit interest subsidies to lower firms' financing costs. Under fee reduction schemes, the government reimburses part of the guarantee fees of firms when they use loan guarantees (Luo et al., 2024). Interest subsidies compensate firms for borrowing costs once they meet specific criteria set by the government, such as undertaking environmentally friendly activities (Jin et al., 2022a).

3.2.2. Environmental Fee-to-tax Reform and Green Technological Innovation

EFTR aims to redirect corporate innovation from conventional to green technologies by increasing tax pressure on polluting activities. Technological innovation ranges from "dirty" to "clean", with some falling in between (Aghion et al., 2016). The EFTR increases firms' tax burdens to steer corporate innovation towards cleaner, environmentally friendly technologies, also known as green technological innovations (Doran and Ryan, 2016). Green technological innovation typically involves exploratory activities that replace traditional technologies with solutions aimed at conserving resources, reducing pollution, promoting resource recycling,

[17] See website by the State Council of China: https://english.www.gov.cn/premier/news/2015/07/31/content_281475158328101.htm [Accessed: 22nd August 2025]

and improving eco-friendly waste disposal (Ahuja and Morris Lampert, 2001; El-Kassar and Singh, 2019).

The EFTR incentivises firms to increase the quantity of green technological innovation to meet environmental compliance, while inadvertently constraining the quality due to resource allocation pressures and signalling incentives. Unlike the previous emission fee system, the EFTR grants local governments the autonomy to adjust pollutant tax rates within a specified range. Due to the multitasking agency problem and rising demands of central governments for environmental accountability, local authorities often prioritise environmental performance by sharply increasing environmental tax rates, even at the cost of GDP losses (Chen et al., 2018b; Li and Masui, 2019). This shift has reshaped the regulatory landscape for firms' operational mechanisms, forcing them to prioritise pollution control over production to quickly demonstrate environmental achievements, such as green-oriented technological innovation, to alleviate the tax pressure. However, due to concerns over intellectual property leaks and the limited expertise of external evaluators (Chiappini et al., 2022; Hu et al., 2023), firms often hesitate to disclose extensive project information about innovation processes. They tend to redirect resources toward straightforward and easily measurable metrics, such as the number of green patents, to quickly signal their environmental compliance, rather than investing in enhancing the quality of innovations (Peng et al., 2025). Empirical evidence shows that increased tax burdens can reduce firms' production of highly cited patents, an indicator of innovation quality (Mukherjee et al., 2017). Therefore, while the EFTR promotes the quantity of corporate green technological innovation, it may simultaneously undermine its quality.

The EFTR intensifies managerial short-termism, causing them to favour visible, low-risk green innovation outputs over substantive quality improvements. The substantial increase in environmental costs enforced by the EFTR exacerbates managerial risk aversion and short-term performance concerns, discouraging firms from high-risk, long-horizon quality breakthroughs in green technological innovation. This shift in managerial attention causes firms to fall into the "familiarity," "maturity," and "proximity" traps (Ahuja and Morris Lampert, 2001; Zhang and Li, 2024), where they develop a "quantity-over-quality" preference on exploratory activities, such as green technological innovation. According to the time-

orientation theory in social psychology, managers with a short decision-making horizon are more likely to pursue immediate benefits. Consequently, firms are incentivised to quickly expand the quantity of green technological innovation achievements rather than invest in quality breakthroughs that are lengthy, costly and involves greater uncertainty (Brav et al., 2018; Huang et al., 2023).

Second, policy uncertainty and compliance pressure under the EFTR drive firms to pursue breadth over depth in green technological innovation, diluting quality due to scattered resource allocation. The EFTR framework allows local governments to adjust pollutant tax rates flexibly, leading to greater policy uncertainty. In response, firms adopt more diversified strategies in green technological innovation to hedge against future EFTR regulatory shifts in their registered cities and explore emerging green market opportunities (Liu et al., 2024). Consequently, firms prefer to spread fixed internal resources across multiple domains within green innovation. While the breadth and quantity of green technological innovation will expand significantly, the depth and the rigour, such as the innovation quality, are compromised due to insufficient resource allocation per project.

Third, financial strain and external financing barriers induced by the EFTR reduce firms' willingness to pursue high-quality green innovation. The increased tax burden under the EFTR significantly strains firms' internal resources, reducing their capacity to invest in high-risk technological innovation projects beyond basic compliance. External investors typically demand a higher risk premium for technological innovation than physical investment due to its inherent greater uncertainty (Yu et al., 2021b). These constraints distort firms' incentives, making them more likely to abandon quality-focused innovation breakthroughs in favour of safer, lower-cost alternatives (Atanassov and Liu, 2020).

Finally, the disparities in cost pressures and regulatory standards incentivise high-polluting firms to prioritise green technological innovation quantity over quality. The EFTR imposes uneven increases in production costs across firms and industries, with high-polluting firms facing significantly higher environmental compliance costs. These firms are more likely to engage in greenwashing or selectively disclose information about the quality of their green achievements (Zhang, 2022). They tend to prioritise the scale of outputs, such as the number of green patents, enabling them to quickly meet regulatory requirements (Fu et al., 2023).

Consequently, the EFTR contributes to rapid gains in the quantity of green technological innovation, while hindering progress in its quality dimension.

Collectively, we can propose the hypotheses as follow:

H1a: The Environmental Fee-to-Tax Reform (EFTR) policy implemented in 2018 significantly promoted the quantity of corporate green technological innovation in China.

H1b: The Environmental Fee-to-Tax Reform (EFTR) policy implemented in 2018 significantly hindered the quality of corporate green technological innovation in China.

3.2.3. The Moderating Role of Government Guarantees

Government guarantees help offset the EFTR's resource-crowding effects and redirect firms toward quality-focused green innovation, aligning with the Double Dividend Hypothesis. Government intervention has become essential in guiding corporate green technological innovation toward higher-quality outcomes, particularly when environmental compliance is typically assessed using quantity-based indicators due to limited governmental expertise and information asymmetries. This, combined with managerial short-sightedness and risk-aversion, biases firms toward low-risk, low-quality innovation. Although the EFTR increases environmental taxation and may initially crowd out productive resources, government guarantees serve as a compensatory tool that reallocates financial support to offset and potentially exceed these losses (Yamazaki, 2022).

The decentralisation of tax authority under the EFTR enables local governments to use guarantees as corrective tools to offset the policy's unintended consequences on the quality of green technological innovation. The shift from centralised to decentralised governance under the EFTR grants local governments complete autonomy over tax enforcement and allows them to retain 100 percent of the resulting tax revenues. This decentralisation incentivises local authorities to channel these funds into guarantee schemes that address the resource distortions caused by the EFTR. Moreover, such guarantees promote closer interactions between local authorities and firms (Gao et al., 2021b), helping to reduce information asymmetries by involving a broader network of financial institutions in large-scale guarantee frameworks (Guo et al., 2016).

Second, government guarantees alleviate financing constraints as well as stabilise loan supply and demand, enabling firms to pursue quality-oriented green innovation. Green technological innovation projects often exhibit characteristics of fluctuating returns and uncertain solvency, which impose significant financing constraints. Government guarantees effectively enhance firms' ability to undertake high-risk, exploratory green R&D activities, especially those targeting quality breakthroughs, by alleviating financing pressure (Atanassov and Liu, 2020).

Third, government guarantees reshape firms' risk-return trade-offs and reduce adverse selection. The government guarantees reconfigure the risk-sharing structure of green technological innovation projects, making firms more willing to pursue quality improvements with higher marginal returns. Due to the high-risk attributes of these projects, characterised by long-term, capital-intensive investments and intangible assets that are difficult to value due to information asymmetry, firms often face adverse selection. Moreover, these projects usually lack sufficient tangible collateral, exceeding the risk tolerance of many financial institutions. Government guarantees reduce these risks and signal firms' development potential to external investors, especially through counter-guarantees and co-guarantees, which act as third-party verification and endorsements (Zhang et al., 2024). By bridging the risk gap between firms and financing institutions, these guarantee mechanisms improve market transparency, reduce collateral and interest rate requirements, and effectively expand firms' access to capital (Jin et al., 2022b; Dechezleprêtre et al., 2023; Hao et al., 2025a). Moreover, by enabling governments and financial institutions to jointly assess and monitor firms, guarantees also help reduce information asymmetry. As firms recognise that high-quality green technological innovations involve greater marginal returns over time, these guarantees encourage them to shift away from low-quality, short-cycle innovation strategies in green transformation.

Furthermore, government guarantees reduce managerial myopia and strengthen firms' commitment to high-quality green innovation under environmental regulation. Even in firms with adequate resources and supportive green production environments, the quality of innovation largely depends on managerial risk appetite and long-term vision. As an additional resource from the government, these guarantees reduce the perceived risk of pursuing high-quality, long-term green innovation. In doing so, they incentivise senior managers' openness

to external knowledge and increase their risk tolerance associated with quality-focused green technological innovation under environmental regulatory pressure (Chapman and Hewitt-Dundas, 2018).

Finally, the government guarantees reshape behavioural incentives in an immature green market by linking guarantee support to quality standards. China's green market remains underdeveloped, with low consumer awareness and weak green purchasing intentions (De Silva et al., 2021), discouraging firms from investing in green innovation beyond basic environmental regulatory compliance. However, government guarantees act as strong policy signals (Zolfagharinia et al., 2023), especially in a context where green industrial development is a strategic priority. In the absence of stable technical standards and market norms in China's green sector, governments increasingly tie guarantee eligibility to quality-based criteria, aiming to promote "cutting-edge and leading-edge" projects with demonstration effects. This not only incentivises firms to meet quality expectations to access guarantees and gain policy endorsements, but also supports their pursuit of competitive advantage. As a result, government guarantees shift both governmental and corporate behaviour away from quantity-oriented innovation strategies and reduce risk aversion, encouraging long-term investment in high-quality green technological innovations.

Collectively, we can propose the following hypothesis:

H2: Government guarantees significantly moderate the negative impact of the Environmental Fee-to-Tax Reform (EFTR) policy implemented in 2018 on the quality of corporate green technological innovation in China.

3.2.4. The Interactive Moderating Effect of Government Guarantees and Firm Properties

3.2.4.1. State-owned and Non-state-owned Firms

State-owned enterprises (SOEs) in China are firms controlled by the government or its agencies. These firms operate under a dual mandate: achieving capital investment and production goals while also fulfilling government directives related to social and political stability (Jiang and Kim, 2020).

First, differences in agency problems and internal governance structures between SOEs and non-SOEs lead to distinct responses to and efficiencies in utilising government guarantees. Due to their perceived "too big to fail" status, SOEs have long benefited from preferential government treatment, including direct subsidies, debt maturity extensions (Dong et al., 2021), and government guarantees. This long-standing support has intensified agency problems and reinforced soft budget constraints, weakening SOEs' sensitivity to marginal policy incentives. Government guarantees are often perceived by SOEs as "default entitlements" rather than strategic resources, where the catering effect outweighs the incentive effects (Liu et al., 2025), leading managers to engage in symbolic compliance rather than substantive, high-quality green technological innovation. In contrast, non-SOEs face greater market pressure and stricter cost constraints, and tend to allocate government support towards productive innovation efforts to obtain marginal revenues. For them, government guarantees serve as a scarce and treasured resource, providing critical support to overcome managerial myopia and enabling firms to pursue higher-quality green innovation. These additional resources offset rising environmental costs while enhancing long-term competitiveness for greater market share (Zhao et al., 2025).

Second, SOE managers, driven by political promotion incentives, tend to prioritise short-term compliance over long-term, high-risk green technological innovation. Unlike non-SOE executives, SOE managers are typically appointed under government supervision and evaluated based on political rather than market-based performance indicators. Their career advancement motivation fosters a preference for stability, superficial compliance, and risk aversion. Such political promotion motives also often lead to excessive indebtedness in SOEs, heightening their financial fragility and further constraining risk-taking behaviour (Talavera et al., 2024). Under these constraints, SOE managers tend to focus on low-risk, easily reportable green technological innovation activities that meet superficial policy requirements in the short term, such as achieving quantity-based targets, while avoiding quality-driven projects that require sustained investment and involve greater uncertainty in the longer term (Liu et al., 2025). Government guarantees further reinforce this behaviour by shielding SOEs from market pressure and risk exposure.

Finally, structural differences in market competition and performance evaluation between SOEs and non-SOEs also shape their distinct responses to government guarantees. SOEs often enjoy preferential resource access and operate in less competitive environments due to their close ties with the government (Yang et al., 2024). Their managerial performance is typically assessed based on government-aligned targets, such as employment stability and fiscal contributions, rather than market-based outcomes. This reduces their incentive to utilise government guarantees for quality-oriented green innovation, especially when these projects involve higher risk and longer return periods. In contrast, non-SOEs face tighter financial constraints and operate under intense market competition. Their performance is evaluated through market-driven indicators, such as profitability, innovation output, and market share, which creates strong incentives to strategically allocate government guarantees toward enhancing green innovation capabilities. For non-SOEs, government guarantees help alleviate financial pressures and offset regulatory compliance costs, enabling them to invest more effectively in improving the quality of green innovation, securing both competitive advantages and sustained government recognition (Hu and Chen, 2025).

Collectively, considering the ownership structure, we propose the following hypothesis:

H3a: The moderating effect of corporate government guarantees on the relationship between the EFTR policy and the quality of corporate green technological innovation varies by ownership structure. Government guarantees exacerbate the negative policy impact in state-owned enterprises (SOEs) while mitigating it in non-state-owned enterprises (non-SOEs).

3.2.4.2. High-tech Certified firms and Non-high-tech Certified firms

High-tech certification in China promotes closer collaboration between governments and firms operating in the high-tech industry, enhancing the effectiveness of government guarantees in improving the quality of green technological innovation. Despite their strong innovation capacity, high-tech firms face more severe financing constraints in green technological innovation, which typically requires specialised expertise, long-term investment and experimentation, making it costly and risky. These characteristics exacerbate information asymmetries between high-tech firms and financial institutions, resulting in a

higher perceived default risk and financing constraints (Cowling et al., 2018). Consequently, high-tech firms are more likely to face “innovation penalties,” such as “innovation premium” in interest rates, particularly when commercial returns remain uncertain in China’s current underdeveloped green market. The government working program "Management Measures for the Recognition of High-tech Enterprises", issued in 2016, allows firms engaged in R&D-intensive and technologically advanced activities across their products and services to apply for high-tech certification (Cowling et al., 2021). Certified firms gain preferential access to government information and targeted financial assistance. These benefits enhance their overall innovation capacity and promote stronger ties with government agencies. As a result, government guarantees can be more effectively leveraged by high-tech firms to support high-quality green innovation, especially in response to regulatory shifts such as the EFTR.

High-tech certified firms are more vulnerable to quality decline in green technological innovation under the EFTR, but benefit more from government guarantees due to tighter internal constraints and greater external financing dependence. Under the EFTR, high-tech certified firms face greater difficulty in maintaining the quality of green technological innovation, as limited internal innovation budgets are often diverted to meet environmental compliance costs or superficial quantity-focused green innovation efforts (Xue et al., 2024). This makes them more likely to fall into the “quantity-over-quality” trap than non-high-tech firms. Besides, despite potentially receiving venture capital, high-tech firms in China rely heavily on more external financing and operate in a highly competitive environment regarding green technological innovation status (Mina et al., 2021). These characteristics make them particularly sensitive to changes in financing conditions. Guarantee schemes are thus particularly effective in alleviating the financing pressure intensified by the EFTR policy for high-tech firms, as they reduce lenders’ risk by covering a portion of default risk and narrowing the perceived risk exposure gap between firms and external lenders (Cowling et al., 2018). This enhances loan accessibility and gives high-tech firms adequate resources to launch and sustain high-quality green technological innovation projects.

Furthermore, external constraints specialised to high-tech firms, such as trade sanctions and technology blockades, further strengthen high-tech firms’ reliance on government guarantees for financial flexibility to pursue quality breakthroughs in green technological innovation, a

fresh domain globally, as a strategic response. In addition to financial barriers, high-tech firms in China increasingly face external pressures such as U.S. export control regulations (ECRs) and technology-related sanctions, which restrict access to critical technologies and global innovation networks. These constraints force high-tech firms to pursue quality breakthroughs in green technological innovation as a new strategic frontier to maintain competitiveness. Government guarantees provide essential resources and financial flexibility that enable high-tech firms to undertake complex, long-term and uncertain green innovation projects, helping firms shift their green innovation strategies from short-term survival to long-term quality advancement under both environmental and geopolitical pressures (Shen et al., 2024).

Finally, compared to non-high-tech firms, high-tech firms, whose profitability depends heavily on innovation-driven products and services, are more likely to leverage government guarantees to improve the quality of their emerging innovation domains, namely green technological innovations. Growing public concern over environmental sustainability has created intense market pressure on high-tech firms to improve green innovation quality as a means of expanding market share, increasing consumer satisfaction, and strengthening competitive advantages (Boeing, 2016). Consequently, although the EFTR may initially impose stronger constraints on the quality of green innovation in high-tech firms, these adverse effects can be more effectively mitigated through targeted support provided by government guarantees.

Collectively, we can propose the following hypothesis:

H3b: The moderating effect of corporate government guarantees on the relationship between the EFTR policy and the quality of corporate green technological innovation varies by high-tech certification in China, with high-tech certified firms exhibiting greater sensitivity to the positive moderating effect than non-high-tech firms.

3.3. Methods

3.3.1. Sample and Data Collection

This chapter selects all Chinese A-share listed firms as the initial sample. Few studies on the effects of EFTR policy extended their observation to subsequent three-year or longer periods after its implementation year. However, it often takes two or more years post-policy to observe the substantial impact of increased environmental taxes on firms' technological innovation (Atanassov and Liu, 2020). For greater credibility, we extend observation on the effects of EFTR policies and the role of government guarantees using time span of 2012 to 2022. To ensure the reliability and consistency of the data, we first excluded: (1) firms belonging to the financial sector; and (2) firms that have been specially treated (i.e., ST, ST* or PT[18]) by the China Securities Regulatory Commission. After these initial exclusions, we obtained a raw sample of 29467 firm-year observations from 3624 A-share listed firms in China. We then applied the following additional screening criteria: (3) firms with missing values in key financial variables were removed. In particular, we excluded firms lacking essential data on the quantity and quality of corporate green technological innovation, as these are the main dependent variables in this study. Firms with missing values for any control variables used in the analysis were also excluded. This process resulted in a sample of 12477 observations from 1529 firms. Next, we excluded firms with missing data in variables essential for estimating corporate government guarantees, such as corporate bond credit spreads, the debt face value, the market value of equity and assets, and the volatility of asset and equity returns. Although we used MATLAB to solve the system of simultaneous equations under the Merton (1974) structural model to estimate some missing values and cross-validated these estimates using data from the China Stock Market and Accounting Research (CSMAR) database, firms with unresolvable missing data were ultimately dropped. These exclusions were necessary to ensure the accuracy of the proxy for corporate government guarantees**.** After these steps, our final sample consists of 9218 firm-year observations from 1477 A-share listed firms in China

[18] ST is short for Special Treatment, which refers to a firm being in an abnormal financial situation, including the existence of two consecutive years of losses or net assets value per share below the book value of equity per share. ST* represents a situation where a company has three consecutive years of losses and faces the possibility of being delisted. PT refers to Particular Transfer, which means that the company's shares are subject to non-normal trading rules, such as being allowed to trade only on Fridays.

from 2012 to 2022. All continuous firm-level variables are winsorised at the 1% and 99% quantile levels to eliminate the effect of extreme values.

The firm-level financial data were obtained from the CSMAR database. The corporate green technological innovation data were sourced from the Chinese Research Data Services Platform (CNRDS). Firms continuously certified as high-tech enterprises from 2012 to 2022 were selected from the sample to facilitate the interactive moderating effect analysis, i.e., **H3b**. Data regarding whether the firms were certified as high-tech in specific years were collected from the Chinese Research Data Services (CNRDS) Platform.

3.3.2. Variable Selection and Measurement

3.3.2.1. Dependent Variables

Quantity of Corporate Green Technological Innovation ($GTIN_{it}$): measured by the logarithm of the number of granted green patents received by firms after adding one. To distinguish green patents from general patents, we utilise classification criteria based on Environmentally Sound Technologies (ESTs) as outlined by the United Nations Framework Convention on Climate Change (UNFCCC)[19]. Specifically, we follow the "IPC Green Inventory" published by the World Intellectual Property Organisation (WIPO), which systematically identifies green patents (Rivera León et al., 2023). We first obtained data on firms' granted patents during the observation period and cross-referenced their IPC classification numbers assigned by the China National Intellectual Property Administration (CNIPA) with the IPC Green Inventory. A patent is classified as green if its IPC code matches an entry in the IPC Green Inventory (Wang et al., 2022). Our analysis includes inventions and utility model patents but excludes industrial design patents, which focus solely on aesthetic improvements and do not reflect substantive technological advancement in line with our definition of exploratory green technological innovation (Zhang et al., 2025a).

Quality of Corporate Green Technological Innovation *($GTIL_{it}$):* measured by the logarithm of the number of citations received by a firm's granted green patents from

[19] According to the United Nations Environment Programme (UNEP), ESTs denote technologies that have the potential to substantially enhance environmental performance. This aligns with our conceptualisation of green technological innovation among Chinese listed firms.

subsequent patents after adding one (Mukherjee et al., 2017). The citations of patents are widely recognised as a robust proxy for innovation quality because they capture not only the existence of an innovation but, more importantly, its technological significance and economic value (Hall et al., 2001). In the context of green innovation, green patents with higher citations demonstrate a greater extent to which subsequent innovators acknowledge, adopt and build upon the patented green innovations, thereby reflecting their practical influence and meaningful contributions to technological progress (Kim and Valentine, 2021). As citations directly reflect the actual acceptance and popularity of green innovations by the broader innovation community and industry stakeholders, they provide a more objective and externally validated assessment of green innovation quality than simple patent counts. Building on this, the measure of citations also helps distinguish genuine, high-impact green innovations from low-quality or symbolic innovations that may be associated with greenwashing strategies.

3.3.2.2. Moderating Variable

Corporate Government Guarantees (CGG) are proxied as a form of government contingent liability. Following the methodology outlined by the International Monetary Fund (IMF) (2009, 2014) and adopting the Contingent Claims Analysis (CCA) framework, a continuous proxy for CGG_t is derived. Specifically, CGG is computed as the disparity between the expected value of firms' stock market-based losses in year t ($ELV_E(t)$), determined from stock market data, and the expected debt market-based losses in year t ($ELV_D(t)$), estimated from corporate bond credit spreads. It is calculated as $CGG_t = ELV_E(t) - ELV_D(t)$ and logarithmically transformed for empirical analysis.

The detailed calculation procedure is provided in **Section 1.3.2.4** of Chapter One. The key difference here is the sample period: whereas Chapter One covers period of 2012-2020, this chapter extends the horizon to 2012-2022. Accordingly, the parameter ***T***, which denotes the time horizon, is adjusted from 8 to 11. The resulting dataset thus provides annual firm-level estimates of government guarantees received by China's A-share listed firms from 2012 to 2022.

3.3.2.3. Control Variables

We also controls some other factors on firm-level and city-level that may have impacts on the quality of corporate green technological innovation. First, several firm-level factors are controlled (e.g., Lin et al., 2021; Nguyen and Qiu, 2022; Yu et al., 2022; Liu et al., 2023): (1) **R&D intensity ($R\&D$):** measured as the ratio of corporate R&D expenditures to total revenues, with logarithmic transformation applied; (2) **Firm size ($Size$):** defined by the firm's total assets with logarithmic treatment; (3) **Return on assets (ROA):** measured by the net income divided by the total assets; (4) **Corporate leverage ratio (Lev):** defined as the firm's total long-term debts divided by its total assets; (5) **Capital expenditure ($Capex$):** measured as the percentage of capital expenditure to total assets, multiplied by 100 for scaling purposes; (6) **Executive shareholding ratio ($ExecS$)**. Additionally, we add a city-level factors to avoid potential interference from heterogeneity of cities (e.g., Huang et al., 2023; Zhou et al., 2023): (7) **Industrial structure ($lnIndus$):** proxied by the logarithm value of the proportion of the total output value of the secondary sector[20] to GDP in the firm's registered city.

The detailed definitions of all variables and their corresponding data processing methods are summarised in **Appendix D1**.

3.3.3. Model Specification

3.3.3.1. The Policy Effect on Corporate Green Technological Innovation

The implementation of the EFTR policy in China in 2018, serving as an exogenous shock, provides a natural setting for a quasi-natural experiment analysis using a Difference-in-Difference (DID) approach. To evaluate the baseline impact of EFTR policy on both the quantity and the quality of corporate green technological innovation (H1a and H1b), we formulate the following models. This method effectively mitigates potential endogeneity concerns in our firm-level analysis of green technological innovation.

[20] The secondary sector in China refers to the mining industry (excluding mining specialities and auxiliary activities), manufacturing industry (excluding metal products, machinery and equipment repair), electricity, heat, gas and water production and supply, and construction industry.

$$GTIL_{it} = \beta_0 + \beta_1 EFTR_{it} + \beta Controls_{it-1} + \gamma_t + \lambda_i + \varepsilon_{it} \quad (3.1\text{-a})$$

$$GTIN_{it} = \beta_0 + \beta_1 EFTR_{it} + \beta Controls_{it-1} + \gamma_t + \lambda_i + \varepsilon_{it} \quad (3.1\text{-b})$$

The subscripts i and t represent the firm and year, respectively. $GTIL_{it}$ and $\mathrm{GTIN_{it}}$ denote the quality and quantity of corporate green technological innovation, respectively. $EFTR_{it}$ is composed of two terms: one indicating whether a firm is subject to the EFTR policy ($Treat_i$), and another representing the policy implementation time ($Post_t$).

Given that high-polluting firms inherently face more significant environmental compliance pressures due to their extensive polluting activities, they are subject to heightened regulatory scrutiny under the EFTR policy. Consequently, we classify high-polluting firms as the treated group in the DID analysis, while non-high-polluting firms serve as the control group (Hu et al., 2023). Building on this, $Treat_i$ is defined as a binary variable, taking the value of 1 if a firm belongs to a high-polluting industry[21], and 0 otherwise. $Post_t$is another binary variable indicating the implementation period of the EFTR policy. It equals 1 for the post-policy period (2018−2022) and 0 for the pre-policy period (2012−2017). $Controls_{it-1}$ are set of the control variables with a one-period lag to avoid potential endogeneity concerns, avoid reverse causality, and account for potential synchronisation disturbances. Additionally, we incorporate year-fixed effects (γ_t) and firm-fixed effects (λ_i) to control for time-invariant and firm-specific heterogeneity, respectively. ε_{it} represents the error term.

Since the classification of the treated group relies on the assumption that high-polluting industries are more affected by the EFTR policy, we employ the propensity score matching (PSM) method to mitigate the potential risk of self-selection bias. PSM enables us to account for observable factors influencing a firm's likelihood of being classified as part of the treated group, thereby reducing the endogeneity concerns arising from the correlation between the

[21] In China, the identification of high-polluting firms primarily follows the "*Directory of Industry Classification Management of Listed Companies for Environmental Verification (2008)*" and the "*Guidelines for Disclosure of Environmental Information of Listed Companies (2010)*" issued by the Ministry of Ecology and Environment of China. These documents classify 14 sectors as highly polluting, which correspond to 19 sectors outlined in the Guidance for Industry Classification of Listed Companies (2012 revised edition) released by the China Securities Regulatory Commission (See **Appendix C1**). We cross-reference the industry codes of these high-polluting sectors with those of China's A-share listed firms to identify high-polluting firms.

variable $Treat_i$ and the error term. A binary logistic regression, as specified in the following **Model (3.2)**, is utilised to estimate a firm's propensity score, representing the probability of the firm being assigned to the treated group under the EFTR policy.

$$\rho(Covariates_i) = Pr[Treat_i = 1|Covariates_i] = E(Treat_i|Covariates_i) \quad (3.2)$$

$\rho(Covariates_i) = Pr[Treat_i = 1|Covariates_i]$ represents the probability of a firm being classified into the treated group, where $Covariates_i$ denotes a vector of observable firm characteristics that may influence $Treat_i$ and $GTIL_{it}$. $E(Treat_i|Covariates_t)$ refers to the estimated expected probability of a firm being subject to the EFTR policy, given the set of covariates. In the propensity score matching process, we incorporate all six firm-level and one regional-level control variables from **Model (3.1),** along with the government guarantees received by firms, as covariates. Given that 3002 firm annual observations in the sample are assigned $Treat_i = 1$out of a total of 9218 observations, we employ 1:2 k-nearest neighbour matching method for efficiency, allowing each treated unit to be matched with up to two control units that closely resembled the treated group in terms of key influencing factors. A tolerance level of 0.05 is incorporated into the caliper matching estimator to mitigate the possibility of poor matches when the closest neighbour is distant in the matching process. This method enabled us to establish a comparable control group for robust evaluation (Rosenbaum and Rubin, 1983).

3.3.3.2. The Moderating Effect of Government Guarantees

Based on the DID estimation of the EFTR policy's impact on the quality of corporate green technological innovation, we further investigate the role of market-implied government guarantees received by firms in this context (**H2**). To achieve this, we develop **Model (3.3)** as follows:

$$GTIL_{it} = \alpha_0 + \alpha_1 EFTR_{it} \times lnCGG_{it} + \alpha_2 EFTR_{it} + \alpha_3 lnCGG_{it} + \alpha Controls_{it-1} + \gamma_t + \lambda_i + \varepsilon_{it} \quad (3.3)$$

In this model, $GTIL_{it}$ represents the quality of corporate green technological innovation, while $EFTR_{it} \times lnCGG_{it}$ denotes the interaction between EFTR policy implementation and corporate government guarantees. If $\alpha_2 < 0$, while $\alpha_1 > 0$, both statistically significant, this indicates that the impact of the EFTR policy on the quality of corporate green technological innovation will remain negative, while corporate government guarantees effectively mitigate this negative impact. Min-Max Normalisation is applied to the $lnCGG_{it}$ in the interaction term ($EFTR_{it} \times lnCGG_{it}$) to address potential multicollinearity concerns. This normalisation involves subtracting each data point from the smallest value in the data set and dividing it by the range (maximum-minimum). This approach ensures a meaningful interpretation of the coefficient α_2 when interaction terms are included. All other symbols and subscripts follow the definitions provided in the baseline **Model (3.1).**

3.3.3.3. The Interactive Moderating Effect of Government Guarantees and Firm Properties

Furthermore, we explore the heterogeneous effects of corporate government guarantees in moderating the negative impact of the EFTR policy on the quality of corporate green technological innovation. Specifically, we examine variations based on firm characteristics, including ownership structure (state-owned enterprises vs. non-state-owned enterprises) and high-tech certification (high-tech certified firms vs. non-high-tech firms), corresponding to **H3a** and **H3b**. To capture these differential effects, we employ a difference in difference in difference (DDD) estimation technique (Olden and Møen, 2022), as specified in **Model (3.4):**

$$GTIL_{it} = \alpha_0 + \alpha_1 EFTR_{it} \times CGG_{it} \times Firmtype_{it} + \alpha_2 EFTR_{it} \times CGG_{it} + \alpha_3 EFTR_{it} \times Firmtype_{it} + \alpha_4 CGG_{it} \times Firmtype_{it} + \alpha_5 EFTR_{it} + \alpha_6 lnCGG_{it} + \alpha_7 Firmtype_{it} + \alpha Controls_{it-1} + \gamma_t + \lambda_i + \varepsilon_{it} \quad (3.4)$$

In this model, $Firmtype_{it}$ represents the characteristics of firm i in year t, indicating whether the firm is a state-owned enterprise (SOE) or high-tech certified. $Firmtype_{it}$ takes a value of 1 if firm i is an SOE or has received high-tech certification in year t, and 0 otherwise. All other symbols and subscripts retain remain consistent with the baseline **Model (3.1).** The analysis of the interactive moderating effects of corporate government guarantees and firm characteristics focuses on the marginal effects perspective, specifically examining the slopes of the policy implementation ($EFTR_{it}$) on corporate green technological innovation quality ($GTIL_{it}$) while holding the moderating variables (CGG_{it} and $Firmtype_{it}$) at different high and low values (Dawson and Richter, 2006). After computing the simple slopes and the regression results, we conduct pairwise comparisons of these slopes to validate the model's robustness.

3.3.4. Descriptive Analysis

As presented in **Table 1**, the descriptive statistics for the key variables indicate that the mean values of ***lnGTIN*** and ***lnGTIL*** are 1.673 and 1.171, respectively, which are broadly consistent with the findings from prior research (e.g., Huang et al., 2023; Wang et al., 2023). The corresponding standard deviation values (1.376 and 1.116) indicate a significant variation in both the quantity and quality of green technological innovation among A-share listed firms in China. Similarly, the government guarantees received by firms ($lnCGG$) exhibit wide variability, with mean and standard deviation values of 3.775 and 3.149, respectively. The mean value of ***Treat***, which is a part of $EFTR_{it}$, indicates that 32.6% of our annual observations belong to high-polluting industries. The statistical characteristics of the other control variables were generally consistent with those reported in existing studies (e.g., Lin et al., 2021; Liu et al., 2023; Zhou et al., 2023).

Table 3.1 Summary Statistics of Variables

Variable	N	Mean	SD	Min	Max
lnGTIN	9218	1.673	1.376	0	7.206
lnGTIL	9218	1.171	1.116	0	8.055
Treat	9218	0.326	0.469	0	1
lnCGG	9218	3.775	3.149	0.002	24.978
R&D	9218	1.144	1.244	0	6.797
Size	9218	22.754	1.345	18.992	28.636
ROA	9218	0.029	0.108	-0.986	7.446
Lev	9218	0.085	0.092	0	0.741
Capex	9218	5.068	4.609	0.001	46.427
ExecS	9218	0.114	0.170	0	0.815
lnIndus	9218	3.651	0.343	2.760	4.479

The correlation coefficient matrix (**Table 3.2)** reveals that most correlation coefficients are below 0.5. The average value of variance inflation factor (VIF) among all the variables is 1.13 (VIF < 10) both when either ***lnGTIL*** or ***lnGTIN*** is used as the dependent variable. The largest VIF value observed is 1.38 for the variable *Size*, which collectively confirms the absence of multicollinearity problems (Wooldridge, 2015).

Table 3.2 Pearson Correlation Matrix of Variables

* represent significance at the 10% levels.

	lnGTIN	***lnGTIL***	***Treat***	***lnCGG***	***R&D***	***Size***	***ROA***	***Lev***	***Capex***	***ExecS***	***lnIndus***
lnGTIN	1										
lnGTIL	0.5724*	1									
Treat	-0.1600*	-0.0940*	1								
lnCGG	0.0062	-0.0839*	0.0483*	1							
R&D	0.0055	0.0051	-0.1451*	0.0387*	1						
Size	0.5032*	0.3287*	0.1426*	0.1394*	-0.1246*	1					
ROA	0.0350*	0.0190	0.0455*	-0.0181	-0.0429*	0.0402*	1				
Lev	0.1171*	0.0557*	0.1663*	0.0535*	-0.1090*	0.3727*	-0.0626*	1			
Capex	0.0167	0.0104	0.1033*	-0.0175	-0.0083	-0.0112	0.0874*	0.1975*	1		
ExecS	-0.0943*	-0.0545*	-0.1273*	-0.0468*	0.0877*	-0.3515*	0.0542*	-0.1653*	0.1203*	1	
lnIndus	-0.1975*	-0.1138*	0.1703*	-0.0480*	-0.0944*	-0.1397*	0.0262	-0.0037	0.1050*	-0.0248	1

3.4. Results

3.4.1. Baseline Regression

The baseline estimation of the impact of the EFTR policy on the quality and quantity of green technological innovation was conducted using standard ordinary least squares (OLS) DID regressions without individual firm-level fixed effects, and FE-DID regressions with both firm- and year-level fixed effects before and after propensity score matching (PSM). Standard errors were clustered at the firm's registered city level in all regressions to mitigate interference from correlations within the city's development.

Table 3.3 Summary of Propensity Score Matching Analysis

ATT denotes Average Treatment Effect on the Treated; ATE denotes Average Treatment Effect (on all); ATU denotes Average Treatment Effect on the Untreated.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
lnGTIL	Unmatched	0.9772	1.1885	-0.2113	0.0213	-9.92
	ATT	0.9776	1.0859	-0.1083	0.0288	-3.76
	ATU	1.1905	0.9002	-0.2904	.	.
	ATE			-0.2321	.	.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
lnGTIN	Unmatched	0.7131	0.6030	0.1101	0.0098	11.18
	ATT	0.7124	0.6024	0.1100	0.0139	7.92
	ATU	0.6017	0.7655	0.1638	.	.
	ATE			0.1473	.	.

Treatment Assignment	Common support		
	Off support	On support	Total
Untreated	163	6053	6216
Treated	7	2995	3002
Total	170	9048	9218

Table 3.3 provides a comprehensive summary of the PSM results, with ***GTIL*** and ***GTIN*** serving as the dependent variables, respectively, using the 1:2 k-nearest neighbour matching method. The upper section of the table shows that, following the 1:2 nearest neighbour matching, the average treatment effect on the treated (ATT) is -0.1083 and 0.1100 for GTIL and GTIN cases, respectively, both statistically significant at the 1% level. The lower section reveals that, out of a total of 9218 observations, only 163 in the untreated group and 7 in the

treated group fall outside the common support. Most observations, particularly those in the control group, were successfully matched.

The balance test results have been presented in **Table 3.4**. The results indicate that the *p*-values of all covariates are higher than 5% after matching, suggesting no statistically significant systematic differences between the treated and control groups after matching. However, *Capex* has a p-value of 0.088 and 0.033 after matching when ***GTIL*** and ***GTIN*** serve as dependent variable, respectively. This bias in the statistical significance may be due to the right-skewed distribution of *Capex* in firm-level samples, where most companies exhibit lower level of capital expenditure compared to a few companies with higher levels. Additionally, *Capex* is closely tied to industry characteristics; capital-intensive industries such as manufacturing and energy typically have high *Capex*, while industries like services and software tend to have lower *Capex*. These factors contribute to the imbalance in *Capex* data, resulting in matching bias. Overall, the 1:2 k-nearest neighbour matching approach proves robust in constructing a treated and control group without significant systematic difference.

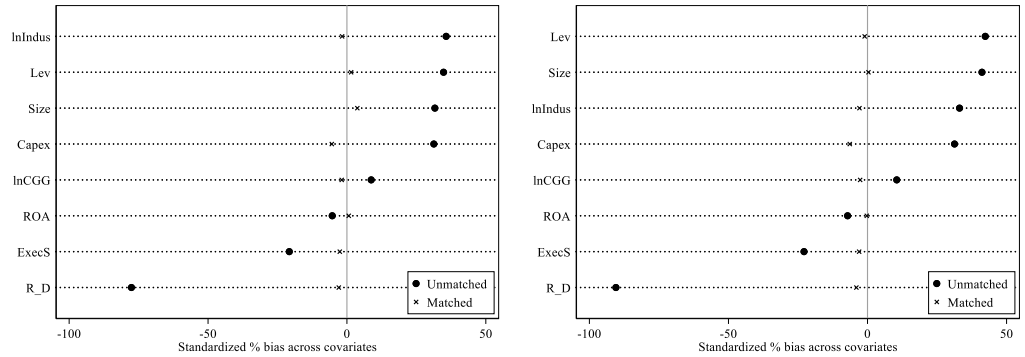
Table 3.4 Balance Test of Propensity Score Matching

* if variance ratio outside [0.93; 1.07] for U and [0.93; 1.07] for M, U represents Unmatched and M represents Matched.

lnGTIL								
Variable	**Unmatched**	**Mean**		**%reduct**		**t-test**		**V(T)/V(C)**
	Matched	**Treated**	**Control**	**%bias**	**|bias|**	**t**	**p>|t|**	
lnCGG	U	3.9209	3.6565	8.7		4.01	0.000	1.26*
	M	3.9151	3.9726	-1.9	78.3	-0.72	**0.472**	1.14*
R&D	U	0.6792	1.4266	-77.6		-35.67	0.000	1.28*
	M	0.68423	0.71259	-2.9	96.2	-1.02	**0.307**	0.81*
Size	U	22.98	22.601	31.7		14.36	0.000	1.09*
	M	22.977	22.933	3.7	88.2	1.41	**0.159**	0.98
ROA	U	-3.0109	-2.9345	-5.3		-2.38	0.018	0.99
	M	-3.0138	-3.0231	0.6	87.8	0.25	**0.801**	1.04
Lev	U	-2.9795	-3.5476	34.8		15.39	0.000	0.82*
	M	-2.9829	-3.0074	1.5	95.7	0.61	**0.542**	0.99
Capex	U	1.4008	1.1139	31.3		13.81	0.000	0.80*
	M	1.3985	1.4381	-4.3	86.2	-1.71	**0.088**	0.86*
ExecS	U	-4.3407	-3.5466	-20.8		-9.62	0.000	1.40*
	M	-4.3265	-4.2277	-2.6	87.6	-0.95	**0.340**	1.12*
lnIndus	U	3.7262	3.6112	35.7		15.81	0.000	0.83*
	M	3.7255	3.7311	-1.7	95.1	-0.77	0.440	1.45*
lnGTIN								
Variable	**Unmatched**	**Mean**		**%reduct**		**t-test**		**V(T)/V(C)**
	Matched	**Treated**	**Control**	**%bias**	**|bias|**	**t**	**p>|t|**	
lnCGG	U	3.9626	3.6381	10.5		4.17	0.000	1.32*
	M	3.9597	4.0418	-2.7	74.7	-0.84	**0.399**	1.15*
R&D	U	0.62816	1.4789	-90.5		-36.09	0.000	1.38*
	M	0.63014	0.66791	-4.0	95.6	-1.17	**0.243**	0.85*
Size	U	23.244	22.754	41.1		15.94	0.000	1.04
	M	23.243	23.239	0.3	99.2	0.10	**0.918**	1.02
ROA	U	-3.0593	-2.9584	-7.2		-2.76	0.006	0.99
	M	-3.0604	-3.0564	-0.3	96.1	-0.09	**0.925**	1.11*
Lev	U	-2.8219	-3.4853	42.3		15.84	0.000	0.72*
	M	-2.8231	-2.8067	-1.0	97.5	-0.37	**0.711**	0.99
Capex	U	1.4193	1.1397	31.3		11.77	0.000	0.77*
	M	1.4183	1.4755	-6.4	79.6	-2.13	**0.033**	0.82*
ExecS	U	-4.5007	-3.6187	-22.8		-9.17	0.000	1.47*
	M	-4.495	-4.3781	-3.0	86.7	-0.94	**0.349**	1.16*
lnIndus	U	3.7071	3.598	33.1		12.63	0.000	0.89*
	M	3.7068	3.7164	-2.9	91.2	-1.07	**0.287**	1.46*

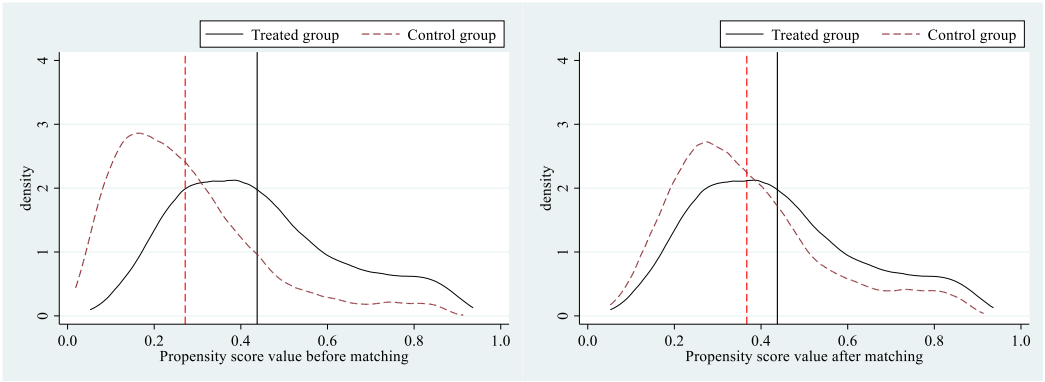
Figures 3.1 and **Figure 3.2** further validate the matching efficiency. **Figure 3.1**, together with **Table 3.4**, shows a substantial reduction in the absolute value of percentage bias when GTIL is used as the dependent variable, with reductions ranging from 78.3% to 96.2% compared to the unmatched case. Similarly, when ***GTIL*** serves as the dependent variable, the percentage bias is reduced by 74.7% to 99.2%. **Figure 3.2** illustrates a notable deviation in the kernel

density function distribution between the two groups before matching, which is significantly reduced after matching.

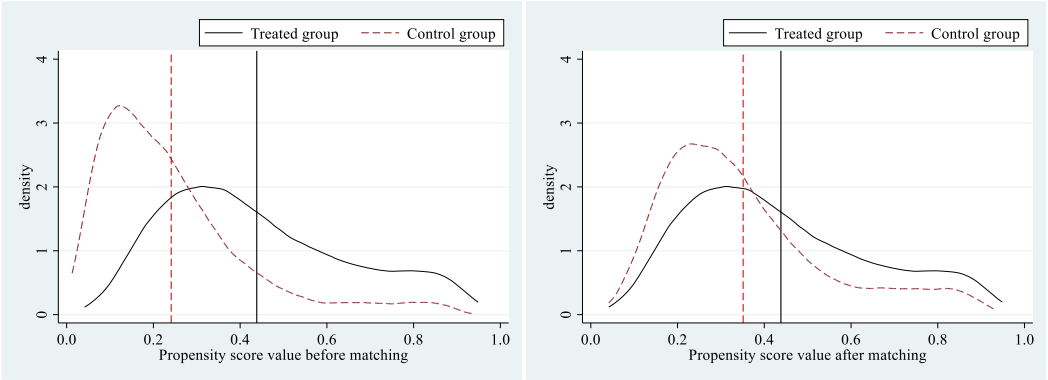


(a) *lnGTIL* **(b) *lnGTIN***

Figure 3.1. The Bias of the Two Groups before and after Propensity Score Matching.



(a) lnGTIL



(b) lnGTIN

Figure 3.2 Kernel Density Function Distributions before and after Propensity Score Matching

The baseline regression results are presented in **Table 3.5**. Columns (1) to (8) report the OLS-DID and FE-DID estimates, with or without control variables, before propensity score matching (PSM). The coefficients of $EFTR_{it}$ remain negative and statistically significant at the 1% level across all specifications when the quality of green technological innovation is used as the dependent variable. Conversely, the coefficients are consistently positive and significant at the 1% level when examining the quantity of green technological innovation. To rigorously validate the robustness of the estimated policy effect across all our hypotheses, we adopt a stepwise approach that progressively strengthens identification assumptions following PSM, including a standard PSM-DID using all matched samples with non-zero weights (***Weight!=.***), a PSM-DID using samples that satisfy the common support hypothesis to eliminate extrapolation bias from extreme propensity scores (***On_Support***), and a frequency-weighted PSM-DID (***Frequency Weighted***), in which samples in the control group are replicated based on the number of times they are matched to treated units. This approach accounts for the fact that certain control group samples may serve as matches for multiple treated group samples, and therefore, should carry greater importance in the regression, thereby achieving better balance in baseline specifications. Across columns (9) to (14), the coefficients of $EFTR_{it}$ remain consistent in direction and statistically significant. Specifically, after mitigating self-selection bias through PSM, the implementation of the EFTR policy in 2018 led to an 8.8%, 8.7%, and 7.9% reduction in the quality of corporate green technological innovation, with statistical significance at the 5% or 1% level, respectively. In contrast, the EFTR policy significantly contributes to the 17.5%, 17.2%, and 13.4% growth in the quantity of corporate green technological innovation, respectively, with statistical significance at 1% or 5% levels.

The significant growth in the quantity, accompanied by a sharp decline in the quality, of corporate green technological innovation suggests that the "crowding-out" effect of the EFTR policy outweighs its "compensation" effect. This finding aligns with existing studies, which indicate that the additional upfront costs imposed by stringent environmental regulations may initially lead to a temporary decline in firm productivity (Hancevic, 2016). As a result, firms may prioritise cost reduction over environmental performance (Hafezi and Zolfagharinia, 2018). Similar evidence has been observed in China, indicating that the Porter hypothesis may

not be directly applicable to Chinese manufacturing firms (He et al., 2020). Environmental regulations may inadvertently incentivise rent-seeking behaviours or reliance on end-of-pipe treatments, thereby diverting resources away from substantive, quality-driven breakthroughs in green production and instead encouraging a focus on quick, quantity-based compliance.

Table 3.5 The EFTR Policy and Corporate Green Technological Innovation

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM								**After PSM (FE-DID)**					
	OLS-DID				**FE-DID**				(***Weight!=.***)		(***On_Support***)		(***Frequency Weighted***)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$
$\boldsymbol{EFTR_{it}}$	**-0.251*****	**0.090*****	**-0.236*****	**0.090*****	**-0.105*****	**0.472*****	**-0.089*****	**0.173*****	**-0.088****	**0.175*****	**-0.087*****	**0.172*****	**-0.079****	**0.134****
	(-4.252)	**(4.452)**	**(-3.936)**	**(5.003)**	**(-3.750)**	**(9.302)**	**(-2.964)**	**(3.059)**	**(-2.541)**	**(3.151)**	**(-2.921)**	**(3.061)**	**(-2.166)**	**(2.242)**
$R\&D_{it-1}$			0.157***	0.058***			-0.016	0.150***	-0.042	0.143***	-0.015	0.148***	-0.030	0.169***
			(4.811)	(6.435)			(-0.800)	(4.486)	(-1.584)	(3.073)	(-0.718)	(4.413)	(-0.937)	(3.369)
$Size_{it-1}$			0.301***	0.133***			0.027	0.383***	0.025	0.373***	0.031	0.384***	0.047	0.390***
			(14.530)	(18.841)			(0.879)	(11.805)	(0.538)	(7.363)	(0.959)	(11.660)	(0.802)	(6.754)
ROA_{it-1}			-0.014	-0.004			-0.022***	-0.013*	-0.022***	-0.011	-0.024***	-0.014*	-0.026***	-0.019
			(-1.540)	(-1.182)			(-3.674)	(-1.812)	(-3.269)	(-1.092)	(-3.928)	(-1.917)	(-3.135)	(-1.554)
Lev_{it-1}			0.025*	-0.004			0.003	-0.020**	0.004	-0.019	0.004	-0.021**	0.001	-0.018
			(1.785)	(-0.766)			(0.436)	(-2.006)	(0.428)	(-1.351)	(0.501)	(-2.120)	(0.081)	(-1.042)
$Capex_{it-1}$			0.051**	0.019**			0.009	0.052**	0.006	0.044	0.008	0.055***	0.024	0.044
			(1.997)	(2.307)			(0.711)	(2.539)	(0.359)	(1.462)	(0.643)	(2.635)	(1.096)	(1.262)
$ExecS_{it-1}$			-0.003	-0.002			-0.003	0.003	-0.009	-0.007	-0.003	0.003	-0.004	-0.006
			(-0.050)	(-1.048)			(-0.095)	(0.640)	(-0.187)	(-0.991)	(-0.088)	(0.565)	(-0.827)	(-0.923)
$lnIndus_{it-1}$			-0.238***	-0.067***			-0.092	-0.762***	-0.005	-0.681***	-0.093	-0.760***	-0.023	-0.922***
			(-4.496)	(-4.473)			(-0.633)	(-4.725)	(-0.031)	(-2.692)	(-0.634)	(-4.731)	(-0.154)	(-3.049)
Constant	1.196***	0.744***	4.992***	3.572***	1.138***	1.557***	-2.071**	-4.566***	1.633	-4.756***	-2.161**	-4.600***	2.133	-4.196**
	(28.816)	(27.990)	(8.459)	(19.806)	(243.071)	(186.832)	(-2.007)	(-4.534)	(1.226)	(-2.839)	(-1.988)	(-4.522)	(1.308)	(-2.064)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9218	9218	9218	9218	9218	9218	9218	9218	3795	3833	6745	6745	6382	6390
Adj. R-squared	0.039	0.024	0.167	0.170	0.751	0.653	0.766	0.709	0.752	0.698	0.768	0.710	0.792	0.754

3.4.2. Robustness Test

3.4.2.1. Parallel Trend Test

We utilise the event study method to construct **Model (3.4)** to evaluate whether the observed baseline effect of the EFTR policy both in terms of its impact on the quantity and quality of green technological innovation are consistent with the presumption of the parallel trend hypothesis (Liu and Wang, 2023). The core diagnostic strategy for testing this hypothesis involves examining whether the exogenous policy intervention appears to have led to any statistically significant differences between the treated and control groups before the policy actually occurs, i.e., "pre-event trends". Such differences is regarded as an evidence against the the strict exogeneity condition of the policy change (Freyaldenhoven et al., 2019).

To minimise extraneous policy noise over an extended timeframe and mitigate potential multicollinearity issues, we consolidated observations of years before 2014 and years after 2020 into two periods, denoted as *beforepre_4* and *afterpost_2,* respectively (Xu and Yao, 2015; He and Wang, 2017). Year 2017 is selected as the base year and excluded from the regression to prevent multicollinearity. Based on this framework, we introduced interaction terms of leads and lags of the treated groups, denoted as pre_* ($Period^*$,$*=$ 1,2,3,4) and $post_*$ ($Period^*$,$*=$ 1,2) to capture the effects of time dummies for the remaining years before and after the EFTR policy implementation within sample period. These interaction terms were combined with the $Treat_i$[22]. pre_* and $post_*$ are set to 0 for all control groups where $Treat_i = 0$. *current* is the proxy for the interaction terms of the time dummy corresponding to the EFTR policy implementation year and $Treat_i$. Other symbols and subscripts maintain the same meanings as described in the baseline models.

$$GTIL_{it} = \omega_0 + \omega_1 beforepre_4 + \omega_2 pre_4 + \omega_3 pre_3 + \omega_4 pre_2 + \omega_5 current + \omega_6 post_1 + \omega_7 post_2 + \omega_8 afterpost_2 + \beta Controls_{it-1} + \gamma_t + \lambda_i + \varepsilon_{it} \quad (3.4)$$

[22] For instance, pre_3 and $post_2$ denotes the interaction term of time dummy of 2015 and time dummy of 2020 with the $Treat_{it}$ term, respectively.

Table 3.6 presents the regression results of the parallel trend test for both the quality and quantity of green technological innovation under different sample specifications in the baseline regressions before and after propensity score matching (PSM). Columns (1) and (2) report the results based on the full sample before PSM, while Columns (3) to (8) employ firm samples that satisfy different assumptions after PSM. All regression results in **Table 3.6** indicate that before the implementation of the EFTR policy, the estimated coefficients for the pre-policy period indicators, including *beforepre_4 (*Year 2012 and 2013*), pre_4 (*Year 2014*), pre_3 (*Year 2015*), and pre_2 (*Year 2016*)*, are statistically insignificant in both the $lnGTIL_{it}$ and $\mathrm{lnGTIN_{it}}$ models. This finding aligns with the core diagnostic principle of the event study approach, i.e., to examine the absence of pre-policy trend. Moreover, their estimated coefficients fluctuate in direction, suggesting no systematic trend differences between the treated and control groups before the policy intervention.

In contrast, the coefficients of the post-policy year dummies for the quantity of green technological innovation, beginning with *Current (2018)*, exhibit consistently positive and statistically significant estimates at the 1% level, indicating a pronounced and immediate policy impact on the treated group. When using $lnGTIL_{it}$ as the dependent variable, the post-policy coefficients similarly show consistently negative signs, with statistical significance gradually increasing, from the 10% to the 5% level over time. This suggests a lagged EFTR policy effect on green innovation quality. In particular, Column (7), which uses sample firms with frequency-weighted treatment after PSM, reveals a more delayed policy response, with significant negative effects only emerging from 2020 onwards at the 10% level. This result may also be explained by the underlying structure of frequency-weighted regressions, wherein control group observations are replicated based on the frequency with which they are matched to treated units. While this approach helps ensure more balanced influence in baseline settings with more stringent constraints set on samples following PSM to test the robustness of the results, it may introduce imbalances in the temporal structure of the matched sample in certain years in dynamic trend tests. Since stable and evenly distributed panel data across time periods is essential for dynamic trend test, such imbalances can amplify noise or dilute effects in certain years, such as a given pre- or post-policy year dummy can be contaminated by effects

from other periods (Sun and Abraham, 2021), leading to less ideal statistical significance in post-policy period in dynamic trend tests.

Nonetheless, the parallel trend assumption is consistently satisfied across all specifications. All pre-EFTR coefficients, including those from the frequency-weighted sample (*sample_PSMfweight*), are statistically insignificant. Additionally, there's generally existing lagged policy effect, the primary goal of a dynamic trend test is to confirm the absence of systematic differences in outcomes before policy treatment, not to require statistically significant post-treatment effects (He and Wang, 2017). The observed delayed significant policy effects likely reflect the gradual transmission of policy impact rather than a failure of the identification framework. Accordingly, we consider the dynamic trend test using the frequency-weighted sample as a robustness check rather than a primary diagnostic tool for parallel trends. The main findings of the chapter remain robust and reliable.

Consequently, no systematic "pre-event trends" were observed in the analysis of the EFTR policy's impact on both the quantity and quality of green technological innovation, thereby satisfying the identification assumption of our DID framework. The results suggest that it was indeed the EFTR policy, implemented in 2018, that led to the increase in green technological innovation quantity and the decline in quality. Furthermore, these impacts intensified over the four years following the policy's implementation, indicating a clear lagged policy impact.

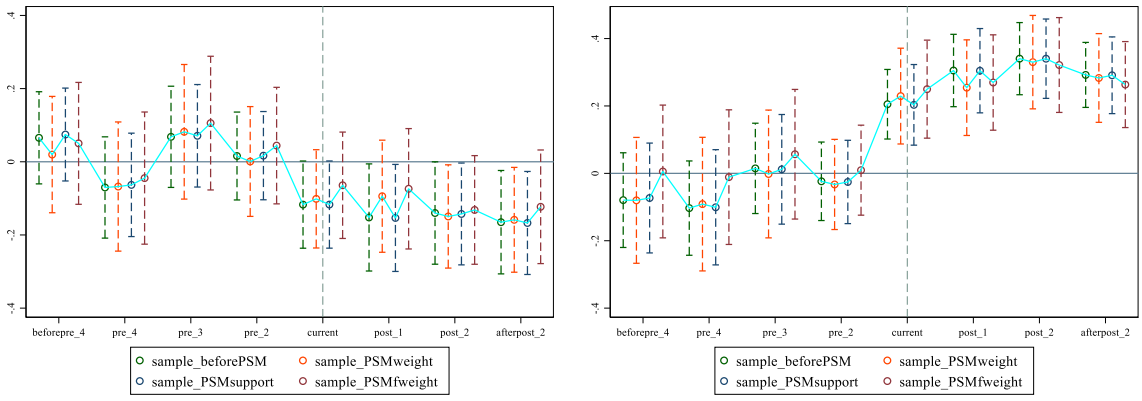
Table 3.6 Parallel Trend Test.

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM		After PSM					
			(*Weight!=.*)		(*On_Support*)		(*Frequency_ Weighted*)	
	(1) $lnGTIL_{it}$	(2) $lnGTIN_{it}$	(3) $lnGTIL_{it}$	(4) $lnGTIN_{it}$	(5) $lnGTIL_{it}$	(6) $lnGTIN_{it}$	(7) $lnGTIL_{it}$	(8) $lnGTIN_{it}$
Beforepre_4	**0.066**	**-0.079**	**0.027**	**-0.080**	**0.074**	**-0.073**	**0.050**	**0.006**
	(1.025)	**(-1.109)**	**(0.341)**	**(-0.846)**	**(1.156)**	**(-0.884)**	**(0.596)**	**(0.055)**
pre_4	**-0.070**	**-0.103**	**-0.065**	**-0.091**	**-0.063**	**-0.101**	**-0.045**	**-0.011**
	(-0.999)	**(-1.446)**	**(-0.745)**	**(-0.907)**	**(-0.880)**	**(-1.160)**	**(-0.487)**	**(-0.111)**
pre_3	**0.068**	**0.015**	**0.079**	**-0.002**	**0.071**	**0.012**	**0.106**	**0.057**
	(0.971)	**(0.216)**	**(0.892)**	**(-0.019)**	**(0.999)**	**(0.145)**	**(1.140)**	**(0.581)**
pre_2	**0.016**	**-0.024**	**-0.003**	**-0.033**	**0.017**	**-0.026**	**0.044**	**0.009**
	(0.258)	**(-0.397)**	**(-0.035)**	**(-0.485)**	**(0.273)**	**(-0.407)**	**(0.547)**	**(0.139)**
Current	-0.117*	0.205***	-0.102	0.229***	-0.117*	0.203***	-0.064	0.250***
	(-1.935)	(3.898)	(-1.503)	(3.180)	(-1.933)	(3.347)	(-0.870)	(3.385)
post_1	-0.152**	0.305***	-0.106	0.254***	-0.154**	0.305***	-0.074	0.270***
	(-2.048)	(5.578)	(-1.371)	(3.532)	(-2.067)	(4.797)	(-0.884)	(3.753)
post_2	-0.140**	0.340***	-0.155**	0.330***	-0.143**	0.340***	-0.132*	0.322***
	(-1.971)	(6.239)	(-2.161)	(4.692)	(-2.019)	(5.693)	(-1.747)	(4.501)
After post_2	-0.165**	0.292***	-0.153**	0.283***	-0.167**	0.291***	-0.123	0.263***
	(-2.302)	(5.943)	(-2.090)	(4.237)	(-2.339)	(5.037)	(-1.561)	(4.068)
$R\&D_{it-1}$	0.139***	0.152***	0.106***	0.148***	0.141***	0.150***	0.164***	0.175***
	(4.258)	(4.699)	(2.922)	(3.263)	(4.427)	(4.541)	(3.890)	(3.487)
$Size_{it-1}$	0.279***	0.387***	0.276***	0.383***	0.281***	0.389***	0.266***	0.398***
	(13.068)	(10.737)	(9.706)	(7.351)	(12.910)	(11.584)	(8.878)	(6.787)
ROA_{it-1}	-0.033***	-0.010	-0.033***	-0.008	-0.034***	-0.011	-0.051***	-0.017
	(-3.454)	(-1.423)	(-3.542)	(-0.749)	(-3.463)	(-1.524)	(-3.377)	(-1.354)
Lev_{it-1}	0.013	-0.019*	0.018	-0.019	0.013	-0.021**	0.028*	-0.018
	(0.915)	(-1.899)	(1.288)	(-1.385)	(0.900)	(-2.081)	(1.665)	(-1.046)
$Capex_{it-1}$	0.058**	0.057***	0.085***	0.052	0.056**	0.059***	0.118***	0.048
	(2.203)	(3.055)	(3.525)	(1.634)	(2.313)	(2.761)	(3.996)	(1.335)
$ExecS_{it-1}$	-0.003	0.003	-0.005	-0.007	-0.003	0.003	-0.003	-0.006
	(-0.433)	(0.581)	(-0.664)	(-1.019)	(-0.416)	(0.528)	(-0.509)	(-0.925)
$lnIndus_{it-1}$	-0.195***	-0.678***	-0.249**	-0.553**	-0.220***	-0.676***	-0.221*	-0.866***
	(-3.077)	(-4.678)	(-2.068)	(-2.110)	(-3.122)	(-4.095)	(-1.824)	(-2.811)
Constant	4.884***	-4.980***	4.678***	-5.456***	4.833***	-5.020***	4.747***	-4.602**
	(7.837)	(-4.423)	(6.957)	(-3.322)	(7.596)	(-4.912)	(6.199)	(-2.263)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9218	9218	3795	3833	6745	6745	6382	6390
Adj. R-squared	0.112	0.713	0.122	0.702	0.115	0.713	0.121	0.756

Figure 3.3 visualises the dynamic trend in the impact of the EFTR policy implementation on the $lnGTIN_{it}$ and $lnGTIL_{it}$ for the two groups, using samples before and after PSM. Standard errors are clustered at the firm's registered city level. It more clearly reveals that, before the implementation of the EFTR, the estimated coefficients of the interaction terms (represented as small hollow dots) remained statistically insignificant and fluctuated around zero. There was no evident pre-event trend in either $lnGTIN_{it}$ or $lnGTIL_{it}$. However, starting from the year 2018 (*Current*), the coefficients exhibit a marked shift. When $lnGTIL_{it}$ is the dependent variable, the coefficients decline significantly below zero, and continue in this negative direction with increasing magnitude over time. In contrast, when $lnGTIN_{it}$ is the dependent variable, the coefficients rise significantly above zero and continue to increase thereafter. These patterns, as illustrated by the solid lines connecting the dots, indicate that the EFTR had a significant positive impact on the quantity of corporate green technological innovation, while exhibiting a negative impact on its quality for firms in the treated group, starting from 2018.

There was no significant difference in the dynamic trends of $lnGTIN_{it}$ or $lnGTIL_{it}$ between the two groups before 2018. The policy had a level effect on $lnGTIN_{it}$ and $lnGTIL_{it}$ for treated firms from 2018 onwards, with significant lagged effects, but no discernible trend effect. Consequently, our baseline regressions on H1a and H1b satisfy the parallel trend hypothesis.



(a) ***lnGTIL*** (b) ***lnGTIN***

Figure 3.3 Dynamic Effect of the EFTR

3.4.2.2. Placebo Test

(a) Time-based Placebo Test

To further address the possibility that the observed increase in the quantity and the reduction in the quality of corporate green technological innovation in firms in the treated group may have been influenced by events preceding the EFTR policy, we conducted a time-based placebo test. An important market-incentivised environmental policy was implemented in China in 2017, namely the "Establishing Pilot Zones for Green Finance Reform and Innovations" (GFRIPZ). This policy aimed to establish eight specific regions as pioneering pilot zones, promoting a more in-depth exploration of the green finance in these regions, which has distinct and representative characteristics. In light of this, we set 2017 as a pseudo time of EFTR policy implementation, alongside 2016, to discover whether the GFRIPZ policy, already implemented in 2017, could have influenced the observed significant increase in the quantity (GTIN) and the decrease in the quality of green technological innovation (GTIL). This time-based placebo test aims to examine whether there was any pre-event trend effect coming from earlier time. The key results in baseline regressions, utilising samples before and after PSM, are re-estimated and presented in **Table 3.7**.

The coefficients of the joint effects were statistically insignificant when setting 2017 and 2016 as the pseudo time of policy implementation in both cases when GTIN and GTIL serve as the dependent variables. This finding confirms that it was indeed the EFTR policy implemented in 2018, that led to an increase in the $lnGTIN_{it}$ and a reduction in the $lnGTIL_{it}$ for treated firms, rather than any events occurring at other times, such as the GFRIPZ policy in 2017.

Table 3.7 Placebo test results

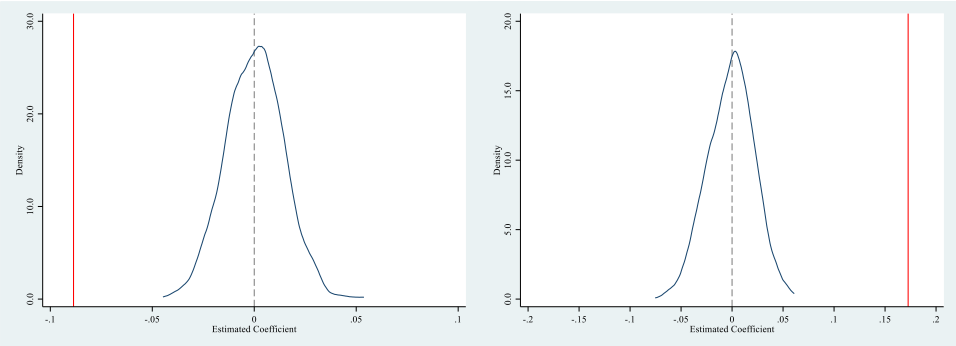
Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM		After PSM (*Weight!=.*)		After PSM (*On_Support*)		After PSM (*Frequency Weighted*)		Before PSM		After PSM (*Weight!=.*)		After PSM (*On_Support*)		After PSM (*Frequency Weighted*)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$	$lnGTIL_{it}$	$lnGTIN_{it}$
$EFTR_{it}$ (2017)	-0.044	0.041	-0.026	0.014	-0.041	0.039	-0.022	0.026								
	(-1.070)	(0.550)	(-0.488)	(0.167)	(-0.998)	(0.532)	(-0.456)	(0.269)								
$EFTR_{it}$ (2016)									-0.038	0.020	-0.033	0.059	-0.037	0.021	-0.036	0.075
									(-0.875)	(0.281)	(-0.551)	(0.703)	(-0.832)	(0.294)	(-0.629)	(0.888)
$Controls_{i\,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.403	-5.209***	0.118	-5.225***	0.508	-5.213***	0.669	-4.851***	0.387	-5.052***	0.141	-5.072***	0.496	-5.054***	0.703	-4.710**
	(0.486)	(-5.080)	(0.100)	(-3.313)	(0.593)	(-5.018)	(0.468)	(-2.656)	(0.469)	(-4.954)	(0.122)	(-3.259)	(0.580)	(-4.886)	(0.494)	(-2.550)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9218	9218	3795	3833	6745	6745	6382	6390	9218	9218	3795	3833	6745	6745	6382	6390
Adj. R-squared	0.766	0.729	0.752	0.714	0.767	0.729	0.791	0.769	0.766	0.729	0.752	0.714	0.767	0.729	0.791	0.769

(b) Firm-based Placebo Test

This chapter categorises a total of 448 firms out of 1477 as high-polluting firms into the treated group for the DID analysis. Although the baseline DID regression model includes firm- and city-level control variables and accounts for firm and year effects, there remains a concern about other omitted factors that could potentially lead to estimation bias. While observable omitted factors have been addressed through propensity score matching (PSM), certain unobservable omitted factors may still influence the identification of policy effects in the baseline results. To further mitigate this concern, we conducted a firm-level placebo test by randomly generating treated groups.

Initially, a total of 448 firms were randomly selected as the fictitious treated group, with 2018 still set as the policy implementation time point. This random sampling process was repeated 1000 times, and 1000 regressions were conducted using the baseline FE-DID regression before PSM, as shown in column (4) of **Table 3.5**. The probability distribution of the pseudo coefficients of $EFTR_{it}$ from these 1000 regressions was then plotted, as shown in **Figure 3.4**. The plot illustrates that the absolute mean value of the bootstrapped pseudo coefficients generally follows a normal distribution, with values mostly clustering around 0. However, the real coefficient of $EFTR_{it}$, represented by the red vertical line, stands as outliers on the left and right side when ***lnGTIL*** and ***lnGTIN*** are dependent variables, respectively. This suggests that our baseline regression results are unlikely to occur when the treated group is randomly assigned. The regression results in **Table 3.5** are not influenced by omitted firm-level factors, further confirming the robustness of the baseline regression results.



(a) *lnGTIL* (b) *lnGTIN*

Figure 3.4 The Firm-Based Placebo Test

3.4.3. Moderating Effect Analysis

The regression results of **Model (3.3)** are presented in **Table 3.8.** Columns (1) shows the results of FE-DID regression using the sample before PSM, while Columns (2) to (4) display the results after PSM. Firm- and year-level fixed effects are included. **Table 3.8** demonstrates that the coefficients of $EFTR_{it}$ remain statistically significantly negative, consistent with those presented in the baseline regressions, indicating that the negative impact of the EFTR policy on the quality of firms' green technological innovation persists. Additionally, the coefficients of the $lnCGG_{it}$ are significantly negative at the 1% level, suggesting that the standalone government guarantees independently have a separate "crowding-out" effect on the quality of corporate green technological innovation. However, the interaction coefficients between the EFTR policy and corporate government guarantees ($EFTR_{it} \times lnCGG_{it}$) are positive and generally statistically significant at the 1% level. This suggests that government guarantees provided in the presence of the EFTR policy significantly mitigate the "crowding-out effect" of the EFTR policy on firms' green technological innovation quality. Collectively, the two 'government interventions' −the EFTR policy and government guarantees −can be seen as substitutes for each other: the EFTR policy, as an external stringent environmental regulation, significantly increases the compliance costs of firms, leading to a significant decline in the quality of green innovation of firms. Government guarantees, on the other hand, are a form of external financial support that may alleviate firms' financing constraints, but at the same time, they introduce the risk of "moral hazard", where firms may be more inclined to choose low-risk, low-return investments over pursue long-term breakthroughs in green innovation quality. However, the situation changes when the EFTR policy and government guarantees operate together. Although government guarantees may individually be unfavourable to green technological innovation, they can serve as a buffer within the EFTR policy environment. These guarantees help firms to alleviate the expenditure pressure of innovation caused by the policy, thus mitigating the negative impact of the EFTR policy on the quality of green technological innovation.

Consequently, **H2** is supported. The cost of sacrificing the quality of green technological innovation resulting from the EFTR policy, as a stringent environmental regulation, can be mitigated by providing government guarantees to firms. This intervention facilitates the

coordination between environmental protection objectives and the long-term sustainable development of firms.

Table 3.8 Moderating Effect Analysis: Government Guarantees

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM	After PSM		
		(*Weight!=.*)	(*On_Support*)	(*Frequency_Weighted*)
	(1)	(2)	(3)	(4)
	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$
$\boldsymbol{EFTR_{it} \times lnCGG_{it}}$	**0.126*****	**0.098***	**0.128*****	**0.113*****
	(3.369)	**(1.961)**	**(3.255)**	**(3.082)**
$EFTR_{it}$	-0.100***	-0.090***	-0.102***	-0.083***
	(-3.802)	(-3.149)	(-3.866)	(-3.553)
$lnCGG_{it}$	-0.456***	-0.402***	-0.459***	-0.410***
	(-22.605)	(-11.947)	(-21.477)	(-18.941)
$R\&D_{it-1}$	0.004	0.020	0.003	0.034***
	(0.200)	(0.647)	(0.115)	(2.732)
$Size_{it-1}$	0.040	0.013	0.037	0.001
	(1.398)	(0.393)	(1.300)	(0.099)
ROA_{it-1}	-0.004	-0.003	-0.001	-0.006
	(-0.111)	(-0.572)	(-0.003)	(-1.357)
Lev_{it-1}	0.009	0.009	0.010	0.008
	(1.304)	(1.046)	(1.369)	(1.583)
$Capex_{it-1}$	0.012	0.009	0.013	0.012
	(1.143)	(0.548)	(1.190)	(1.265)
$ExecS_{it-1}$	-0.001	-0.004	-0.002	-0.004
	(-0.360)	(-0.855)	(-0.443)	(-1.566)
$lnIndus_{it-1}$	-0.247***	-0.250**	-0.256***	-0.254***
	(-2.837)	(-2.351)	(-2.893)	(-4.101)
Constant	-1.297*	-1.865**	-1.383*	2.135***
	(-1.722)	(-1.997)	(-1.794)	(4.758)
Year and Firm FE	Yes	Yes	Yes	Yes
N	9218	3795	6745	6382
Adj R-squared	0.771	0.763	0.772	0.790

3.4.4. Interactive Moderating Effect Analysis

To investigate the interactive moderating effects of corporate government guarantees and firm characteristics, specifically ownership structure and high-tech certification, on the relationship between the EFTR and the quality of green technological innovation, we adopt a three-step empirical strategy to ensure robustness. First, we conduct subgroup regressions based on firm characteristics to explore heterogeneity in the moderating effect of government guarantees. This approach allows us to examine whether the magnitude and direction of the estimated moderating effect differ across firm types. However, subgroup regressions alone

can only reveal the statistical significance of within-group effects; they do not test whether the observed differences in coefficients across groups are statistically significant. To address this limitation, second, we complement the subgroup analysis with inter-group coefficient difference tests using Fisher's permutation method. Compared with alternatives such as the Chow test or standard Wald test, which rely on assumptions like homoscedasticity across subgroups or independence of error terms that are unlikely to hold in our panel dataset, Fisher's permutation test is more appropriate. It utilises a bootstrap-based resampling procedure to evaluate empirical p-values against the one-tailed alternative hypothesis that the coefficient of one group is significantly greater than that of the other. This provides a robust statistical test for the statistical significance of inter-group differences (Cleary, 1999).

Finally, we incorporate triple-term interaction terms ($EFTR_{it} \times lnCGG_{it} \times Firmtype_{it}$). This allows us to capture the baseline effect of the EFTR, the overall moderating effect of corporate government guarantees, and the interaction between firm characteristics and the moderating effect within a single specification. Unlike subgroup regressions, which may suffer from differences in subgroup sample sizes, this model with triple interaction terms uses the full sample and avoids estimation bias from sample variation. More importantly, the significance of the triple interaction terms directly indicates whether the moderating effects of government guarantees vary significantly across firm types. This provides a rigorous and comprehensive test of inter-group coefficient differences that cannot be fully captured by subgroup regressions or Fisher's permutation tests alone.

3.4.4.1. Heterogeneity Analysis

Table 3.9 and **Table 3.10** presented the subgroup regressions exploring the heterogeneity among groups of SOEs and non-SOEs, as well as groups of firms with and without high-tech certification, regarding the moderating effect of government guarantees on the impact of the EFTR policy in hindering the quality of green technological innovation. All regressions control for firm- and year-level fixed effect, with standard errors clustered at firm's registered city level.

All coefficients of $EFTR_{it}$ in **Table 3.9** and **Table 3.10** remain negative, with statistical significance observed only in the non-SOE and high-tech groups. Specifically, in **Table 3.9**, the coefficients of $EFTR_{it} \times lnCGG_{it}$ for SOEs are negative but statistically insignificant, suggesting that government guarantees provided to SOEs may further exacerbate the negative impact of the EFTR on the quality of green technological innovations. Conversely, the coefficients of $EFTR_{it} \times lnCGG_{it}$ for non-SOEs are positive and statistically significant at the 5% or 10% levels, indicating that government guarantees can significantly mitigate the negative impact of the EFTR on the quality of green technological innovation in non-SOEs. These results imply that the magnitude and direction of the moderating role of government guarantees differ substantially between SOEs and non-SOEs. To formally assess the statistical significance of these inter-group differences, we employ Fisher's permutation test using 1000 bootstrap replications. The results support the heterogeneity: the empirical p-value in sample before propensity score matching (PSM) is 0.064, showing statistical significance at the 10% level. After addressing potential self-selection bias through PSM, the empirical p-values across different matched samples are 0.048, 0.017, and 0.056, respectively, statistically significant at the 5% and 10% levels. Consequently, for SOEs, increased access to government guarantees appears to aggravate the hindering effect of the EFTR policy on green technological innovation. In contrast, for non-SOEs, government guarantees have a positive moderating effect, helping to alleviate the negative impact of the EFTR policy on green technological innovation quality.

From **Table 3.10**, the coefficients of $EFTR_{it} \times lnCGG_{it}$ in the high-tech group are positive and statistically significant, primarily at the 1% level, indicating that increased access to government guarantees for high-tech firms can effectively mitigate the disruption to the quality of their green technological innovations caused by the EFTR policy. High-tech firms are better positioned to benefit from government support in the context of stringent environmental regulations, possibly due to their stronger innovation capacity and technological orientation. In contrast, the coefficients of $EFTR_{it} \times lnCGG_{it}$ in the non-high-tech group are also positive but not statistically significant, suggesting that the mitigating effect of government guarantees is weaker for these non-high-tech certified firms. Similarly, the empirical p-values: 0.021, 0.026, 0.020, and 0.022, respectively, across samples before

and after PSM, consistently indicate significance at the 5% level. These results provide robust evidence that the moderating effect of government guarantees differs significantly between high-tech and non-high-tech firms, thus supporting the heterogeneity proposed in H3b.

Table 3.9 Heterogeneity Analysis: State-owned and Non-State-owned Enterprises

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM		**After PSM**					
			(*Weight!=.*)		(*On_Support*)		(*Frequency_Weighted*)	
	SOEs	Non-SOEs	SOEs	Non-SOEs	SOEs	Non-SOEs	SOEs	Non-SOEs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$
$\boldsymbol{EFTR_{it} \times lnCGG_{it}}$	**-0.040**	**0.135****	**-0.030**	**0.121***	**-0.032**	**0.143****	**-0.012**	**0.096***
	(-0.718)	**(2.034)**	**(-0.338)**	**(1.810)**	**(-0.556)**	**(2.127)**	**(-0.132)**	**(1.785)**
$EFTR_{it}$	-0.027	-0.099**	-0.003	-0.099**	-0.033	-0.099**	-0.015	-0.087**
	(-0.575)	(-2.184)	(-0.043)	(-2.303)	(-0.692)	(-2.183)	(-0.190)	(-2.310)
$lnCGG_{it}$	0.071	-0.478***	0.119	-0.444***	0.066	-0.484***	0.117	-0.413***
	(1.210)	(-11.583)	(1.306)	(-9.286)	(1.064)	(-11.996)	(1.165)	(-12.982)
$R\&D_{it-1}$	0.019	-0.017	0.022	-0.054*	0.020	-0.015	0.013	-0.063***
	(0.696)	(-0.496)	(0.770)	(-1.738)	(0.736)	(-0.436)	(0.327)	(-2.708)
$Size_{it-1}$	0.005	0.084**	0.014	0.060**	0.002	0.081*	-0.025	0.022
	(0.137)	(2.005)	(0.269)	(2.120)	(0.043)	(1.865)	(-0.408)	(1.144)
ROA_{it-1}	-0.019**	0.002	-0.015	-0.004	-0.019**	-0.001	-0.015	-0.010
	(-2.396)	(0.198)	(-1.595)	(-0.389)	(-2.394)	(-0.100)	(-1.535)	(-1.450)
Lev_{it-1}	0.002	0.003	-0.001	0.005	0.004	0.003	-0.004	0.018**
	(0.167)	(0.351)	(-0.085)	(0.479)	(0.355)	(0.389)	(-0.239)	(2.331)
$Capex_{it-1}$	0.021	-0.003	0.043*	0.012	0.020	-0.004	0.067**	0.019
	(1.177)	(-0.181)	(1.887)	(0.635)	(1.090)	(-0.188)	(2.344)	(1.303)
$ExecS_{it-1}$	-0.001	-0.001	-0.003	-0.003	-0.001	-0.001	-0.005	-0.003
	(-0.312)	(-0.188)	(-0.641)	(-0.471)	(-0.289)	(-0.208)	(-0.954)	(-0.539)
$lnIndus_{it-1}$	-0.232	0.090	-0.220	-0.050	-0.229	0.085	0.051	-0.164
	(-1.555)	(0.592)	(-1.173)	(-0.364)	(-1.526)	(0.542)	(0.261)	(-1.521)
Constant	1.866**	-0.967	1.483	0.042	1.952**	-0.883	1.307	1.348*
	(1.994)	(-0.752)	(1.026)	(0.043)	(2.077)	(-0.661)	(0.800)	(1.867)
Year and Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	3030	4049	1836	2197	3000	3967	3011	3601
Adj R-squared	0.815	0.775	0.800	0.772	0.815	0.777	0.831	0.809
Fisher's permutation test Empirical p-value	0.064*		0.048**		0.017**		0.056*	

Table 3.10 Heterogeneity Analysis: High-tech and Non-High-tech Enterprises

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Before PSM		**After PSM**					
			(*Weight!=.*)		(*On_Support*)		(*Frequency_Weighted*)	
	High-tech	Non-High-tech	High-tech	Non-High-tech	High-tech	Non-High-tech	High-tech	Non-High-tech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$	$lnGTIL_{it}$
$\boldsymbol{EFTR_{it} \times lnCGG_{it}}$	**0.132*****	**0.096**	**0.108***	**0.140**	**0.140*****	**0.096**	**0.140*****	**0.118**
	(2.632)	**(1.540)**	**(1.646)**	**(1.357)**	**(2.794)**	**(1.543)**	**(2.646)**	**(1.182)**
$EFTR_{it}$	-0.093**	-0.022	-0.103**	-0.024	-0.093**	-0.022	-0.126***	-0.012
	(-2.458)	(-0.578)	(-2.316)	(-0.541)	(-2.444)	(-0.581)	(-3.276)	(-0.254)
$lnCGG_{it}$	-0.485***	-0.388***	-0.470***	-0.379***	-0.502***	-0.390***	-0.515***	-0.337***
	(-16.855)	(-8.809)	(-9.864)	(-5.173)	(-17.255)	(-8.792)	(-15.377)	(-4.950)
$R\&D_{it-1}$	0.026	0.005	0.029	0.043	0.028	0.004	0.071**	0.063
	(0.937)	(0.233)	(0.768)	(1.111)	(1.011)	(0.177)	(2.423)	(1.447)
$Size_{it-1}$	0.074***	0.017	0.085**	0.006	0.066**	0.018	0.095***	0.023
	(2.945)	(0.676)	(2.248)	(0.098)	(2.548)	(0.714)	(3.520)	(0.392)
ROA_{it-1}	-0.004	-0.023***	-0.009	-0.026***	-0.007	-0.023***	-0.004	-0.037***
	(-0.642)	(-3.415)	(-0.936)	(-2.831)	(-1.043)	(-3.402)	(-0.562)	(-3.766)
Lev_{it-1}	0.003	0.002	0.007	0.004	0.002	0.002	0.006	0.010
	(0.402)	(0.214)	(0.628)	(0.026)	(0.247)	(0.213)	(0.708)	(0.435)
$Capex_{it-1}$	0.003	0.035**	0.031	0.047	0.003	0.036**	0.054***	0.070*
	(0.184)	(2.399)	(1.501)	(1.570)	(0.210)	(2.444)	(3.259)	(1.953)
$ExecS_{it-1}$	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001	-0.004
	(-0.004)	(-0.459)	(-0.192)	(-0.442)	(-0.018)	(-0.519)	(-0.128)	(-0.746)
$lnIndus_{it-1}$	-0.275***	-0.071	-0.195	-0.118	-0.257***	-0.075	-0.316***	-0.033
	(-2.724)	(-0.696)	(-1.313)	(-0.597)	(-2.623)	(-0.740)	(-2.720)	(-0.143)
Constant	-0.629	-0.374	0.041	-1.287	-0.750	-0.331	-0.162	1.308
	(-0.825)	(-0.468)	(0.036)	(-0.728)	(-0.952)	(-0.411)	(-0.187)	(0.708)
Year and Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	4095	2788	2087	1774	4006	2762	3199	3295
Adj R-squared	0.804	0.782	0.787	0.790	0.807	0.782	0.828	0.829
Fisher's permutation test Empirical p-value	0.021**		0.026**		0.020**		0.022**	

3.4.4.2. Triple Interactive Effect Analysis

To provide more robust evidence for H3a and H3b, we further employ the triple interactive effect technique specified in **Model (3.3)**, building on the subgroup regressions and Fisher's permutation tests presented in **Table 3.9** and **Table 3.10.** This approach directly tests the heterogeneity in the moderating effects of government guarantees across firm characteristics by examining their interaction in the presence of the EFTR policy's impact on the quality of corporate green technological innovation.

As shown in **Table 3.11,** columns (1) to (4) examine the interactive moderating effects of government guarantees and firm ownership type (state-owned vs. non-state-owned), with all the coefficients of $EFTR_{it}$ remaining negative and statistically significant, primarily at the 1% level. However, in columns (5) to (8), the EFTR policy effect is not statistically significant, indicating no significant directional differences in the impact of the EFTR policy on the quality of green technological innovation between high-tech and non-high-tech firms. The coefficients of $EFTR_{it} \times lnCGG_{it} \times SOE_{it}$ and $EFTR_{it} \times lnCGG_{it} \times Hightech_{it}$ are the key focus in the triple interaction effect analysis. All the coefficients of $EFTR_{it} \times lnCGG_{it} \times SOE_{it}$ in **Table 3.11** are negative and statistically significant at either the 1% or 5% level, suggesting a significant difference in the direction of the moderating effect of government guarantees between SOEs and non-SOEs. This further strengthens the robustness of the results from subgroup regressions for SOEs in **Table 3.9**, where the *t-statistics* of the coefficients of $EFTR_{it} \times lnCGG_{it}$are somewhat low. Specifically, government guarantees received by SOEs indeed exacerbate the negative impact of the EFTR policy on their green technological innovation quality, while mitigating it in non-SOEs, thereby supporting H3a. In contrast, all coefficients of $EFTR_{it} \times lnCGG_{it} \times Hightech_{it}$ are significantly positive at the 1% level, indicating that compared to non-high-tech firms, high-tech firms exhibit higher sensitivity in using more corporate government guarantees to mitigate the negative impact of the EFTR policy on their green technological innovation quality. **H3b** is thus supported.

Additionally, all the coefficients of $EFTR_{it} \times lnCGG_{it}$ in **Table 3.11** are positive and statistically significant at the 1% level, confirming the robustness of the moderating effect of government guarantees in mitigating the negative impact of the EFTR policy. Therefore, by combining the subgroup regressions in **Table 3.9** and **Table 3.10** with the triple interactive

effect analysis in **Table 3.11,** we find that government guarantees and firm characteristics interactively moderate the impact of the EFTR policy on the quality of firms' green technological innovations, exhibiting varying directions and magnitudes. Regarding firm ownership, state-owned enterprises (SOEs) receiving more government guarantees experience a stronger inhibitory effect on their green technological innovation quality in the presence of the EFTR policy. In contrast, for non-state-owned enterprises (non-SOEs), receiving government guarantees effectively mitigates this negative impact. Both high-tech certified firms and those without high-tech certification can reduce the crowding-out effect of the EFTR policy on their green technological innovation quality by obtaining more government guarantees, with the effect being more pronounced for high-tech certified firms.

Table 3.11 The Interactive Moderating Effects: Government Guarantees and Firm Properties.

Values of t-statistics of the coefficients of the variables are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	SOEs and Non-SOEs				**High-tech and Non-high-tech**			
		After PSM				**After PSM**		
	Before PSM	(*Weight!=.*)	(*On_Support*)	(*Frequency Weighted*)	**Before PSM**	(*Weight!=.*)	(*On_Support*)	(*Frequency Weighted*)
	(1) $lnGTIL_{it}$	(2) $lnGTIL_{it}$	(3) $lnGTIL_{it}$	(4) $lnGTIL_{it}$	(5) $lnGTIL_{it}$	(6) $lnGTIL_{it}$	(7) $lnGTIL_{it}$	(8) $lnGTIL_{it}$
$\boldsymbol{EFTR_{it} \times lnCGG_{it} \times SOE_{it}}$	**-0.357*****	**-0.361****	**-0.366*****	**-0.456*****				
	(-2.764)	**(-2.422)**	**(-2.822)**	**(-6.110)**				
$\boldsymbol{EFTR_{it} \times lnCGG_{it} \times Hightech_{it}}$					**0.419*****	**0.335*****	**0.433*****	**0.329*****
					(6.131)	**(3.986)**	**(6.325)**	**(4.531)**
$\boldsymbol{EFTR_{it} \times lnCGG_{it}}$	**0.420*****	**0.466*****	**0.426*****	**0.301*****	**0.306*****	**0.244*****	**0.309*****	**0.222*****
	(5.326)	**(5.549)**	**(5.400)**	**(6.579)**	**(6.557)**	**(4.370)**	**(6.604)**	**(4.379)**
$EFTR_{it} \times SOE_{it}$	0.302***	0.345***	0.297***	-0.027				
	(4.161)	(4.340)	(4.093)	(-0.538)				
$lnCGG_{it} \times SOE_{it}$	-0.430***	-0.379***	-0.433***	-0.392***				
	(-6.550)	(-4.325)	(-6.550)	(-10.579)				
$EFTR_{it} \times Hightech_{it}$					-0.109**	-0.098*	-0.111**	-0.112**
					(-2.320)	(-1.842)	(-2.368)	(-2.331)
$lnCGG_{it} \times Hightech_{it}$					-0.451***	-0.416***	-0.464***	-0.413***
					(-15.957)	(-9.379)	(-16.244)	(-13.158)
$\boldsymbol{EFTR_{it}}$	**-0.335*****	**-0.319*****	**-0.335*****	**-0.015**	**-0.023**	**-0.019**	**-0.023**	**-0.039**
	(-6.947)	**(-6.199)**	**(-6.946)**	**(-0.408)**	**(-0.655)**	**(-0.448)**	**(-0.650)**	**(-1.033)**
$lnCGG_{it}$	-0.115*	-0.186**	-0.114*	-0.113***	-0.019	-0.026	-0.011	-0.096***
	(-1.951)	(-2.511)	(-1.931)	(-3.326)	(-0.571)	(-0.581)	(-0.329)	(-2.838)
SOE_{it}	-0.057*	-0.010	-0.058*	-0.025				
	(-1.786)	(-0.233)	(-1.818)	(-0.458)				
$Hightech_{it}$					0.203***	0.191***	0.205***	0.213***
					(9.105)	(6.292)	(9.161)	(9.454)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.258***	-4.544***	5.184***	-1.623***	0.979*	-1.271*	-1.092**	-1.494***
	(17.654)	(-11.682)	(17.106)	(-3.015)	(1.918)	(-1.771)	(-2.124)	(-2.809)
Year and Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9218	3795	6745	6382	9218	3795	6745	6382
Adj R-squared	0.143	0.150	0.147	0.138	0.157	0.156	0.161	0.142

3.5. Conclusions and Implications

Technological innovation plays a crucial role in enhancing total factor productivity, leading to high-quality economic growth. Within this process, the quality of green-oriented technological innovation serve as the key indicator of firm's actual technological innovative capacity and is essential for coordinating economic growth with sustainability goals (Wang et al., 2023). Given the imperfect economic institutions during the transition period and ongoing environmental degradation in China, the impact of environmental regulations, which act as a form of government intervention, on corporate development and national economic growth, particularly in promoting sustainability, has attracted significant attention from policymakers and scholars. Developing countries like China, along with many developed nations, have also implemented various forms of government guarantees as interventions to guide private-sector activities toward achieving social and economic objectives, such as improved environmental performance and innovation. Therefore, it is crucial to examine the effectiveness of these guarantees, particularly their role within the framework of current environmental policies on green innovation. Furthermore, it is vital to understand whether the effects of government guarantees differ across firm characteristics in the context of environmental regulations' impact on the quality of green technological innovations.

To address these questions, we take the "Environmental Fee-to-Tax" Reform (EFTR), introduced in China in 2018, as a representative case of market-based environmental regulation. We employ a Difference-in-Differences (DID) model, supplemented by robustness checks and interaction effect analysis, to assess the impact of environmental regulations on the quality of green technological innovation, building on the analysis of its effect on the green innovation quantity. This study also investigates the role of government guarantees in this context, particularly how firm characteristics shape these effects. Based on these findings, recommendations are made for relevant stakeholders.

First, this chapter identifies both the compensation and crowding-out effects of the EFTR on corporate green technological innovation capability, assessed through quantity and quality dimensions. Following the implementation of the EFTR in 2018, firms in China experienced a significant increase in the quantity, but a decline in the quality, of green technological innovation. These findings are validated through a series of robustness checks, including

placebo tests, parallel trend tests, and propensity score matching. This chapter further demonstrates that standalone government guarantees also hinder the quality of green technological innovation. However, when government guarantees are introduced after the EFTR policy, they generally significantly mitigate the hindering effect of the EFTR policy on corporate green technological innovation. Governments should be more careful in choosing scenarios for providing government guarantees and avoid offering assistance indiscriminately to prevent potential moral hazards created among firms. It would be more effective to allocate government guarantees within the framework of stringent environmental policies. Besides, building on the "double dividend hypothesis," which suggests that revenues from environmental taxes can be reallocated as government guarantees to stimulate growth in other sectors, we recommended that governments implement tiered tax rate system, with higher tax rates for enterprises in regions with severe environmental pollution (Jin et al., 2024). The increase in tax revenue would allow for a larger scale of government guarantees to be provided to enterprises within the EFTR policy framework, reducing the part of the quality of green technological innovations that may be sacrificed for regulatory compliance. Additionally, financial institutions could offer loans at favourable interest rates to firms and provide a grace period for meeting environmental performance standards. This would give firms the time and financial resources to improve their environmental practices and innovate in green technologies, despite the tax and fee burdens imposed by the EFTR during the transition period. Such financial support would ensure cash flow and promote high-quality green technological innovation, while offsetting the potential costs of environmental compliance. Moreover, corporate managers should proactively establish environmental systems and emergency response mechanisms, utilising green finance tools such as green insurance within government guarantee schemes, particularly in regions where future increases in environmental tax rates under the EFTR have already been announced.

This chapter also highlights the interactive moderating effect of government guarantees and firm characteristics - specifically ownership structure and high-tech certification - in the context of the EFTR policy's impact on the quality of corporate green technological innovation. In state-owned enterprises (SOEs), increased government guarantees significantly exacerbate the negative effect of the EFTR. In contrast, non-state-owned enterprises (non-

SOEs) benefit from government guarantees, which effectively mitigate the policy's adverse impact on their green technological innovation quality. This finding supports Jin et al. (2024), who argue that the EFTR is more effectively implemented in non-SOEs, particularly in addressing their environmental violations. Based on this, the Chinese government should consider reducing preferential government guarantees for SOEs while offering more targeted guarantees to non-SOEs. Given the potential debt discipline effect from reduced government guarantees for SOEs, which could exacerbate their financing constraints (Jin et al., 2023), financial institutions should provide more tailored financing solutions for SOEs to mitigate potential reductions in their investment in green technological innovation under the stringent EFTR.

Moreover, our findings indicate that both high-tech certified and non-certified firms can mitigate the crowding-out effect of the EFTR on their green technological innovations by securing more government guarantees. However, this mitigating effect is more pronounced for high-tech certified firms. The government should consider providing more preferential guarantees to high-tech certified firms, which face greater financing constraints due to their higher-risk profile. These guarantees would help them secure the necessary funding to pursue high-quality green technological innovation within the context of the EFTR. Additionally, corporate managers should prioritise investment in green technologies to strengthen their environmental commitment, which can signal development potential. By improving the quality of technological innovations, firms increase their likelihood of obtaining high-tech certification, thereby benefiting from the significant mitigating effects of government guarantees on the negative impact of the EFTR.

Concluding Remarks

Reflections on Research Aims and Motivation

China's remarkable economic transformation over the past four decades has rapidly elevated it to the world's second-largest economy, attracting global attention from industry, policymakers, and academia. However, this growth trajectory has also generated significant environmental challenges, ranging from intensive energy consumption to severe air and water pollution. Within the one-party political system in China, the government plays a decisive role in shaping the trajectory of the socio-economic system, directly influencing both national development strategies and corporate decision-making. In response, the Chinese government has committed to promoting green transition, seeking to balance environmental protection with sustained economic growth. Achieving this balance requires not only government interventions but also the institutional arrangements that mobilise market forces. Environmental policies, particularly those tied to taxation and green financing, have created important regulatory frameworks for internalising the external costs of pollution and constraining corporate polluting behaviour. However, the effectiveness of these policies depends critically on their interaction with broader market dynamics, especially the financial and technological sectors, which shape firms' access to external funding and drive improvements in total factor productivity.

While existing research has fruitfully examined either the effectiveness of market forces or government intervention in promoting sustainability, there remains a lack of integrated perspectives considering their joint effectiveness. Few studies account for the complex complementarities and trade-offs between these forces, or the heterogeneous responses of firms with different attributes. In particular, limited attention has been given to measuring the extent and dynamic characteristics of market forces. Moreover, government guarantees, one of the most important forms of state support for green transformation, remain underexplored. While government guarantees can release firms' financing constraints and promote genuine green innovation, they may also weaken disciplinary effects by cushioning firms from market and regulatory pressures. In this context, the central motivation of this thesis is to address a critical gap in the literature by comprehensively examining the nature and characteristics of market-based forces arising from the dynamic interaction between the two pillar sectors of

finance and technology, and their interplay with government-led regulations and government guarantees. Specifically, this thesis investigates how these institutional designs that integrate market- and government-based forces jointly shape corporate environmental performance and effectively guide green transition while safeguarding financial resilience in China and other emerging economies.

Accordingly, by combining regional- and firm-level analyses, adopting diverse methodological approaches, and accounting for heterogeneity in ownership and technological intensity, this thesis addresses four key questions: (1) How do financial development (FD) and technological innovation (TI) co-evolve, and do the market forces generated by this co-evolution reduce corporate greenwashing? (2) Do green finance policies improve firms' genuine environmental performance, particularly their green innovation capacity, while ensuring financial stability? (3) How do stringent environmental regulations reshape the quantity and quality of corporate green innovation? (4) Under what conditions do government guarantees complement or undermine these market- and state-led mechanisms, especially across heterogeneous firms?

Summary of Chapters and Findings

The first chapter investigates whether and how financial development (FD) and technological innovation (TI) co-evolve, measures the degree of the resulting coupling coordination between FD and TI at provincial level, and how this coupling coordination influences corporate greenwashing behaviour. It finds that FD and TI in China co-evolve in an asymmetric, mutually beneficial pattern, gradually forming a coupling coordination relationship. This coordination exhibits slow growing trend and strong positive spatial autocorrelation across provinces in China, with spillover effects from coastal to inland regions. This chapter further reveals that higher FD-TI coupling coordination (CCD) significantly reduces corporate greenwashing. More importantly, it distinguishes that government guarantees allocated to firms strengthen this mitigating effect in non-state-owned enterprises (non-SOEs) but weaken it in state-owned enterprises (SOEs). Overall, this chapter highlights the disciplinary power of market forces generated by cross-sectoral dynamics, while revealing the contingent moderating role of government guarantees.

The second chapter evaluates the effectiveness of green finance policies, using the Green Finance Reform and Innovation Pilot Zone (GFRIPZ) policy as a quasi-natural experiment within a staggered difference-in-differences framework. This chapter reveals that the GFRIPZ policy significantly reduces corporate stock price crash risk. The analysis further reveals the interaction effect of GFRIPZ policy and government guarantees when they act as a policy mix, uncovering that high levels of government guarantees weaken the mitigating effect of GFRIPZ policy, with the adverse interaction especially pronounced among high-tech certified firms. To explain the underlying mechanism, the chapter constructs a two-stage stochastic frontier analysis (SFA) model to measure firm-level green innovation efficiency separately at the R&D and commercialisation stages. The results show the GFRIPZ policy significantly enhances green innovation efficiency, particularly at the commercialisation stage, which in turn reduces stock price crash risk. Overall, this chapter demonstrates that stepwise green finance policies effectively strengthen firms' green innovation capabilities while safeguarding financial resilience. Additionally, it highlights the unintended consequences of excessive government guarantees when combined with market-oriented government regulatory tools. This chapter contributes to the literature on sustainable finance and corporate risk management by identifying green innovation efficiency as a key underlying channel and government guarantees as a double-edged moderator.

The third chapter evaluates the effectiveness of stringent environmental regulation directly imposed by the government, using the Environmental Fee-to-Tax Reform (EFTR) as a case study in a difference-in-differences (DID) research framework. The findings reveal a dual outcome: while the EFTR significantly increases the quantity of green innovation, it simultaneously reduces its quality, reflecting both compensation and crowding-out effects of stringent environmental regulation. The analysis further examines the role of government guarantees in the EFTR context. The results show that government guarantees play a decisive role in heterogeneous ways. They exacerbate the negative impact of the EFTR on green innovation quality among SOEs but mitigate it in non-SOEs. Moreover, high-tech certified firms benefit more from government guarantees in offsetting the adverse effect of the EFTR on green innovation quality than their non-high-tech counterparts. Overall, this chapter highlights the trade-offs inherent in stringent environmental regulation between quality and

quantity, and demonstrates how government guarantees can either stabilise or destabilise green innovation outcomes depending on firm characteristics. It contributes to the literature on environmental economics and corporate governance by revealing how policy mixes influence the effectiveness of stringent environmental regulation.

What Have We Learned from this Thesis that We didn't Know?

The central new knowledge of this thesis lies in advancing our understanding of emerging markets, using China as a representative case, by examining how the interaction between institutional arrangements, spanning market mechanisms and government regulatory tools, jointly shape corporate environmental strategies and genuine green outcomes during China's green transition. A particular focus is placed on the role of government guarantees, conceptualised as contingent liabilities borne by the state, which both complement and constrain market and regulatory effectiveness. The findings provide several important insights, primarily in five dimensions, that extend beyond existing research.

The first aspect is the adoption of an interdisciplinary approach that combines concepts and models from biology and physics, offering new insights into the integration of finance and technology. While existing studies have discussed the phenomenon of the integration between finance and technology (e.g., Huang et al., 2025), examined the temporal or spatial patterns of their coordination (e.g., Wang and Tan, 2021), or analysed its effects within a single sector (e.g., Hendrikse et al., 2020), this thesis goes further in two ways. First, it conceptualises the integration of finance and technology as a process of co-evolution, drawing on biological theory. Second, it applies a coupling coordination degree model, adapted from physics, to measure the extent and characteristics of this co-evolution as coupling coordination degree across Chinese provinces.

The second aspect is the expansion of research on the effectiveness of market forces in driving the green transition. Existing studies typically capture the integration between financial development (FD) and technological innovation (TI) using binary indicators or exogenous shocks generated by government policies (e.g., Chen et al., 2024; Zhao et al., 2024; Li et al., 2025a). This thesis quantifies the degrees of coupling coordination between FD and TI at the provincial level, thereby offering the first systematic measurement of the strength and

variation of market forces arising from the integration of FD and TI across regions. This approach contributes to the literature on institutional complementarity and corporate environmental governance, linking regional dynamics of FD and TI to firm-level greenwashing and exploring these effects from the perspective of stakeholder theory.

The third aspect is adding new insights by distinguishing the heterogeneous consequences of different forms of environmental regulatory tools implemented by governments, including market-oriented instruments such as green finance policies and stringent environmental taxation reforms. Existing studies generally argue that environmental regulations enhance corporate and regional environmental performance, such as green innovation, while often imposing short-term financial performance costs (e.g., Huang et al., 2023; Dogah et al., 2025), consistent with Porter's hypothesis (Porter and Vanderlinde, 1995). Conversely, other studies suggest that Porter's hypothesis may not be applicable in China, where stringent regulations can worsen corporate environmental outcomes due to the rising costs of green transition (e.g., He et al., 2020; Hu et al., 2023). This thesis provides more granular evidence by showing that green finance policies, namely the GFRIPZ policy, safeguard corporate financial resilience, measured by stock price crash risk, through improvements in green innovation efficiency. By contrast, the Environmental Fee-to-Tax Reform (EFTR) has dual effects on corporate environmental commitments from separate quality and quantity dimensions. A key contribution lies in consistently distinguishing between market-oriented and government-led environmental regulatory instruments, and in disaggregating corporate green innovation outcomes into efficiency, quality, and quantity. This differentiation avoids oversimplified conclusions arising when both environmental regulations and green innovation are assessed in only one dimension, thereby offering a deeper understanding of policy effectiveness.

The fourth aspect, and the most important contribution of this thesis, is its systematic analysis of government guarantees in the context of environmental governance. This work demonstrates both the complementarities and boundaries of government guarantees in shaping the effectiveness of market mechanisms and state interventions in regulating corporate environmental performance and safeguarding financial stability. Existing studies on government guarantees primarily focus on the banking perspective (e.g., Luo et al., 2024), or examine the effects of implicit guarantees on firm outcomes (Dong et al., 2021; Jin et al.,

2023). By contrast, this thesis provides the firm-level measurement of the actual levels of government guarantees as a form of government contingent liability, enabling direct analysis of their moderating role. The findings highlight the double-edged nature of government guarantees: while they alleviate financing constraints and encourage green transformation, they may also undermine regulatory effectiveness by reducing the cost of non-compliance, incentivising excessive risk-taking, and weakening pressures for sustainable innovation. Empirical evidence across the three chapters shows that these effects are highly context-dependent. When interacting with market mechanisms, government guarantees strengthen the disciplining effect of FD-TI coupling coordination. By contrast, within policy mixes involving environmental regulations, government guarantees show heterogeneous roles: they weaken the effect of market-oriented green finance polices on shielding firms from stock price crash risk, while mitigate the negative effects of stringent environmental regulations, specifically the EFTR, on green innovation quality. Furthermore, the moderating effects vary systematically across ownership structures, technological attributes, and regulatory environments.

Finally, the fifth aspect is the role of corporate heterogeneity in shaping policy effectiveness. The results consistently highlight the importance of firm characteristics, particularly state ownership and high-tech certification, in moderating the impact of both market and government forces. Given the long-standing preferential access of state-owned enterprises (SOEs) and high-tech certified enterprises to government resources in China (e.g., Wan et al., 2022; Geng and Pan, 2024), and their central role in the national green transition, it is essential to distinguish their responses when additional support, such as government guarantees, is provided. This thesis reveals clear asymmetries. SOEs frequently benefit disproportionately from government guarantees, while this comes at the cost of weaker market discipline from FD-TI coupling coordination in mitigating greenwashing and an aggravated negative impact of EFTR on green innovation quality. By contrast, non-SOEs tend to leverage guarantees more productively: they enhance market discipline and help alleviate the adverse impact of stringent environmental regulations. High-tech certification further shapes heterogenous outcomes. In the context of green finance policies, such as the GFRIPZ, high-tech firms experience a significantly stronger risk-mitigating effect on stock price crash risk when they

are provided higher levels of government guarantees, whereas under stringent regulation, such as the EFTR, high-tech certified firms are better positioned to use guarantees to offset the policy's adverse impact on green innovation quality. Overall, these findings demonstrate that firm heterogeneity fundamentally directs the effectiveness of institutional arrangements, highlighting the need for tailored, rather than one-size-fits-all, policy designs that align government support with firms' ownership structures and technological attributes to achieve genuine green outcomes.

Collectively, these insights advance debates in sustainable finance, corporate governance, and environmental economics by showing how institutional design shapes both the complementarities and the tensions between market- and state-led governance.

Possible Limitations of this Work

First, the analysis relies on Chinese A-share listed firms due to data availability, which may not fully reflect the dynamics of small and medium-sized enterprises (SMEs) or non-listed firms that play an important role in China's green transition. Second, although rigorous econometric methods were applied, quasi-natural experiments such as the GFRIPZ policy and EFTR provide strong internal validity but may have limited generalisability to other policy contexts. Finally, while China offers a valuable and representative case, its unique institutional environment, characterised by strong state involvement, may constrain the direct applicability of the findings to other emerging markets or developed economies.

Future Research Directions

This thesis opens several promising avenues for future research. First, from a theoretical perspective, future studies could refine theories of institutional complementarity and substitution by examining how firm-level government guarantees interact with alternative governance mechanisms such as carbon markets, emissions trading schemes, or direct R&D subsidies. Second, from a sample perspective, extending the analysis to SMEs, private firms, and international comparative datasets would enhance the external validity of the findings. Micro-level data, including firm surveys or proprietary loan-level information, could also provide deeper insights into how guarantees influence firm behaviour. Third, from a methodology perspective, the application of machine learning techniques to detect

greenwashing or classify patent quality could complement econometric approaches. Mixed-methods designs, combining quantitative analysis with case studies or interviews, would further illuminate causal mechanisms. Beyond these, the analytical framework developed here could be extended to adjacent fields such as ESG investment, supply chain sustainability, or digital finance in the green transition, thereby broadening its applicability. Finally, future research would benefit from investigating the long-term impacts of guarantees and regulatory policies, assessing whether their effects persist, diminish, or evolve over time. Addressing these directions will allow future scholarship to build on this thesis and further advance both academic theory and practical policy design in sustainable economic transitions.

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Appendices

Appendix A - Chapter 1

Appendix A1. The Evaluation Index System of FD and TI

Table A1 The Evaluation Index System of FD and TI

The evaluation index system of financial development (FD) and technological innovation (TI), along with its indicators, is constructed based on established studies (e.g., Svirydzenka, 2016; Wang and Tan, 2021; Chen et al., 2018; Haschka and Herwartz, 2020) and data availability in China. The weights of each indicator are determined using the entropy method (e.g., Cui et al., 2019; Tan et al., 2022), which assigns objective weights according to the degree of variation of the indicator across provinces and years. In this framework, indicators with greater variability carry larger weights, thereby reducing potential bias from subjective judgment. The detailed four-step calculation process is presented in **Section 1.3.2.2.** The sum of indicator weights within each system is normalised to one. Based on this, the index system is applied to calculate the comprehensive levels of FD and TI, denoted as U_1 and U_2. These values form the basis for the coupling coordination degree model: they are first used in **Model (1.4) (Section 1.3.2.2)** to estimate the coupling degree (CD), and subsequently in **Model (1.5)** to compute the coupling coordination degree (CCD). The CCD thus reflects the extent of coordinated co-evolution between FD and TI at the provincial level.

System	Category	Indicator	Weight
Financial Development (U_1)	Depth	**Financial Interrelations Ratio (FIR):** Total deposit and loan balance of (banking) financial institutions / GDP	0.0224
		Banking institutions depth 1 (BID1): Private-sector credit by banking institutions / GDP	0.0194
		Banking institutions depth 2 (BID2): Total assets of banking institutions / GDP	0.0297
		Stock Market Depth 1 (SMD1): Stock market capitalization of the A-share market / GDP	0.1055
		Stock Market Depth 2 (SMD2): Total value of stocks traded in the A-share market / GDP	0.0537
		Insurance Depth (ID): Primary insurance premium income / GDP	0.0249
		Bond Market Depth (BMD): Total value of bonds traded of financial institutions and non-financial institutions / GDP	0.4259
		Government Bonds Depth (GBD): Total local government bonds issuance / GDP	0.0820
	Access (Width)	**Financial Institutions Service Access (FISA):** Number of financial institution branches (per 10,000 persons)	0.0196
		Financial Institutions Service Width (FISW): Number of (banking) financial institution branches (per 100 square kilometres)	0.0806
		Financial Industry Personnel Width (FIPW): Personnel engaged in the financial industry in cities and towns / Resident population of the region	0.0506
		Insurance Width (IW): Primary insurance premium income / Resident population of the region	0.0386
	Efficiency	**Savings-investment Conversion Rate (SCR):** Total social fixed assets investment (excluding rural households) / Total savings	0.0141
		Loan-to-deposit Ratio (LR): Loan balance of (banking) financial institutions / Deposit balance of (banking) financial institutions	0.0115
		Financial Industry Labour Efficiency (FILE): Annual value added of the financial industry / Personnel engaged in the financial industry in cities and towns	0.0215

System	Category	Indicator	Weight
Technological Innovation (U_2)	Input	**Government Expenditure (GE):** General public budget expenditure on science and technology / Total general public budget expenditure	0.0303
		Higher Education R&D Projects Expenditure (HE-PE): Input of funds in R&D projects of higher education by region	0.0475
		Intramural Expenditure on R&D in High-tech Industry (HI-R&DE): Intramural expenditure on R&D in high-tech industry	0.0915
		Full-time Equivalent of R&D Personnel in High-tech Industry (HI-R&DP): Full-time equivalent of R&D personnel in high-tech industry	0.0867
		Expenditure on New Products Development in High-tech Industry (HI-NPDE): Expenditure on new products development in high-tech industry	0.1046
		Expenditure for Technology Acquisition and Renovation in High-tech Industry (HI-TA&TRE): Expenditure for technology acquisition and renovation in high-tech industry	0.1066
		(Fixed Assets) Investment in the High-tech industry (HI-FAI): (Fixed assets) investment in high-tech industry	0.0588
	Output	**Patent applications in the high-tech industry (HI-PA):** Patent applications in High-tech industry	0.1076
		New products development in the high-tech industry (HI-NPD): New products development in high-tech industry	0.0776
		Sales Revenue of New Products in High-tech Industry (HI-NPSR): Sales revenue of new products in high-tech industry	0.1049
		The number of transfers and licensing of patent ownership of higher education (HE-PT&PL): Number of transfer and and licensing of patent ownership of higher education	0.0866
		Value of technical markets transactions (TMTV): Value of technical markets transactions	0.0973

Appendix A2. Estimated Values of Coupling Coordination Degrees of FD and TI by Regions in China

Tables A2.1 to **A2.4** in **Appendix A2** report the estimated values of the coupling coordination degree (CCD) between financial development (FD) and technological innovation (TI) for 30 Chinese provinces from 2012 to 2020, grouped into four major regions (Eastern, Central, Western, and Northeast China). For each province, the tables present the comprehensive development levels of FD and TI (denoted as U1 and U2) and their corresponding CCD. Here, U1 and U2 measure the relative comprehensive development of the financial and technological systems, while the CCD captures the extent to which these two systems evolve in a coupled coordinated manner. Higher CCD values indicate stronger coordination between FD and TI, whereas lower values suggest imbalance or lag in one system relative to the other. These provincial CCDs provide the empirical foundation for the descriptive and spatial analyses in Section 1.4.2 and the regression analyses in Section 1.4.3, including identifying the temporal trends, regional disparities, spatial clustering, and the subsequent impact of CCD on corporate greenwashing.

Table A2.1 CCDs in Eastern China from 2012 to 2020.

Region	***Beijing***			***Tianjin***			***Hebei***			***Shanghai***			***Jiangsu***		
Year	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)
2012	0.4259	0.2490	0.1321	0.2798	0.1189	0.0515	0.1684	0.0437	0.0184	0.3542	0.1835	0.0858	0.3322	0.0598	0.2036
2013	0.4315	0.2396	0.1446	0.2940	0.1318	0.0567	0.1790	0.0492	0.0209	0.3571	0.1803	0.0901	0.3436	0.0645	0.2160
2014	0.4601	0.2919	0.1536	0.3079	0.1426	0.0630	0.1948	0.0589	0.0244	0.3903	0.2519	0.0921	0.3586	0.0718	0.2302
2015	0.4833	0.3583	0.1523	0.3280	0.1723	0.0672	0.2163	0.0905	0.0242	0.3920	0.2594	0.0911	0.3908	0.0976	0.2390
2016	0.5264	0.4594	0.1671	0.3404	0.2162	0.0621	0.2348	0.1054	0.0288	0.4001	0.2600	0.0985	0.4176	0.1086	0.2802
2017	0.5146	0.3913	0.1791	0.3306	0.1908	0.0626	0.2379	0.0989	0.0324	0.3979	0.2422	0.1034	0.4232	0.1081	0.2965
2018	0.5417	0.4342	0.1983	0.3284	0.1884	0.0617	0.2461	0.1055	0.0348	0.3990	0.2225	0.1139	0.4245	0.1004	0.3234
2019	0.6203	0.6679	0.2217	0.3304	0.1979	0.0602	0.2583	0.1094	0.0407	0.4284	0.2557	0.1318	0.4593	0.1118	0.3983
2020	0.6592	0.7448	0.2535	0.3560	0.2210	0.0727	0.2842	0.1243	0.0525	0.4508	0.2868	0.1440	0.4988	0.1258	0.4921
Region	***Zhejiang***			***Fujian***			***Shandong***			***Guangdong***			***Hainan***		
Year	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)
2012	0.2938	0.0855	0.0871	0.2165	0.0517	0.0425	0.2469	0.0476	0.0782	0.3545	0.0582	0.2714	0.1415	0.0575	0.0070
2013	0.3094	0.0926	0.0989	0.2301	0.0593	0.0473	0.2634	0.0537	0.0897	0.3782	0.0662	0.3089	0.1495	0.0623	0.0080
2014	0.3273	0.1070	0.1073	0.2381	0.0653	0.0492	0.2727	0.0579	0.0954	0.3907	0.0743	0.3134	0.1501	0.0733	0.0069
2015	0.3560	0.1348	0.1191	0.2629	0.0935	0.0511	0.3048	0.0801	0.1078	0.4210	0.0907	0.3464	0.1559	0.1105	0.0053
2016	0.3690	0.1405	0.1319	0.2936	0.1034	0.0719	0.3261	0.0966	0.1170	0.4565	0.1018	0.4267	0.1715	0.1435	0.0060
2017	0.3683	0.1263	0.1457	0.2951	0.0950	0.0798	0.3290	0.0877	0.1336	0.4687	0.0972	0.4964	0.1558	0.1350	0.0044
2018	0.3840	0.1233	0.1763	0.2944	0.0849	0.0885	0.3300	0.0865	0.1372	0.4942	0.0938	0.6357	0.1570	0.1234	0.0049
2019	0.4100	0.1354	0.2088	0.3019	0.0883	0.0940	0.3318	0.0939	0.1291	0.5240	0.1045	0.7214	0.1753	0.1134	0.0083
2020	0.4485	0.1588	0.2548	0.3215	0.1070	0.0998	0.3712	0.1127	0.1684	0.5636	0.1246	0.8094	0.1877	0.1230	0.0101

Table A2.2 CCDs in Central China from 2012 to 2020.

Region	***Shanxi***			***Anhui***			***Jiangxi***		
Year	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)
2012	0.1568	0.0571	0.0106	0.1952	0.0403	0.0360	0.1600	0.0347	0.0188
2013	0.1806	0.0642	0.0166	0.2089	0.0454	0.0419	0.1726	0.0369	0.0240
2014	0.1755	0.0706	0.0134	0.2396	0.0690	0.0477	0.1894	0.0453	0.0284
2015	0.1848	0.1150	0.0101	0.2702	0.0937	0.0569	0.2237	0.0778	0.0322
2016	0.1868	0.1230	0.0099	0.2829	0.0913	0.0702	0.2303	0.0813	0.0346
2017	0.1977	0.1128	0.0135	0.2878	0.0871	0.0787	0.2532	0.0866	0.0475
2018	0.1986	0.1018	0.0153	0.3071	0.0914	0.0972	0.2689	0.0824	0.0635
2019	0.2121	0.1128	0.0179	0.3179	0.0931	0.1096	0.2902	0.0874	0.0812
2020	0.2330	0.1351	0.0218	0.3523	0.1144	0.1346	0.3252	0.1122	0.0997
Region	***Henan***			***Hubei***			***Hunan***		
Year	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)
2012	0.1733	0.0361	0.0250	0.2116	0.0408	0.0492	0.1695	0.0310	0.0266
2013	0.1965	0.0385	0.0388	0.2179	0.0411	0.0549	0.1857	0.0334	0.0356
2014	0.2105	0.0446	0.0441	0.2438	0.0520	0.0679	0.2015	0.0413	0.0399
2015	0.2396	0.0664	0.0497	0.2777	0.0798	0.0745	0.2335	0.0649	0.0458
2016	0.2493	0.0733	0.0527	0.2905	0.0910	0.0783	0.2591	0.0917	0.0491
2017	0.2641	0.0782	0.0622	0.2897	0.0764	0.0922	0.2571	0.0753	0.0580
2018	0.2649	0.0730	0.0674	0.3031	0.0766	0.1102	0.2647	0.0760	0.0647
2019	0.2773	0.0811	0.0729	0.3302	0.0899	0.1321	0.2881	0.0853	0.0808
2020	0.3014	0.0938	0.0880	0.3518	0.1070	0.1431	0.3142	0.0949	0.1027

Table A2.3 CCDs in Western China from 2012 to 2020.

Region	***Inner Mongolia***			***Guangxi***			***Chongqing***			***Sichuan***		
Year	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)
2012	0.1381	0.0577	0.0063	0.1498	0.0385	0.0131	0.1865	0.0656	0.0184	0.2203	0.0489	0.0482
2013	0.1372	0.0575	0.0062	0.1556	0.0401	0.0146	0.1927	0.0675	0.0204	0.2312	0.0520	0.0550
2014	0.1416	0.0612	0.0066	0.1619	0.0493	0.0139	0.2079	0.0739	0.0253	0.2453	0.0610	0.0593
2015	0.1690	0.1123	0.0073	0.1731	0.0780	0.0115	0.2375	0.0965	0.0330	0.2673	0.0919	0.0555
2016	0.1777	0.1476	0.0068	0.1815	0.0884	0.0123	0.2527	0.1070	0.0381	0.2890	0.1078	0.0646
2017	0.1682	0.1167	0.0069	0.1960	0.0921	0.0160	0.2599	0.1013	0.0450	0.3045	0.1028	0.0837
2018	0.1643	0.1048	0.0070	0.1970	0.0831	0.0181	0.2611	0.0948	0.0490	0.3080	0.0877	0.1026
2019	0.1566	0.1139	0.0053	0.2016	0.0809	0.0204	0.2734	0.1030	0.0542	0.3219	0.0928	0.1157
2020	0.1709	0.1274	0.0067	0.2217	0.1018	0.0237	0.2992	0.1172	0.0684	0.3417	0.1100	0.1240
Region	***Guizhou***			***Yunnan***			***Shaanxi***			***Gansu***		
Year	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)
2012	0.1514	0.0451	0.0117	0.1305	0.0379	0.0076	0.2058	0.0494	0.0363	0.1364	0.0539	0.0064
2013	0.1529	0.0426	0.0128	0.1350	0.0395	0.0084	0.2166	0.0503	0.0438	0.1433	0.0590	0.0072
2014	0.1686	0.0540	0.0149	0.1439	0.0499	0.0086	0.2408	0.0626	0.0537	0.1557	0.0716	0.0082
2015	0.2141	0.1383	0.0152	0.1767	0.0954	0.0102	0.2786	0.1120	0.0538	0.1769	0.1153	0.0085
2016	0.2211	0.1459	0.0164	0.1800	0.1042	0.0101	0.2828	0.1114	0.0574	0.1858	0.1356	0.0088
2017	0.2310	0.1291	0.0221	0.1822	0.0987	0.0112	0.2820	0.1015	0.0623	0.1874	0.1297	0.0095
2018	0.2328	0.1210	0.0243	0.1809	0.0839	0.0128	0.2832	0.0946	0.0679	0.1887	0.1212	0.0104
2019	0.2322	0.1084	0.0268	0.1833	0.0831	0.0136	0.3020	0.0985	0.0845	0.1925	0.1295	0.0106
2020	0.2518	0.1422	0.0283	0.1968	0.0997	0.0150	0.3275	0.1112	0.1034	0.2118	0.1504	0.0134

Region	***Qinghai***			***Ningxia***			***Xinjiang***			
Year	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	
2012	0.1037	0.0704	0.0016	0.1310	0.0645	0.0046	0.1240	0.0470	0.0050	
2013	0.1139	0.0728	0.0023	0.1384	0.0703	0.0052	0.1309	0.0531	0.0055	
2014	0.1253	0.0852	0.0029	0.1450	0.0847	0.0052	0.1341	0.0615	0.0053	
2015	0.1504	0.1600	0.0032	0.1783	0.1379	0.0073	0.1517	0.1025	0.0052	
2016	0.1617	0.1821	0.0038	0.1834	0.1469	0.0077	0.1599	0.1166	0.0056	
2017	0.1653	0.1701	0.0044	0.1915	0.1348	0.0100	0.1562	0.1146	0.0052	
2018	0.1686	0.1596	0.0051	0.2053	0.1372	0.0130	0.1495	0.1045	0.0048	
2019	0.1441	0.1513	0.0028	0.2042	0.1359	0.0128	0.1472	0.1107	0.0042	
2020	0.1439	0.1527	0.0028	0.2001	0.1317	0.0122	0.1538	0.1250	0.0045	

Table A2.4 CCDs in Northeast China from 2012 to 2020.

Region	***Liaoning***			***Jilin***			***Heilongjiang***		
Year	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)	CCD	FD (U1)	TI (U2)
2012	0.2215	0.0629	0.0383	0.1691	0.0528	0.0155	0.1780	0.0465	0.0216
2013	0.2361	0.0753	0.0413	0.1905	0.0556	0.0237	0.1839	0.0503	0.0227
2014	0.2461	0.0834	0.0440	0.1847	0.0685	0.0170	0.1990	0.0649	0.0242
2015	0.2619	0.1288	0.0365	0.2088	0.1100	0.0173	0.2226	0.1095	0.0224
2016	0.2669	0.1455	0.0348	0.2154	0.1242	0.0173	0.2384	0.1223	0.0264
2017	0.2684	0.1355	0.0383	0.2269	0.1342	0.0197	0.2282	0.1288	0.0211
2018	0.2712	0.1193	0.0453	0.2238	0.1180	0.0213	0.2295	0.1291	0.0215
2019	0.2696	0.1162	0.0454	0.2291	0.1229	0.0224	0.2390	0.1220	0.0268
2020	0.2878	0.1298	0.0529	0.2468	0.1514	0.0245	0.2576	0.1417	0.0311

Appendix B - Chapter 2

Appendix B1. Estimated results from the two-stage technical inefficiency effects production function models

Table B1.1 Estimated results for the R&D stage technical inefficiency effects model

Panel 1 to 8 report the estimated frontier coefficients, inefficiency-effects coefficients, and variance parameters from the R&D stage technical inefficiency effects model for sample firms across eight industries, classified according to the *Guidance for Industry Classification of Listed Companies (2012 revision)* issued by the China Securities Regulatory Commission (CSRC). Z-statistics are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. The frontier constant is omitted due to the structure of the truncated-normal BC-SFA model.

Panel 1 - Firms in Manufacturing (Broad Industry Code: C)

Panel 1 reports the estimated coefficients for sample firms in the manufacturing industry, based on 12221 firm-year observations. All R&D input coefficients are positive and statistically significant, confirming their expected contribution to green innovation output (measured by the natural logarithm of the number of granted green patents). Firms with high-tech and high-polluting attributes in this industry exhibit higher expected R&D inefficiency, indicating that high-tech certification and environmental burden increase the difficulty of converting inputs into green innovation outputs. Both the parameters σ_u and σ_v are statistically significant, indicating both significant variation in inefficiency and inherent volatile characteristics across firms in this industry at the R&D stage.

Variable	Estimated MLE coefficients
Frontier	
lnRDperson	0.841*** (3.60)
lnRDexpense	2.696*** (12.22)
lnRDsubsidy	1.640*** (7.73)
lnRDfixedasset	1.777*** (7.59)
Constant	-
Key influencing factors of inefficiency term $\mu_{R\&D,it}$	
Hightech	3.214*** (5.83)
Pollut	5.038*** (9.93)
Constant	153.263*** (41.29)
Parameters (standard deviations of the inefficiency term $\mu_{R\&D,it}$ and the noise term $v_{R\&D,it}$)	
σ_u	8.993** (2.34)
σ_v	24.299** (2.49)

Panel 2 - Firms in Construction (Broad Industry Code: E)

Panel 2 reports the estimated coefficients for sample firms in the construction industry, based on 536 firm-year observations. All R&D input coefficients are positive and statistically significant. Firms with high-tech certification exhibit significantly higher expected inefficiency at the R&D stage, suggesting that technological upgrading in this industry may involve substantial adjustment costs and uncertainty. The high-polluting industry dummy is omitted, reflecting the limited role of pollution intensity in explaining efficiency variation within this industry. Both σ_u and σ_v are statistical insignificant, which is consistent with the small sample size and inherently low R&D intensity of this industry. Overall, results for the Construction industry remain interpretable and align with expectations for a low-R&D and heterogeneous industry.

Variable	Estimated MLE coefficients
Frontier	
lnRDperson	4.151* (1.96)
lnRDexpense	9.411*** (5.71)
lnRDsubsidy	4.554** (2.42)
lnRDfixedasset	11.895*** (5.56)
Constant	-
Key influencing factors of inefficiency term $\mu_{R\&D,it}$	
Hightech	16.427*** (2.85)
Pollut	Omitted
Constant	110.550*** (3.83)
Parameters (standard deviations of the inefficiency term $\mu_{R\&D,it}$ and the noise term $v_{R\&D,it}$)	
σ_u	14.701 (0.01)
σ_v	54.709 (0.19)

Panel 3 - Firms in Wholesale and Retail trade (Broad Industry Code: F)

Panel 3 reports the estimated coefficients for sample firms in the wholesale and retail trade industry, based on 532 firm-year observations. Most R&D input coefficients are positive and statistically significant, confirming their expected contribution to green innovation output. The coefficient of R&D subsidies is statistically insignificant, suggesting that green innovation activities in this industry are primarily market-driven rather than policy-driven. High-tech certification is associated with higher expected R&D inefficiency, while the high-polluting industry dummy is omitted. The estimated variance parameters indicate both structural inefficiency variation and the inherently volatile characteristics across firms of this industry.

Variable	Estimated MLE coefficients
Frontier	
lnRDperson	1.071*** (6.51)
lnRDexpense	0.177* (1.69)
lnRDsubsidy	0.081 (0.84)
lnRDfixedasset	0.400*** (3.05)
Constant	-
Key influencing factors of inefficiency term $\mu_{R\&D,it}$	
Hightech	1.270** (2.10)
Pollut	Omitted
Constant	2.388 (0.03)
Parameters (standard deviations of the inefficiency term $\mu_{R\&D,it}$ and the noise term $v_{R\&D,it}$)	
σ_u	0.438** (2.02)
σ_v	3.472** (2.55)

Panel 4 - Firms in Transportation, Storage and Postal Services (Broad Industry Code: G)

Panel 4 reports the estimated coefficients for sample firms in the transportation, storage and postal Services industry, based on 409 firm-year observations. All R&D input coefficients show expected signs, with R&D personnel and fixed assets significantly improving green innovation output in this industry. High-tech certified firms exhibit higher expected R&D inefficiency, while the pollution-intensity dummy is omitted. The variance parameters suggest that random noise dominate inefficiency variation, which aligns with the characteristics of this service-oriented industry, where green innovation outcomes are more strongly affected by external volatility such as fluctuations in market demand, energy prices, and policy adjustments.

Variable	Estimated MLE coefficients
Frontier	
lnRDperson	1.339*** (4.73)
lnRDexpense	0.081 (0.45)
lnRDsubsidy	0.068 (0.51)
lnRDfixedasset	0.462*** (2.67)
Constant	-
Key influencing factors of inefficiency term $\mu_{R\&D,it}$	
Hightech	2.091** (2.25)
Pollut	Omitted
Constant	0.595 (0.02)
Parameters (standard deviations of the inefficiency term $\mu_{R\&D,it}$ and the noise term $v_{R\&D,it}$)	
σ_u	0.156 (0.02)
σ_v	4.884*** (18.21)

Panel 5 - Firms in Accommodation and Catering (Broad Industry Code: H)

Panel 5 reports the estimated coefficients for sample firms in the accommodation and catering industry, based on 30 firm-year observations. Due to the very small sample size of this industry, most frontier coefficients are statistically insignificant, which is also consistent with the limited role of formal R&D in driving green innovation output within this industry. Both industry-level dummy variables are omitted, indicating limited observable cross-firm heterogeneity in inefficiency conditional on the small sample. Random noise term σ_v is statistically significant, suggesting that firm performance in this service-oriented industry is strongly affected by operational volatility and external shocks.

Variable	Estimated MLE coefficients
Frontier	
lnRDperson	0.080 (0.35)
lnRDexpense	0.024 (0.50)
lnRDsubsidy	0.054 (1.09)
lnRDfixedasset	0.062* (1.73)

Constant	-
Key influencing factors of inefficiency term $\mu_{R\&D,it}$	
Hightech	Omitted
Pollut	Omitted
Constant	1.686 (0.01)
Parameters (standard deviations of the inefficiency term $\mu_{R\&D,it}$ and the noise term $v_{R\&D,it}$)	
σ_u	0.068 (0.01)
σ_v	0.354*** (7.74)

Panel 6 - Firms in Information transmission, Software, and Information technology services (Broad Industry Code: I)

Panel 6 reports the estimated coefficients for sample firms in the information transmission, software, and information technology services industry, based on 911 firm-year observations. Among the R&D inputs, R&D expenditure and fixed asset investment significantly contribute to green innovation output, while R&D personnel and R&D subsidies are statistically insignificant, reflecting the capital- and technology-intensive nature of this industry. High-tech certified firms in this industry exhibit slightly lower expected R&D inefficiency, while the pollution-intensity dummy is omitted due to the limited heterogeneity of pollution-related activities in this industry. The inefficiency term dominates random noise in magnitude, and both are statistically significant, suggesting that green innovation performance in this industry is more shaped by persistent firm-specific inefficiency compared to external random shocks such as competitive pressure and demand volatility. Overall, the results are economically consistent with the dynamic and innovation-driven characteristics of this industry.

Variable	**Estimated MLE coefficients**
Frontier	
lnRDperson	0.261 (0.47)
lnRDexpense	2.983*** (4.53)
lnRDsubsidy	0.036 (0.06)
lnRDfixedasset	1.334*** (3.13)
Constant	-
Key influencing factors of inefficiency term $\mu_{R\&D,it}$	
Hightech	-2.2549 (-0.25)
Pollut	Omitted
Constant	2.264 (0.25)
Parameters (standard deviations of the inefficiency term $\mu_{R\&D,it}$ and the noise term $v_{R\&D,it}$)	
σ_u	19.153*** (42.68)
σ_v	5.905*** (3.73)

Panel 7 - Firms in Real estate (Broad Industry Code: K)

Panel 7 reports the estimated coefficients for sample firms in the real estate industry, based on 350 firm-year observations. Frontier estimates of R&D personnel, R&D expenditure, and fixed asset investment indicate that both human capital and capital-intensive inputs are important drivers of green innovation in this industry. R&D subsidies exhibit a positive but statistically marginal effect, consistent with the relatively moderate reliance on government-funded support in this industry. High-polluting attributes is associated with higher expected R&D inefficiency, while the high-tech certification dummy are not statistically significant. The parameter σ_u is statistically insignificant, indicating limited variation in inefficiency across firms in real estate industry at the R&D stage. Random shocks, such as fluctuations in contract cycles and operational volatility dominate observed variation in green innovation output, while persistent R&D inefficiency plays only a limited role. Overall, the results are consistent with the characteristics of a low R&D-intensive, service-driven industry where green innovation outcomes are shaped primarily by external uncertainty.

Variable	**Estimated MLE coefficients**
Frontier	
lnRDperson	0.999*** (6.06)
lnRDexpense	0.410*** (2.69)
lnRDsubsidy	0.142* (1.83)
lnRDfixedasset	0.292*** (3.56)
Constant	-
Key influencing factors of inefficiency term $\mu_{R\&D,it}$	
Hightech	1.791 (1.36)
Pollut	0.225*** (4.52)
Constant	-0.001 (0.01)

Parameters (standard deviations of the inefficiency term $\mu_{R\&D,it}$ and the noise term $v_{R\&D,it}$)	
σ_u	0.004 (0.01)
σ_v	2.672*** (26.46)

Panel 8 - Firms in Leasing and Business services (Broad Industry Code: L)

Panel 8 reports the estimated coefficients for sample firms in the leasing and business services industry, based on 834 firm-year observations. R&D expenses significantly contribute to green innovation output while weak evidence of R&D fixed assets can be found. R&D personnel and subsidies exhibit statistically insignificant positive effects. High-tech certified firms in this industry show marginally lower expected R&D inefficiency, whereas the pollution-intensity dummy is omitted. The random noise dominates inefficiency variation, suggesting that green innovation outcomes in this sector are more strongly influenced by external operational volatility, such as demand fluctuations and market uncertainty, relative to persistent firm-level inefficiency.

Variable	**Estimated MLE coefficients**
Frontier	
lnRDperson	0.335 (1.03)
lnRDexpense	1.747*** (5.67)
lnRDsubsidy	0.234 (0.97)
lnRDfixedasset	0.502* (1.87)
Constant	-
Key influencing factors of inefficiency term $\mu_{R\&D,it}$	
Hightech	-1.635* (-1.91)
Pollut	Omitted
Constant	1.997 (0.03)
Parameters (standard deviations of the inefficiency term $\mu_{R\&D,it}$ and the noise term $v_{R\&D,it}$)	
σ_u	4.616 (4.26)
σ_v	10.056*** (40.84)

Table B1.2 Estimated results for the commercialisation stage technical inefficiency effects model
Panel 1 to 8 report the estimated frontier coefficients, inefficiency-effects coefficients, and variance parameters from the commercialisation stage technical inefficiency effects model for sample firms across eight industries. Z-statistics are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. The frontier constant is omitted due to the structure of the truncated-normal BC-SFA model.

Panel 1 - Firms in Manufacturing (Broad Industry Code: C)

Panel 1 reports the estimated coefficients for sample firms in the manufacturing industry, based on 12221 firm-year observations. The frontier estimates show that green patent outputs from R&D stage and energy consumption significantly increase commercialisation-stage green performance (measured by the natural logarithm of a firm's main business income), reflecting the strong reliance of manufacturing firms on both technological achievements from R&D stage and energy-intensive operational capacity. The share of non-R&D employees exhibits no statistically significant effect. Higher carbon emissions significantly reduce commercialisation-stage green innovation efficiency, consistent with the expected negative role of pollution-intensive production in hindering green value realisation. Neither high-tech certification nor pollution-intensity significantly explains firm-level inefficiency variation. Both inefficiency and noise terms are statistically significant and differ in magnitude. Random shocks, such as market fluctuations, demand uncertainty, and production volatility, play a more dominant role relative to persistent inefficiency in shaping commercialisation green innovation outcomes in this industry. The results align with the capital- and production-intensive nature of manufacturing, where external volatility can heavily influence the conversion of green innovation achievements into realised green economic returns.

Variable	Estimated MLE coefficients
Frontier	
lnGreengrant	0.332*** (41.95)
lnNonRDperson	-0.082 (-1.27)
lnEnergyconsume	0.862*** (62.23)
lnFirmCO2	-0.336*** (-31.41)
Constant	-
Key influencing factors of inefficiency term $\mu_{commercial,it}$	
Hightech	-0.018 (-0.34)
Pollut	0.207 (0.59)
Constant	-0.824*** (-2.94)
Parameters (standard deviations of the inefficiency term $\mu_{commercial,it}$ and the noise term $v_{commercial,it}$)	
σ_u	0.662*** (7.13)
σ_v	0.729*** (38.27)

Panel 2 - Firms in Construction (Broad Industry Code: E)

Panel 2 reports the estimated coefficients for sample firms in the construction industry, based on 536 firm-year observations. The frontier results show that green patent outputs, non-R&D labour, and energy consumption all significantly enhance commercialisation-stage green innovation performance, reflecting the labour-intensive and energy-dependent characteristics of this industry. Higher carbon emissions substantially reduce commercialisation-stage green innovation efficiency, consistent with the constraints faced by pollution-intensive activities. Both high-tech certified and high-polluting firms exhibit significantly higher expected inefficiency, suggesting that technological upgrading and heavy environmental burdens increase the difficulty of transforming green achievements into realised green economic returns in this industry. The variance parameters show that inefficiency dominates random shocks, implying that persistent structural inefficiencies, rather than short-term volatility, play the central role in shaping commercialisation-stage outcomes. The results align with the operational rigidity and high compliance costs characteristic of the construction industry.

Variable	Estimated MLE coefficients
Frontier	
lnGreengrant	0.041*** (18.59)
lnNonRDperson	0.377*** (25.16)
lnEnergyconsume	2.407*** (27.43)
lnFirmCO2	-1.485*** (-17.81)
Constant	-
Key influencing factors of inefficiency term $\mu_{commercial,it}$	
Hightech	17.796*** (4.83)
Pollut	3.386 (16.12)
Constant	-32.057*** (-4.65)
Parameters (standard deviations of the inefficiency term $\mu_{commercial,it}$ and the noise term $v_{commercial,it}$)	

σ_u	5.436*** (9.52)
σ_v	0.000036 (0.33)

Panel 3 - Firms in Wholesale and Retail trade (Broad Industry Code: F)

Panel 3 reports the estimated coefficients for sample firms in the wholesale and retail trade industry, based on 532 firm-year observations. Green patents and energy consumption significantly enhance commercialisation-stage performance, reflecting the sector's strong dependence on logistical capacity and operational scale. Non-R&D personnel have no significant effect, consistent with the service-oriented and labour-intensive nature of the retail sector where technological capabilities are not primarily driven by staffing structure. Higher carbon emissions significantly reduce commercialisation-stage green innovation efficiency. Neither high-tech certification nor pollution intensity significantly explains firm-level inefficiency variation, which is expected given the relatively homogeneous technological and environmental profiles within this industry. Random shocks dominate inefficiency variation, suggesting that commercialisation outcomes are shaped more by external market competition and logistical disruptions than by persistent structural inefficiency. The findings are consistent with the volatility-driven and operationally sensitive characteristics of the industry.

Variable	Estimated MLE coefficients
Frontier	
lnGreengrant	0.134*** (6.42)
lnNonRDperson	-0.229 (-1.15)
lnEnergyconsume	0.715*** (29.81)
lnFirmCO2	-0.088*** (-8.11)
Constant	-
Key influencing factors of inefficiency term $\mu_{commercial,it}$	
Hightech	-1.194 (-0.04)
Pollut	-4.934 (-0.01)
Constant	-1.008*** (-0.07)
Parameters (standard deviations of the inefficiency term $\mu_{commercial,it}$ and the noise term $v_{commercial,it}$)	
σ_u	0.085 (0.01)
σ_v	0.502*** (31.55)

Panel 4 - Firms in Transportation, Storage and Postal Services (Broad Industry Code: G)

Panel 4 reports the estimated coefficients for sample firms in the transportation, storage and postal Services industry, based on 409 firm-year observations. Green patent outputs exhibit a marginally positive effect on commercialisation-stage green innovation efficiency, while energy consumption strongly enhances green commercialisation outcomes, reflecting the sector's dependence on energy-intensive logistical operations. Higher carbon emissions significantly reduce commercialisation-stage efficiency. High-tech certified firms in this industry show significantly higher expected inefficiency, suggesting that technological upgrading in this industry remains risky and complex, requiring substantial adjustment before improvements translate into commercial performance. Pollution intensity does not significantly explain the variation in inefficiency within this industry. Structural inefficiency is the dominant contributor to shape variation in commercialisation-stage green innovation outcomes, while random noise plays a limited role. The results align with the structural characteristics of the transportation and storage industry, where persistent operational inefficiencies, rather than external shocks, primarily shape the commercialisation of green innovation.

Variable	Estimated MLE coefficients
Frontier	
lnGreengrant	0.040* (1.68)
lnNonRDperson	0.261 (0.36)
lnEnergyconsume	0.775*** (19.08)
lnFirmCO2	-0.179*** (-7.92)
Constant	-
Key influencing factors of inefficiency term $\mu_{commercial,it}$	
Hightech	0.673*** (3.09)
Pollut	-0.032 (-0.26)
Constant	0.899*** (8.94)
Parameters (standard deviations of the inefficiency term $\mu_{commercial,it}$ and the noise term $v_{commercial,it}$)	
σ_u	0 .984*** (15.80)
σ_v	0.00009 (0.17)

Panel 5 - Firms in Accommodation and Catering (Broad Industry Code: H)

Panel 5 reports the estimated coefficients for sample firms in the accommodation and catering industry, based on 30 firm-year observations. Given the very small sample size and the low R&D intensity of this sector, most frontier coefficients are statistically insignificant, except for energy consumption and carbon emissions. Higher energy use significantly enhances commercialisation-stage green innovation performance, reflecting the energy-intensive nature of service delivery in this industry, while higher carbon emissions reduce the commercialisation efficiency of green innovation. None of the industry-level inefficiency determinants are statistically significant, indicating limited explanatory power for cross-firm heterogeneity in inefficiency conditional on a small sample. The noise term dominates the composed error, suggesting that commercialisation-stage green innovation efficiency in this industry are driven mainly by external shocks, such as seasonality and operational volatility, rather than persistent firm-level inefficiency. These results are consistent with the service-oriented characteristics of the accommodation and catering industry.

Variable	Estimated MLE coefficients
Frontier	
lnGreengrant	0.829 (1.11)
lnNonRDperson	40.433 (0.86)
lnEnergyconsume	5.814*** (2.74)
lnFirmCO2	-5.128** (-2.40)
Constant	-
Key influencing factors of inefficiency term $\mu_{commercial,it}$	
Hightech	-0.110 (-0.01)
Pollut	-6.166 (-0.02)
Constant	-0.332 (-1.25)
Parameters (standard deviations of the inefficiency term $\mu_{commercial,it}$ and the noise term $v_{commercial,it}$)	
σ_u	0.046 (0.01)
σ_v	0.847*** (7.54)

Panel 6 - Firms in Information transmission, Software, and Information technology services (Broad Industry Code: I)

Panel 6 reports the estimated coefficients for sample firms in the information transmission, software, and information technology services industry, based on 911 firm-year observations. Green patent output and energy consumption significantly enhance commercialisation-stage green innovation performance, reflecting the sector's reliance on technological innovation and energy-intensive computing infrastructure. Carbon emissions significantly reduce commercialisation-stage efficiency. Both industry-level inefficiency determinants are statistically insignificant, indicating limited heterogeneity in inefficiency given the relatively homogeneous technological environment of this industry. The persistent inefficiency dominates random noise, suggesting that commercialisation-stage green innovation outcomes are primarily shaped by firm-specific capability differences, such as technological competitiveness, digital infrastructure, and human capital, rather than external demand fluctuations. The results align with the innovation-driven and capability-intensive characteristics of this industry.

Variable	Estimated MLE coefficients
Frontier	
lnGreengrant	3.342*** (22.95)
lnNonRDperson	0.094 (1.27)
lnEnergyconsume	0.977*** (6.233)
lnFirmCO2	-4.564*** (-7.41)
Constant	-
Key influencing factors of inefficiency term $\mu_{commercial,it}$	
Hightech	-21.045 (-0.34)
Pollut	-26.398 (-0.83)
Constant	-16.092*** (-3.11)
Parameters (standard deviations of the inefficiency term $\mu_{commercial,it}$ and the noise term $v_{commercial,it}$)	
σ_u	8.541*** (4.35)
σ_v	1.144*** (4.22)

Panel 7 - Firms in Real estate (Broad Industry Code: K)

Panel 7 reports the estimated coefficients for sample firms in the real estate industry, based on 350 firm-year observations. The frontier results indicate that energy consumption strongly enhances commercialisation-stage performance, reflecting the heavy reliance of real estate activities on energy-intensive construction and development processes. Carbon emissions significantly reduce commercialisation-stage green innovation efficiency, while green patent output does not materially contribute to economic returns, consistent with the

low-technology and asset-intensive nature of this industry. Firms classified as pollution-intensive in this industry exhibit significantly lower expected inefficiency, likely reflecting their larger operational scale and stronger capacity in generating commercialisation values. The random noise dominates persistent inefficiency, indicating that commercialisation outcomes in this industry are primarily driven by external shocks, such as market cycles, regulatory adjustments, and financing conditions, rather than firm-specific capability differences. The results align with the scale-driven and policy-sensitive characteristics of this industry.

Variable	Estimated MLE coefficients
Frontier	
lnGreengrant	0.036 (1.43)
lnNonRDperson	-1.204 (-4.15)
lnEnergyconsume	2.835*** (35.86)
lnFirmCO2	-1.862*** (-23.29)
Constant	-
Key influencing factors of inefficiency term $\mu_{commercial,it}$	
Hightech	4.7180 (0.06)
Pollut	-2.656*** (-30.09)
Constant	-7.467 (-0.06)
Parameters (standard deviations of the inefficiency term $\mu_{commercial,it}$ and the noise term $v_{commercial,it}$)	
σ_u	0.377 (0.12)
σ_v	0.265*** (22.66)

Panel 8 - Firms in Leasing and Business services (Broad Industry Code: L)

Panel 8 reports the estimated coefficients for sample firms in the leasing and business services industry, based on 834 firm-year observations. The frontier results indicate that green innovation output from the R&D stage significantly enhances commercialisation-stage green innovation performance, consistent with the knowledge- and technology-intensive nature of this industry. Carbon emissions exhibits a strong negative effect on commercialisation-stage efficiency, reflecting the industry's increasing reliance on low-carbon operational models. The effects of non-R&D personnel and energy consumption are statistically insignificant, which aligns with the light-asset and service-oriented characteristics of this industry. High-tech certified firms exhibit significantly lower expected inefficiency, suggesting that technological capability is a key driver of efficiency variation within this industry. The pollution-intensity dummy remains insignificant, reflecting limited heterogeneity in pollution-related activities. Both structural inefficiency and noise components are statistically significant, with persistent inefficiency dominating random shocks. The results are consistent with the innovation-driven and capability-dependent features of the leasing and business services industry, where technological sophistication plays a central role in translating green innovation into commercial value.

Variable	Estimated MLE coefficients
Frontier	
lnGreengrant	0.131*** (4.35)
lnNonRDperson	0.116 (0.95)
lnEnergyconsume	0.020 (0.31)
lnFirmCO2	-0.493*** (-6.71)
Constant	-
Key influencing factors of inefficiency term $\mu_{commercial,it}$	
Hightech	-3.827* (2.93)
Pollut	1.406 (0.59)
Constant	-2.053 (-0.96)
Parameters (standard deviations of the inefficiency term $\mu_{commercial,it}$ and the noise term $v_{commercial,it}$)	
σ_u	2.019*** (4.16)
σ_v	0.652*** (9.31)

Appendix B2 The nineteen industries classification

Table B2 The nineteen broad industries classification in China

Table B2 presents nineteen broad industries and the number of sectors included in each broad industry to which the sample firms in Chapter Two belong following the Guidance for Industry Classification of Listed Companies (2012 revised edition) released by the China Securities Regulatory Commission. This document classifies A-share listed companies in China into 90 different sectors across 19 broad industries. The sample firms in the Chapter 2 spread in industries with Code C, E, F, G, H, I, K, and L.

Broad Industry code	Industry name
A	Agriculture, Forestry, Animal husbandry, and Fisheries
B	Mining
C	Manufacturing
D	Electricity, Heat, Gas, Water production and supply
E	Construction
F	Wholesale and Retail trade
G	Transportation, Storage and Postal Services
H	Accommodation and Catering
I	Information transmission, Software, and Information technology services
J	Finance
K	Real estate
L	Leasing and Business services
M	Scientific research and technical services
N	Water, Environmental, and Public facilities management
O	Residential services, Repairs and other services
P	Education
Q	Health and Social care
R	Culture, Sports and Entertainment sector
S	Comprehensive

Appendix C - Chapter 2 and Chapter 3

Appendix C1 High-polluting Industries in China

The criteria outlined in the "*Directory of Industry Classification Management of Listed Companies for Environmental Verification (2008)*" and the "*Guidelines for Disclosure of Environmental Information of Listed Companies (2010)*", both issued by the Ministry of Ecology and Environment of China, has classified 14 sectors as highly polluting, which correspond to 19 sectors outlined in the *Guidance for Industry Classification of Listed Companies* (2012 revised edition) released by the China Securities Regulatory Commission. We cross-reference these classifications with industry codes of China's A-share listed firms to accurately identify those operating in high-polluting sectors.

Table C1 High-polluting industries in China.

Industry code	Industry name
B06	Coal mining and washing
B07	Petroleum and natural gas extraction
B08	Ferrous metal mining and processing
B09	Non-ferrous metal mining and processing
B10	Non-metallic mining and processing
C15	Alcohol, beverages and refined tea manufacturing
C17	Textile manufacturing
C19	Leather, fur, feathers and related products manufacturing and footwear manufacturing
C22	Paper and paper products manufacturing
C25	Petroleum processing, coking and nuclear fuel processing
C26	Chemical raw materials and chemical products manufacturing
C27	Pharmaceutical manufacturing
C28	Chemical fibre manufacturing
C29	Rubber and plastic products manufacturing
C30	Non-metallic mineral products manufacturing
C31	Ferrous metal smelting and rolling processing
C32	Non-ferrous metals melting and rolling processing
C33	Metal products manufacturing
D44	Electricity and heat production and supply

Appendix D - Chapter 1, 2 and 3

Appendix D1. Variable Definitions and Data Processing

Table D1 Variable Definitions and Data Processing

Variable	Definition	Data source	Data processing Methods
Bio_FD	Proxy for the biological population density of financial development (FD), measured by the annual value added of the financial industry	National Bureau of Statistics of China	Province-year Min–Max normalisation
Bio_TI	Proxy for the biological population density of technological innovation (TI), measured by the annual value added of the high-tech industry		
U_1	Comprehensive development level of FD, constructed from an entropy-weighted composite of 15 indicators	National Bureau of Statistics of China; the China Regional Financial Operation Report; China Electronic Local Government Bond Market Access (CELMA); China Statistical Yearbook on Science and Technology	Indicators data is Min–Max normalised; entropy method is applied to derive objective weights from cross-province and year variation; linear aggregation is used to obtain U_1
U_2	Comprehensive development level of TI, constructed from an entropy-weighted composite of 12 indicators		Same processing as U_1
CCD	Coupling coordination degree between FD and TI at the provincial level. First obtain CD and D, where $CD = \left[\frac{U_1 \times U_2}{\left(\frac{U_1+U_2}{2}\right)^2}\right]^{\frac{1}{2}}$, $D = \alpha \times U_1 + \beta \times U_2$ with $\alpha = \beta = 0.5$; then $CCD = \sqrt{CD \times D}$		Annual estimates for 30 provinces based on U_1 and U_2
GW	Corporate greenwashing: within-industry normalised gap between ESG disclosure scores and ESG rating scores. Higher values indicate greater greenwashing	Bloomberg ESG database; Sino-Securities Index Information Service	ESG disclosure scores and ESG rating scores are normalised by industry-year mean and standard deviation. GW is winsorised at the 1% and 99% quantiles
CGG	Corporate government guarantees: measured as the difference between expected equity-market and debt-market losses. $CGG_t = ELV_E(t) - ELV_D(t)$	China Stock Market and Accounting Research (CSMAR) database	Option-based estimation of $ELV_E(t)$; corporate bond credit-spread-based $ELV_D(t)$; CGG values are logarithmically transformed after adding one, and winsorised at the 1% and 99% quantiles
NCSKEW	Negative conditional skewness of firm-specific weekly returns over the fiscal year. Higher values indicate a greater risk of stock price crashes	CSMAR	Calculated form firm-specific weekly returns using the residuals of a regression on market-weighted average returns, as specified in Model (2.1) and Model (2.2)
DUVOL	Down-to-up volatility: log ratio of variance of weekly returns in "down weeks" versus "up weeks"	CSMAR	Calculated form firm-specific weekly returns using the residuals of a regression on market-weighted average returns, as specified in Model (2.1) and Model (2.3)
GFRIPZ	Green Finance Reform and Innovation Pilot Zone (GFRIPZ) policy dummy: equals 1 if a firm is located in a designated pilot city in year t, and 0 otherwise	Official policy document "Establishing Pilot Zones for Green Finance Reform and Innovations" in 2017 and 2019	Binary indicator constructed by matching each firm's registered city with the official list of pilot zone in 2017 and 2019

Variable	Definition	Data source	Data processing Methods
GTIN	Green technological innovation quantity: Ln(natural logarithm of the number of granted green patents received by a firm+1)	Chinese Research Data Services (CNRDS) Platform	Winsorised at the 1% and 99% quantiles
GTIL	Green technological innovation quality: Ln (the number of citations received by a firm's granted green patents from subsequent patents+1)		
EFTR	Environmental Fee-to-Tax Reform (EFTR) policy dummy: equals 1 if a firm is subject to EFTR in the post-policy period, and 0 otherwise	Official policy document: Environmental Protection Tax Law, implemented on 1st January, 2018	Constructed as the interaction term *Treat* × *Post*. Treat is the EFTR treated group dummy equal to 1 if a firm belongs to a high-polluting industry, 0 otherwise. Post is the post-policy dummy, equal to 1 for years after EFTR implementation, 0 for pre-policy years
Size	Firm size: Ln(total assets)	CSMAR	Winsorised at the 1% and 99% quantiles
ROA	Return on assets: net income divided by total assets	CSMAR	
Lev	Corporate leverage ratio: total long-term debts divided by total assets	CSMAR	
CF	Cash-flow ratio: Net cash flows from operating activities divided by total assets	CSMAR	
TobinQ	Tobin's Q: market value of the firm divided by total assets	CSMAR	
ExecS	Executive shareholding ratio: shares held by executives divided by total shares	CSMAR	
Capex	Capital expenditure: percentage of capital expenditure to total assets, multiplied by 100 for scaling	CSMAR	
R&D	R&D intensity: Ln(RD expenditures / total revenues)	CSMAR	
Sigma	Stock volatility: standard deviation of firm-specific weekly returns within a fiscal year	CSMAR	
Dturnover	Detrended stock turnover ratio fluctuation: average monthly stock turnover ratio in year t minus that in year t-1, capturing trading heterogeneity	CSMAR	
LnIndus	Industrial structure: Ln(the total output value of the secondary sector / GDP in firm's registered city)	National Bureau of Statistics of China, the Statistical Communiqué of the National Economic and Social Development	
lnCityFin	Urban financial development: Ln(the total deposits and loans held by financial institutions in the city)	National Bureau of Statistics of China, the Statistical Communiqué of the National Economic and Social Development	