The Impact of Environmental Regulations on Green Transition Performance —— Evidence from China

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Declaration of Originality

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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Upon seeing this doctoral thesis, my thoughts inevitably turn to the hard work I have devoted over the past four years. But now, as it lies tangible before me, I believe every effort was worth it.

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Related Publications

The following list indicates the related publications derived from the author's PhD research.

Journal Articles

Shi, Q., Xiao, S., **Chang, K*.** and Wu, J., 2021. Stock option, contract elements design and corporate innovation output–an analyse based on risk-taking and performance-based incentives. *Nankai Business Review International*, 12, 574-598. (Emerald 2022Literati Awards – Outstanding Paper)

Chang, K., Liu, L., Luo, D*. and Xing, K., 2023. The impact of green technology innovation on carbon dioxide emissions: The role of local environmental regulations. *Journal of Environmental Management*, 340, 1-15.

Conference Papers

Qu, R., **Chang, K.,** Bititci, U., Xuan, J. and Xu, B*., 2023. Consumer perception and adoption of a circular chemical economy. *2023 International Conference on Resource Sustainability*, Guildford, United Kingdom.

Working Papers

Chang, K., Luo, D*., Dong, Y. and Xiong, C., 2023. The Impact of Green Finance Policy on Green Innovation Performance —— Evidence from China. (*Journal of Environmental Management*, R&R – Major Revision).

Chang, K., Luo, D*., Liu, N. and Mi, B., 2023. The Impact of Green Bond Issuance on Green Innovation Performance —— Evidence from China. (*International Review of Financial Analysis*, R&R – Minor Revision).

Abstract

In recent years, global warming issues caused by environmental pollution have sparked widespread debate. Globally, countries are actively paying attention to climate change and exploring green transition modes. One promising and effective strategy can be green innovation (GI). However, market failures suggest that government intervention is necessary to promote the effectiveness of technological innovation, and hence, its positive social impacts on emissions reduction. In this context, this thesis develops three empirical studies to investigate the relationship between the environmental regulation (ER) and green transition performance.

The first study (Chapter 3) investigates how the ER influences the relationship between GI and CO_2 emissions reduction in China. Employing data from 30 provinces during the period 2003–2019, this study applies the panel fixed-effect, spatial durbin model (SDM), system generalised method of moments model (SYS-GMM), and difference-in-difference (DID) model to investigate this relationship while considering endogeneity and spatial impact. The results indicate that ERs positively moderate the impact of green knowledge innovation (GKI) on CO_2 emissions reduction but have a much weaker moderation effect on green process innovation (GPI). Among different types of regulatory instruments, the investment-based environmental regulation (IER) is the most effective in promoting the relationship between GI and emissions reduction, followed by the command-and-control-based environmental regulation (CER). Expenditure-based environmental regulation (EER) is less effective, and can encourage short-termism and opportunistic behaviour among enterprises, who may opt to paying the discharge fee to avoid substantial investment in GI. Moreover, it is found green technological innovation has spatial spillover effects on CO_2 emissions in neighbouring regions, particularly for IER and CER. Lastly, the findings remain robust considering the heterogeneity across regions due to the different economic stages and industrial structures. This chapter shows that the market-based regulatory instrument, IER, works

best in promoting the emissions reduction effect of GI among Chinese enterprises. It also encourages the emissions reduction effect of GKI, which may assist enterprises in achieving long-term sustained growth. The chapter recommends further development of the green finance system to maximise the positive impact of this policy instrument.

The second study (Chapter 4) investigates the impacts of China's Green Credit Guideline (GCG) on enterprises' GI performance by employing a panel data on the Chinese listed enterprises from 2007 to 2019. The findings reveal that the GCG enhances the GI performance of both heavily polluting (HPEs) and green (GEs) enterprises. The HPEs focus more on GI increment, while GEs strive to promote both GI quality and increment. Heterogeneity analyses show that state-owned enterprises (SOEs) and high external finance dependent (EFD) enterprises are more motivated to enhance GI when stimulated by the GCG. Furthermore, penalty-based environmental regulation has no significant moderating effects on the relationship between the GCG and GI for both types of enterprises. Incentive-based environmental regulation has positive moderating effects on GI overall for HPEs, and only on GI quality for GEs. Voluntary environmental regulation has positive moderating effects for both types of enterprises and this effect is more prominent for GI quality performance, especially for GEs. Moreover, the mechanism analysis shows that the GCG can enhance GI performance by improving the efficiency of green investment utilisation. To further promote the positive impact of the GCG, more targeted bank lending should be encouraged towards the HPEs to assist enterprises' structural transformation. Meanwhile, different environmental policy instruments should also be effectively deployed together to leverage their synergistic effects.

The third study (Chapter 5) mainly explores the effect of green bonds in promoting enterprises' green transformation. As an important part of the green financial system, green bonds are issued to provide a market-based financing channel for environmentally friendly projects, such as GI, energy conservation, and emissions reduction. Using panel data of Chinese listed enterprises from 2007 to 2019, this study

investigates the impacts of green bond issuance (GBI) on GI performance. The empirical results show that the GBI can enhance the GI performance of both green bond issuing and peer enterprises, with the former one paying more on the GI quality and the latter focusing more on GI increment. In addition, the GI performance of green bond issuing enterprises is better than that of green bond peer enterprises after GBI. Furthermore, the heterogeneity analysis shows that external supervision (formal and informal ways) is important to effectively trigger the GI incentives of GBI. The relationship between GBI and GI is more prominent among SOEs, non-heavily polluting enterprises, and in the eastern region. Such relationship remains hold for green bond peer enterprises in general. The mechanism analysis reveals that GBI effectively promotes the GI performance of bond issuing enterprises and their peers through different channels. For the former, it acts through the promotion of R&D investment but for the latter, it enhances the capital utilisation efficiency. Consequently, it is suggested that effective polies should be set in place to ensure that the desired positive outcomes of green bond issuance are achieved, and enterprises are guided towards more sustained development path.

Keywords: Environmental regulations, Green credit guideline, Green bonds, Green innovation, Peer effects, CO_2 emissions, China

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Chapter 1: Introduction

1.1. Research Background

Since the industrial revolution, economic growth has witnessed great success. However, it was also accompanied by great sacrifices of natural resources and the environment (Choi et al., 2020). The unrestrained usage of fossil fuels has resulted in a significant increase in CO_2 emissions, which has reached 37.49 billion Mt in 2022, an increase of 66% compared to the levels recorded in 1992.[1] Similarly, China's remarkable economic achievements over the past decades have significantly increased energy consumption and related CO_2 emissions. In 2005, China's CO_2 emissions exceeds that of the US for the first time, making it the world's largest CO_2 emitter (Wang et al., 2017a). According to the IEA, China emitted 11.9 billion Mt CO_2 emissions in 2021, while the corresponding figure of the world was approximately 36.3 billion Mt.[2]

The abnormal elevation in the atmospheric concentration of greenhouse gases has resulted in global warming (Sun et al., 2022). This rise in global temperatures has severely disrupted the ecological balance of earth, contributing to an unnatural increase in sea levels and a higher frequency of extreme weather events (Kahn et al., 2021). Furthermore, uncontrolled consumption of fossil fuels—a non-renewable energy source—may lead to an energy crisis in human development (Van der Ploeg, 2016). This consumption is coupled with extensive pollution emissions (Du et al., 2023). Both climate change and pollution emissions pose a grave threat to human socio-economic activities (Baldauf et al., 2020). Therefore, as economic development continues, the impacts of this high-pollution growth are beginning to surface and escalate at an alarming rate (Madaleno et al., 2022). Consequently, shifting towards a low-carbon economic development strategy is significant for countries' continued growth (Lin and

[1] https://www.statista.com/statistics/276629/global-co2-emissions/
[2] https://www.iea.org/
https://www.statista.com/statistics/276629/global-co2-emissions/

Li, 2022).

In response, along with other countries, China proposed several initiatives to reduce CO_2 emissions. For instance, it promised to reduce its CO_2 emissions by 60%–65% in 2030 compared with the 2005 level (Tang et al., 2018). This represents an emissions reduction of about 12 billion tons per year (Yan, 2015). By 2060, the country is aiming to achieve carbon neutrality.[3] To fulfil these objectives, the government introduced a series of environmental policies, such as Law on the Prevention and Control of Environmental Pollution by Solid Waste (2004), Law on Energy Conservation (2007), Circular Economy Promotion Law (2008), and Atmospheric Pollution Prevention and Control Law (2015 Revision), among others. Furthermore, the Ministry of Industry and Information Technology has established entry conditions for various sectors, including cement, printing and dyeing, and casting. These environmental protection policies specify both production technology standards and pollutant discharge benchmarks (Ren et al., 2018).

Importantly, employing instruments such as fines, taxes, subsidies, and emissions trading can help in overcoming environmental externalities (Chen et al., 2021b; Xu et al., 2023a). The Chinese Ministry of Environmental Protection has issued market-based policies, like Administrative Regulations on Levy and Use of Pollutant Discharge Fee (2003), Measures for Environmental Administrative Punishment (2010), Notice on the adjustment of the subsidies for energy-efficient vehicles (2011), and Guiding opinions on further promoting compensable use and pilot tests of emissions trading (2014), among others. Moreover, enterprises that fail to meet the emissions target face severe punishments in the form of high discharge fees or additional tax payments (Ma et al., 2021). Thus, compared with the polluters, 'cleaner' enterprises which have green technologies and are capable of meeting the environmental regulation (ER)[4]may realise cost savings, and hence, comparative advantages (Ramos et al., 2018).

[3] https://www.nature.com/articles/d41586-020-02927-9
[4] All abbreviations of this thesis can be found in Appendix 3 (Section of Appendix).

To effectively address environmental pollution, it is necessary to progressively regulate enterprises' environmental management activities (He et al., 2016). However, the confluence of the public goods nature of environmental resources, negative externalities associated with pollution issues, and economic rationality of enterprise entities often result in 'market failure' (Campiglio, 2016; Dong et al., 2020). Consequently, achieving energy conservation and pollution control by solely relying on market mechanisms is difficult (Dong et al., 2020). As such, the role of ER as a tool for guiding and promoting enterprise behaviour becomes increasingly crucial (Qi et al., 2023). Meanwhile, one of the important strategies to combat environmental pollution is green innovation (GI) (Albitar et al., 2023). GI is also termed as 'low carbon technology innovation', 'eco-technology innovation', 'environmental technology innovation', and 'sustainability technology innovation' (Albitar et al., 2023). Current consensus suggests that such technological advancements are essential for achieving sustainable development and the green transition (Valero-Gil et al., 2023). While GI shares certain similarities with traditional innovation, significant differences exist; for instance, the conventional drivers of innovation may not stimulate GI (Liu et al., 2020b). Beyond the fundamental aim of generating economic benefits, GI also strives to achieve environmental and societal gains (Wei et al., 2023). Therefore, a singular innovation policy is insufficient to incentivise enterprises towards GI. Instead, appropriate ER tools are necessary to guide and promote GI.

As the world's largest developing country, China is experiencing deep industrialisation, and its economic and social development inevitably results in heightened pressure on resources and the environment (Yan et al., 2022). Confronted with escalating resource and environmental constraints, China is actively seeking a new economic development model that balances economic growth and environmental sustainability (Wang and Lei, 2022). GI is, therefore, a critical component of China's new economic development model. Research suggests that most green technological advancements are primarily 'policy driven', indicating the crucial role of policy incentives and support in fostering such progress (Wang et al., 2022a). The Porter Hypothesis (PH) and its proponents posit that effective ER policies can stimulate innovation (Lin and Chen, 2020). Conversely, some scholars contend that stringent ERs impose an economic burden, potentially crowding out technological innovation (Jaffe and Stavins, 1995). If designed appropriately, ERs aimed at environmental improvement can facilitate the sustainable development of China's economy and society by stimulating green technological innovation and reducing CO_2 emissions (Lin and Chen, 2020). This thesis aims to examine the relationship among ER, GI, and CO_2 emissions in the Chinese market. It strives to provide insights and references for the green transformation of China and other emerging economies.

1.2. Development of Research Questions

Climate change has caused numerous catastrophic issues, including global warming, thereby necessitating global mitigation efforts (Hong et al., 2019). As the world's second-largest economy and the source of nearly a third of global CO_2 emissions, the effectiveness of China's environmental commitments and measures is of paramount importance (Du et al., 2023). To mitigate the greenhouse effect and strive for carbon neutrality, the Chinese government has implemented several rigorous environmental policies aimed at fostering the country's green transformation and encouraging GI activities (Xing et al., 2021).

However, to solve the environmental issues fundamentally, tougher regulation is far from enough (Tang et al., 2020). Rather, effective policies are needed to promote the transition towards green economy (Peng, 2020). Theoretically, the pressure of meeting ERs may trigger enterprises' inputs in green technology innovation as it may enhance their CO_2 emissions reduction capability (Liu et al., 2021). In practice, how these three factors, ERs, green technology innovation and CO_2 emissions reduction, are influencing each other. That is, what is the transmission mechanism among these three factors? Does tougher regulation guarantee additional green investments and whether these additional investments can further reduce CO_2 emissions? Further, it needs to be studied whether different types of ER tools and green technology innovation impact the transmission mechanism differently. Finally, given the different levels of economic development and severity of environmental governance in different regions, are the tested transmission mechanisms affected by regional heterogeneities in China? Chapter 3 aims to explore these questions based on a sample of Chinese provincial-level data over the period 2003–2019. A comprehensive understanding of the effectiveness of ERs and their transmission mechanisms are of critical importance to China's economic transformation. It may also provide valuable guidance to different regions to adjust and optimise their ER tools.

On the one hand, the Chinese government has traditionally relied on penalty-based ER tools for environmental governance (Pan et al., 2019; Peng et al., 2021). Such regulatory mechanisms have imposed a heavy burden on enterprises, resulting in heightened resistance towards environmental issues and falling short of stimulating GI (Pan et al., 2019; Tang et al., 2020). In contrast, market-based environmental regulation (MER), especially for the investment-type policy, can effectively incentivise enterprises to transition towards greener practices and harness more capital to bolster GI activities (Goulder et al., 2022; Sun et al., 2021). Then, exploring the development of efficient MER tools, such as the Green Credit Guideline (GCG), is important to foster China's green economic transformation (Zhou et al., 2019a; Hu et al., 2021). On the other hand, environmental policy mainly exerts influence over pollution emissions by shaping enterprise behaviour (Ambec et al., 2013). Hence, the study of environmental regulatory instruments should delve deeper into the specific behaviours of micro-enterprises to enhance its relevance. Thus, this thesis further investigates the impact of GCG on the GI activities of micro-enterprises in Chapter 4.

MERs, especially investment-type ones, are playing an increasingly important role due to their characteristics of flexibility, autonomy, and strong economic efficiency (Tian and Feng, 2022). The GCG is also an important policy in the Chinese market-based regulation system (Lu et al., 2022). The GCG encourages banks to grant larger and cheaper loans to green businesses while pressuring HPEs by constraining their credit applications. Therefore, such market-based environmental regulations can assist China to achieve its emissions reduction targets more effectively as they may lead to profound economic restructuring and green transition of the Chinese economy (Tan et al., 2022). Meanwhile, among the different types of enterprises, HPEs are also more likely to be the most affected ones by GCG (Hu et al., 2021). With higher profit potential, they should be keen on promoting green technologies to achieve more sustained growth. Meanwhile, green enterprises (GEs) should be motivated to continue investing into GI to maintain their competitive advantages (Xu and Li, 2020). Considering the important role played by GCG in economic transformation and its profound impacts on Chinese enterprises, this thesis aims to empirically test whether GCG could promote GI among HPEs under heterogeneous conditions. Further, as different types of ERs are being implemented in China and they may have synergistic effects, understanding how these policy instruments affect the relationship between GCG and GI can be important. One may ask also about the impacts of GCG on GEs and whether such impacts are consistent with those identified on HPEs. Based on panel data of the Chinese listed enterprises from 2007 to 2019, Chapter 4 aims to provide a comprehensive understanding of the relationship between the GCG and green transition among Chinese enterprises.

Like other types R&D activities, GI also involves high capital investment, high risk of failure, and long development period. As such, an effective financial system which can provide multiple funding support to GI activities in a market-oriented manner is quite necessary (Hu et al., 2021). Besides green credit, green bonds can be effective funding mechanism (Wang et al., 2022c). On the one hand, only those enterprises with superior green performance may gain support from the regulatory bodies and investors in the bond issuing process. On the other hand, green bond issuance (GBI) also has a showcase effect, signifying the enterprises' intention/determination of engaging into more GI activities. This may also increase peer pressure on other competitors, accelerating the green transition process of the whole industry (Gupta and Barua, 2018).

Given the potential positive impact of GBI in the overall economic structural transformation process and its growing importance in the Chinese market, Chapter 5 empirically test whether the intended positive impact of GBI could actually be achieved. This chapter asks: Do enterprises issuing more green bonds issued deliver better GI performance under heterogeneous conditions? If so, what are the impact mechanism between GBI and GI activities? Considering the positive publicity effect of GBI, this study further investigates whether GBI can encourage peer enterprises to participate more in GI activities. Employing a panel data of the Chinese listed enterprises from 2007 to 2019, Chapter 5 aims to provide a comprehensive understanding of the relationship between the GBI and green transition among Chinese enterprises.

1.3. Contributions

First, as the concept of environmental protection, technology innovation, and CO_2 emissions reduction were initiated in the western countries, most discussions about the PH are based on the sample of developed economies. However, developing countries are contributing to most of the newly generated emissions nowadays. As the world's biggest developing country, the development model of China has always been criticised and the country has tried hard to balance its economic growth with the amount of pollution generated over the past decade. The Chinese government has initiated policies to regulate enterprises' behaviour while simultaneously stimulating GI. Then, a question worth asking is how the country is performing now or whether the policies adopted have achieved desired outcome. If China's reforms seem successful, these 'best practices' may then be generalised to other emerging economies. This can improve energy efficiency at the global level and help all countries achieve more sustained development in the future.

Second, this thesis further investigates the effect of green technological innovation on CO_2 emissions under the moderation effect of ERs. Currently, most studies focus primarily on the relationship between ERs and technology innovation. Research has not comprehensively examined whether these 'GI' have achieved the desired outcome of CO_2 emissions reduction, especially when they are influenced by different types of ERs. This is the gap this study aims to fill. Furthermore, the thesis further considers different ERs and investigates their respective impacts on the proposed transmission mechanism. Different ERs can have different enforcement power, allowing us to gain a better understanding of the PH under China's context. This thesis also considers regional heterogeneity as the environmental governance levels and economic development patterns vary significantly among different regions in China. Considering the heterogeneity of different GI, this thesis also employs different GI to capture enterprises' different innovation behaviours. Some GIs tends to be long-term oriented, while others are more of short-term solutions. To achieve the government's industrial transformation and emissions reduction targets, the sustained changes are preferred. Therefore, this thesis can supplement the PH by considering the heterogeneity in GI.

Third, as an important MER, GCG are playing a crucial role in environmental governance in the Chinese market. However, studies show that different regulatory tools may have a synergistic effect on enterprises' innovation and emissions reduction (Yuan, 2019). Given the important role played by command- and voluntary-based regulatory tools in China, this thesis also investigates their moderation effect on the relationship between GCG and GI among HPEs. Then, the thesis examines the heterogeneity relationship between the GCG and GI among HPEs with different ownership structures and different degrees of reliance on external financing. Next, while some studies focus on the impact of GCG on the performance of HPEs (Yao et al., 2021; Cui et al., 2022; Peng et al., 2022), little is known about the impact of such policies on GEs. Despite generating less pollution, GEs are also incentivised by GCG to consolidate their competitiveness, and thus, may display different behaviours. This thesis conducts a comparative analysis of HPEs and GEs, and provides valuable information for policymakers. Furthermore, the thesis investigates the relationship between GCG and green transition efficiency among listed enterprises in China, aiming to explore the potential internal mechanism that links GCG and GI.

Fourth, as debt and equity finance are the two major funding sources for enterprises, most studies focus on the pricing or stock market reactions to GBI (Zerbib, 2019; Tang and Zhang, 2020). Few analyse whether the issuance of green bonds has assisted enterprises to deliver superior green performance. This thesis aims to fill in this gap. Moreover, due to the positive publicity created by GBI and potential long-term benefits of GI, this thesis further investigates the spillover effects of GBI on enterprises from the same industry, thereby expanding its scope beyond studying enterprises implementing GBI to its impact on other enterprises. By exploring the spillover effects of GBI, this thesis broadens the understanding of PH's influence, thus further contributing to the practical application of the PH in the Chinese market. Furthermore, this thesis examines the heterogeneity relationship and mechanism analysis between the GBI and GI, and their spillover effects further by considering different supervision ways, enterprise characteristics, and regions. These insights have significant theoretical and practical implications for understanding the policy performance of specific green financial instruments.

Fifth, this thesis employs the Word Embedding model as a novel quantification methodology for variables, which improves the precision of variable measurements and bolsters the robustness of the empirical findings. When quantifying specific variables, the usage of various semantically similar words is often vital because single words typically capture only a fragment of the information particular to a variable's characteristic. Studies frequently rely on manually identifying synonyms to expand the word set (Loughran and McDonald, 2011), although this approach falls short in thoroughly and accurately measuring textual features due to its high subjectivity and potential for bias. The Word Embedding model in machine learning offers a solution to this issue (Li et al., 2021). It utilises a neural network to parse large volumes of financial text deeply, generating a word similarity model where similar words can be trained. The similarity dictionary produced by this model permits comprehensive and objective variable measurement (Li et al., 2021). The process involves first gathering keywords from literature and text characteristics. The Word Embedding model is then used to train and derive the similarity dictionary, which is subsequently applied to construct these variables.

1.4. Structure of the Thesis

This thesis has six chapters. Chapter 1 provides an overview research background. Chapter 2 analyses the theoretical framework and reviews the literature. Chapter 3 is the first main chapter which investigates the impact of different ERs and GI on CO_2 emissions. In Chapter 4, the thesis examines the effect of GCG on enterprise GI performance. Chapter 5 mainly investigates the effect of GBI on enterprise GI performance. Finally, Chapter 6 presents the main findings from the three studies, and draws some general conclusions and policy implications. It also provides future research suggestions.

Chapter 2: Literature Review

2.1. The History and Background of Chinese Environmental Policies

Since the United Nations Conference on the Human Environment in 1972, China has embarked on over four decades of ecological and environmental protection and management. Concurrent with economic development, social progress, and burgeoning public environmental awareness, China has instituted a foundational national policy for environmental protection, implemented a sustainable development strategy, and constructed a comprehensive environmental policy system. This system includes command-and-control, market-based, and voluntary-based environmental regulations (Shen et al., 2020). Specifically, the evolution of China's environmental policy has unfolded through the following stages.

The initial stage, spanning from 1972 to 1983, marked the exploration and inception of China's environmental protection initiatives. The First United Nations Conference on the Human Environment in 1972 enlightened the Chinese government about the repercussions of environmental issues on economic and social development. Consequently, in 1973, the government adopted the 'Regulations on the Protection and Improvement of the Environment (for Trial Implementation)', signalling a nascent era in China's environmental protection. [5] During this phase, the importance of environmental protection gradually came into the limelight, with the state commencing the enactment of laws and regulations for its implementation. In 1979, the 'Law of the People's Republic of China on Environmental Protection (for Trial Implementation)' was instituted, thereby offering legal reinforcement to environmental protection endeavours.[6] China embarked on preliminary explorations in managing the industrial 'three wastes' during this period and designated Beijing, Hangzhou, Suzhou, Guilin,

[5] https://www.gov.cn/jrzg/2009-08/30/content_1404821.htm.
[6] http://www.npc.gov.cn/zgrdw/wxzl/gongbao/2014-06/23/content_1879667.htm.

and additional key cities for focused treatment.[7] Nevertheless, due to economic development constraints and prevailing ideologies, environmental policies were not extensively efficacious, and the state promulgated merely a modest number of command-and-control regulations.

The second stage, designated as the initial establishment stage (1984-1991), witnessed the Chinese government elevating environmental protection to a fundamental state policy in 1983, thereby underlining its significance in China's economic and social development.[8] In 1984, the State Council issued the 'Decision on the Work of Environmental Protection', introducing policies and strategic plans that propelled advancements in environmental protection. Subsequently, in 1989, the Third National Conference on Environmental Protection was convened by the State Council, during which environmental protection initiatives were embedded into the government's work report and amalgamated into the national economic and social development plan.[9] By 1991, the state had crafted and promulgated pivotal environmental laws, including the 'Law on Prevention and Control of Water Pollution', 'Law on Prevention and Control of Air Pollution', and 'Regulations on Prevention and Control of Environmental Noise Pollution'. With the augmentation of environmental policies and the initial formation of a policy system, which included the introduction of a sewage charging system[10] and a 'three simultaneous' system, a foundational framework for environmental protection was established.

The third stage, spanning from 1992 to 2002, is characterised as the period of framework enhancement. In 1992, China promulgated the 'Environment and Development Report of the People's Republic of China', advocating the deployment of a sustainable development strategy. During this stage, the eminence of environmental protection was further elevated. The State underscored the necessity to establish and

7 https://www.gov.cn/gongbao/shuju/1981/gwyb198104.pdf.
8 https://www.gov.cn/test/2009-09/29/content_1429602.htm.
9 https://www.mee.gov.cn/zjhb/lsj/lsj_zyhy/201807/t20180713_446639.shtml.
10 https://www.mee.gov.cn/xxgk/xzsysf/201407/t20140715_278777.shtml.

refine a comprehensive system of environmental policies, laws, standards and management, all attuned to the socialist market economic system. Concurrently, environmental economic policies and economic instruments began to wield influence. The State delineated avenues for investment in environmental protection, inaugurated a pilot emission permit system, and executed a pioneering atmospheric emissions trading policy in six cities: Taiyuan, Liuzhou, Guiyang, Pingdingshan, Kaiyuan, and Baotou.[11] Additionally, considerable national efforts were directed towards promoting cleaner production and refining the sewage fee system.

The fourth stage signifies a period of developmental elevation, commencing in 2003 when the Chinese Government introduced the scientific concept of development.[12] A pivotal moment occurred in 2005, with the Chinese government identifying the establishment of a resource-conserving and environmentally-friendly society as a strategic task within the long-term planning of national development. In the same year, the State Council issued the 'Decision on Strengthening Environmental Protection through the Implementation of the Scientific Outlook on Development', thereby elevating environmental protection to a more prominent strategic position.[13] Throughout this stage, the Chinese government enhanced the control of total pollutant outputs and employed binding target management. The Chinese market also saw a flourishing of environmental economic policies, with the introduction of industrial policies and experimental environmental economic strategies such as eco-compensation, green credit, green insurance, and green securities. Concurrently, China's National Climate Change Programme was inaugurated.[14] The ongoing refinement of strategic environmental policy at the national level intensified the introduction of environmental protection policies, gradually establishing a comprehensive environmental policy system.

[11] http://www.tanpaifang.com/paiwuquanjiaoyi/2014/09/0737710.html.
[12] https://www.gov.cn/test/2009-10/10/content_1435066.htm.
[13] https://www.amac.org.cn/businessservices_2025/ywfw_esg/esgzc/zczgsc/202007/t20200714_9837.html.
[14] https://www.ccchina.org.cn/WebSite/CCChina/UpFile/File189.pdf,

The fifth stage, spanning from 2013 to the present, is characterised as the reform and breakthrough phase. Since 2013, China has prioritised ecological civilisation, embedding it within the comprehensive framework of socialist endeavours with Chinese characteristics, with the aim to build a beautiful China. In 2015, a new environmental protection law was enacted, levying strict penalties and fines on enterprises and institutions that discharge pollutants.[15] In 2018, 'ecological civilisation' was inscribed into the Constitution, and a national conference on ecological environmental protection was convened, propelling the cause of ecological environmental protection into a new stage of historical development.[16] During this stage, the Chinese government has bolstered accountability mechanisms for eco-environmental protection, vigorously advanced green development, and reformed environmental economic policies. Through the promotion of a green finance system, the aim is to realise the 'Carbon Peak' and 'Carbon Neutrality' goal at an expedited pace.

2.2. Theoretical Background

Neoclassical theory argues that if an enterprise wants to meet the requirements of the ERs, this may increase its costs in various aspects, such as paying pollution taxes, purchasing pollution control equipment and technology, etc. (Xie et al., 2017). This will internalise the cost of pollution to those polluters, and hence, increase their cost of production and lower their market competitiveness (Gollop and Roberts, 1983). Moreover, with lower profits, it will further restrain enterprises' green technology investment opportunities, further lowering their future emissions reduction capacity (Jaffe et al., 2005). Consequently, one may argue that ERs can negatively impact enterprises' GI and CO_2 emissions reduction capacity as the increased production cost will crowd-out innovation investments (Levinson and Taylor, 2008).

[15] https://www.xinhuanet.com/politics/2015-01/01/c_127350817.htm.
[16] https://www.mee.gov.cn/gkml/sthjbgw/qt/201803/t20180315_432486.htm.

Later in the late 2000s, Porter (1991) and Porter and Van Der Linde (1995) challenged the above view and proposed the PH. PH argues that stringent but properly designed ERs can actually stimulate GI, which may offset compliance costs and enhance enterprises' productivity. This can create a win-win situation that enables the enterprise to simultaneously achieve increased profit and lower emissions. Porter and Van Der Linde (1995) further noted that an appropriately designed ER system should be based on the market mechanism and can effectively encourage enterprises' best practices. To achieve this, an ER should have the following characteristics: Broad coverage: It should provide the largest potential space for enterprise innovation; Continuity: It should stimulate continuous innovation; Flexibility: The environmental policies can be implemented in stages with certain level of discretionary power being given to enterprises; and Enforceability: An effective appraisal system should be put in place to control and punish wrong-doings, and encourage government-enterprise collaboration (Porter and Van Der Linde, 1995).

The PH provides a new dynamic perspective to understand the impact of ERs on enterprises' innovation behaviour, and thus, on emissions reduction. Many studies have demonstrated the validity of the hypothesis (Brännlund, 2009). These studies show that a well-functioning ER system can improve enterprises' resource allocation efficiency, thereby leading to continued enterprise innovation, higher technological efficiency, and lower CO_2 emissions (Ford et al., 2014; Calel and Dechezlepretre, 2016). The compensation effect of ERs has increased enterprises' willingness to invest in GI. The resulting technological progress can improve enterprises' green competitiveness and accelerate the development of an environmentally friendly industry (Zhao et al., 2015). However, some neoclassical economists oppose the idea and argue that in practice, ERs could make enterprises bear much higher costs and divert valuable capital from promising innovative projects to ones that concentrate on emissions reduction only (Ford et al., 2014). Research also shows that some Chinese environmental policy instruments do not provide sufficient impetus for GI (Wang et al., 2022a; Xu et al., 2023b).

These contradictory findings are mainly due to the different types of regulation tools (Frondel et al., 2008; Iraldo et al., 2011). Xie et al. (2017) find that compared with command-and-control policies, flexible ERs, such as market-based instruments, are more conducive for promoting productivity and enterprises' innovation capability. Effective market-based policies can provide enterprises with greater flexibility in the abatement process, allowing them to select either the most suitable technological solution or the timing for the adjustment (Peng et al., 2021). Although there is no clear hierarchical relationship among the policy tools, their effectiveness varies among different regions due to their respective advantages and limitations, and diversified local conditions (Fischer et al., 2003). Iraldo et al. (2011) also provided a useful summary of different types of ERs. Specifically, the form of ER may be as important as its stringency in determining the nature of its relationship with economic performance. Consequently, when analysing the impact of environmental policy tools on GI, one should consider the types of policy tools and the diversified local background (Frondel et al., 2008). Moreover, Garcés-Ayerbe and Cañón-de-Francia (2017) argued that environmental policies should also cooperate with other regulatory or supervisory approaches. They believed that if ERs could be aligned with the specific condition of enterprises or/and regions, a win-win situation could be created both economically and environmentally.

2.3. The Relationship between Environmental Regulations, Green Innovation, and CO_2 Emissions Reduction

ERs are set by the government to reduce the CO_2 emissions. This can be achieved by changing the behaviour of enterprises, such as encouraging them to invest more in GI (Ouyang et al., 2020). In general, green technological advancement can improve the operational efficiency and pollution reduction capacity of enterprises (Gerlagh, 2007; Weina et al., 2016; Nikzad and Sedigh, 2017). ERs provide the impetus, driving increased GI and enterprise development. Examining the manufacturing sector of 17 European countries, Rubashkina et al. (2015) demonstrated the positive relationship between ER and innovation outputs. The continuous advancement in green technologies has also reduced the CO_2 emissions, and hence, improved environmental quality (Churchill et al., 2019; Costantini et al., 2017). As suggested by Rennings and Rammer (2011), the market itself may not be able to promote green technology innovation effectively unless sufficient incentives are provided to enterprises. Enterprises are only willing to engage more in GI if they are given significant economic benefits or are subject to severe punishment for non-compliance. This has reiterated the important role played by government regulations. However, some studies argue that the positive relationship between GI and CO_2 emissions reduction is not as stable (Weina et al., 2016). For instance, the actual impact of green technology innovation on CO_2 emissions reduction can be affected by the development stage of different regions (Fan et al., 2006). Innovation requires a large amount of capital and time input, especially for more advanced innovation (Shen et al., 2020). Zhang et al. (2018) argued that enterprises are more likely to invest in more advanced green innovation to reduce CO_2 emissions and build up long-term competition capacity, especially under the appropriate regulation.

Among different regulation tools, CER and MER are the two main regulation tools in Chinese market. CER refers to the ER based on government mandates (Tang et al., 2020). By publishing programmatic guidance on the region's environmental regulatory objectives, such as the objective of gradually developing the green finance market, achieving Carbon Peak in 2030, and Carbon Neutral in 2060, in China, CER can encourage enterprises to undertake emissions reduction-related technology innovation to meet government policy requirements in the long term (Chen and Chen, 2018). MER refers to ERs based on market forces. It can be further categorised into expenditure- (EER) and investment-based ERs (IER) based on their different impacts on enterprises' R&D capacity (Böhringer et al., 2012; Li and Zhao, 2021). EER focuses on the expenditures incurred to meet emissions targets, such as paying for the pollution discharge fee, as costs to the enterprise and are deducted directly from its funding pool. This can inevitably reduce the capital available for GI, and consequently, negatively affect the enterprise's long-term emissions reduction capability (Sun et al., 2021). Meanwhile, IER views expenditure on GI as long-term investment incurred by enterprises. As it may help enterprises build up capacity in meeting emissions reduction targets, future continued payment and punishment can be avoided. This can then reduce the economic burden for enterprises and help them build up competitive advantages over the long run (Sun et al., 2021). Therefore, by providing programmatic emissions reduction targets for a region or province over the long term, CER could stimulate enterprises to devote more resources toward GI. Meanwhile, among the two types of MER, EER may not be able to address the emissions reduction issue fundamentally, while the IER seems more long-term oriented as it encourages enterprises to build up the emissions reduction capacity via R&D.

Specifically, leveraging the power of the government, CER drives green innovation of enterprises. These regulations may affect environmental laws across a wide range of fields including market access, product standards, product bans, and technology knowledge dissemination (Shen et al., 2020). If the regulations or rules are disregarded, the enterprise is likely to lose the support of the government. As environmental protection and emissions reduction is generally long-term oriented, the ultimate goal of CER is to make enterprises adopt effective measures for the achievement of long-term sustainable emissions reduction target (Huang and Zhai, 2021). Therefore, under government mandates, enterprises are more likely to develop advanced GI and reduce pollution to maintain their status and obtain pioneer competitive advantages.

EERs are expected to change enterprises' behaviour by levying charge on non-compliance. Consequently, when investments in technology innovation is higher than the costs of discharge fee, enterprises will have little incentive to innovate, and *vice versa* (Sun et al., 2021). In China, the situation has become even more complicated due to the deficiencies of the discharge fee system (e.g. limited levy scope and low standard of requirement) (Shen et al., 2020). Considering the flaws of EER and investments needed for GI, one may conclude that EER could hardly generate a positive moderation effect on the CO_2 emissions reduction via GI.

Meanwhile, IER aim to promote GI and environmental performance by providing investments, and influencing the enterprises' financing and operating process (Zhang, 2021). Unlike EER, which may trigger enterprises to adopt short-term measurements to bypass financial punishments, IER are expected to incentivise enterprises to develop green technologies for emissions reduction and benefit from green investment over the longer term. Therefore, this type of market-based mechanism is expected to provide a much stronger incentive for enterprises to promote green technologies for more sustainable growth, and hence, generate a much wider positive impact on the whole society (Sun et al., 2021). Crucially, to attract more sustainable green investments, enterprises are more likely to develop relatively advanced GI to build up competitive competence and a higher market status.

Considering the important role that ERs and GI play in reducing CO_2 emissions, this thesis seeks to explore the transmission mechanism among these three factors. As Xie et al. (2017) pointed out, the heterogeneity of regulation tools plays a critical role in environmental governance. Hence, Chapter 3 aims to determine whether different types of ERs and GI have varying impacts on this transmission mechanism. Moreover, considering the disparities in economic development and environmental governance across different regions, the study also investigates the presence of regional heterogeneities.

2.4. Green Credit Guideline and Green Innovation Performance

According to Sun et al. (2019), China's GCG pursues two interrelated targets, environmental protection and economic development, by using several financial mechanisms. Instead of punishing enterprises, it aims to achieve balanced or harmonised development between the external environment and enterprise behaviours (Sun et al., 2019). According to the GCG, all commercial banks must strengthen the management of enterprise environmental performance and establish an information sharing mechanism to develop green credit (Yao et al., 2021). The GCG delineates several key principles. First, it advocates a stringent entry mechanism that compels credit-granting financial institutions to evaluate not just an enterprise's economic performance and risks, but also its environmental performance and potential ecological threats, thereby restricting credit to enterprises with bad environmental performance. Second, it mandates the establishment of mechanisms for information exchange and dynamic tracking for enterprises that have secured loans via examination and approval, warranting the termination of their credit should environmental issues arise. Third, it emphasises the necessity of fostering closer coordination and cooperation with governmental and environmental protection departments, enhancing information sharing to forge a connection between environmental conservation and financial credit. It aims to establish a powerful database to assess the environmental performance when enterprises apply for credit, track their follow-up activities, and share this information with other government institutions for coordinated management and control (Zhang, 2021; Yao et al., 2021).

The overall aim of the GCG is to foster GI performance. This includes the creation of technologies or approaches that promote energy efficiency, emissions reduction, and environmental protection (Chen et al., 2006). Similar to the conventional forms of innovation, GI propels an enterprise's technological growth, enabling them to generate more inventive products and services in the future (Aldieri et al., 2020). Moreover, the eco-friendly nature of such innovation substantially benefits the environment (Huang and Li, 2017). Thus, GI can concurrently accomplish the dual objectives of environmental conservation and economic growth (Ganda, 2019; Shao et al., 2021). This aligns well with the demands of GCG.

In the past decades, numerous HPEs have sought structural transformation to maintain their viability and attract consistent capital from financial institutions. This has underscored the importance of achieving qualified environmental performance (Berrone et al., 2013). For Chinese enterprises, despite capital market reforms, loans still represent their primary financing resource, particularly for HPEs (Xing et al., 2020). To guarantee financial backing, HPEs are motivated to reduce emissions in compliance with green credit policy requirements (Shi et al., 2022). This also assists them in cultivating a positive relationship with local government authorities (Hu et al., 2021). Meanwhile, GEs should be motivated by GCG to continue investing into GI to maintain their competitive advantages (Xu and Li, 2020).

In China, the GCG is becoming increasingly pivotal in environmental protection, fostering the green transition of diverse enterprises. Consequently, Chapter 4 explores whether GCG bolsters GI amongst HPEs and GEs under various conditions. Furthermore, research indicates that different types of regulation tools may synergistically impact enterprises' innovation and emissions reduction (Yuan, 2019). Given that China has implemented various ERs, these policies may have a synergistic effect. Thus, it would be valuable to understand how these policy instruments influence the relationship between GCG and GI.

2.5. Green Bond Issuance and Green Innovation Performance

As a crucial market-based environmental policy instrument, green bonds have attracted great attention since its initial offering. This attention is primarily due to their dual nature as an environmental regulatory tool advocated by the government and as a preferred financing option for enterprises (Lee et al., 2023). Most previous studies concentrate on aspects related to green bond pricing and yield (Zerbib, 2019; Larcker and Watts, 2020). Issuing green bonds can generate positive publicity for enterprises and enhance short-term performance and boost long-term value (Tang and Zhang, 2020;

Flammer, 2021). This positive impact is more significant when a third party underwrites the GBI, and/or when the initial offering yields high cumulative excess returns.

Besides bolstering enterprise performance, green bonds are designed to finance enterprises' GI activities. With an average maturity of 17 years compared to the 12.2-year term of traditional bonds, green bonds align well with the extended lifecycle of innovation activities (Roch et al., 2023; Huang et al., 2022). Consequently, they ensure continuous funding for enterprises' GI (Herrera and Minetti, 2007). Unlike the indirect financing method of bank credit, bond financing is direct and does not impose excessive intermediary fees on enterprises (Tang and Zhang, 2020). This highlights the potential cost benefits of green bond financing in the Chinese market. Banks acting as intermediaries in providing credit financing bear operational costs, such as reviewing loan applications and administering loans. These costs are transferred to the borrower in the form of higher interest rates, which is not the case in the bond market where these costs are comparatively low. Further, due to the eco-friendly features, enterprises may issue green bonds at a lower cost than traditional bonds and easily access preferential policies like tax benefits (Tang and Zhang, 2020). This has enhanced the appeal of GBI. Lastly, the signalling effect of green bonds may help issuers mitigate information asymmetry and further reduce financing costs (Flammer, 2021). Given their clearly defined fund usage, enterprises issuing green bonds may enjoy elevated social status and support from environmental advocates. This, in turn, creates a more conducive environment for the innovative activities (Tang and Zhang, 2020; Dong et al., 2021).

The literature posits that green bonds have emerged as an effective and significant regulation tool in environmental governance. Therefore, considering the potential positive influence exerted by GBI on the overall process of economic structural transformation, and its escalating importance in the Chinese market, this thesis seeks to empirically verify whether enterprises issuing green bonds can demonstrate superior GI performance under varied conditions. If so, what are the mechanisms through which GBI impacts GI activities? Concurrently, due to the positive publicity effect of GBI, this study further investigates whether GBI can incentivise peer enterprises to engage more intensively in GI activities.

Chapter 3: The Impact of Green Technology Innovation on Carbon Dioxide Emissions: The Role of Local Environmental Regulations

3.1. Introduction

It has been a global effort to counter climate change and achieve air quality improvements by reducing greenhouse gas emissions. The adoption of the Paris Agreement provides a durable framework guiding the global effort, under which the governments are being pressured to submit their intended Nationally determined contributions. Demographic, institutional and economic factors have long been seen as major attributes related to worldwide environmental degradation. As the world's second-largest economic entity holding one-fifth of the world's total population, China is also among the countries affected most severely by environmental degradation. In 2005, China's CO_2 emissions exceeded those of the US for the first time, making it the world's largest CO_2 emitter (Wang et al., 2017a). With the country's continued economic expansion, the cost of such high-pollution growth is increasing at an alarming pace. Therefore, the transition to a low-carbon economic development model is crucial for the country's sustained growth and CO_2 emissions reduction (Balsalobre-Lorente et al., 2018; Zhou et al., 2019b).

This chapter is motivated by a growing body of literature on drivers of carbon emissions reduction (Mongo et al., 2021). Green technology innovation (GTI) has been recognised as an important driver of environmental quality improvement via reduced energy intensity, improved production process efficiency, and increased sustainable and environmentally friendly products and services (Cheng et al., 2021). The green process innovation (GPI) and green knowledge innovation (GKI) are commonly adopted by enterprises in achieving emissions reduction targets over different time horizons (Zhang et al., 2017b; Wang et al., 2021). However, as suggested by the resource-based view, enterprises would only conduct GTI if it enables them to gain competitive advantages (Hart and Dowell, 2011). This has therefore called for effective and enforceable mechanisms, like government regulations, to direct enterprises' behaviour. Despite the potential compliance costs incurred by enterprises, Porter (1991) argues that the flexible environmental regulations can, in fact, promote the environmental benefits of innovation effectively. It helps enterprises save discharge fees or additional tax payments in case of noncompliance and assists them to gain government green subsidies (Peng, 2020).

In line with this belief, the Chinese government also initiated a series of environmental policies, including the command-and-control environmental regulation (CER) (e.g. *Atmospheric Pollution Prevention and Control Law (2015 Revision)*) and the market-based environmental regulation (MER) (e.g. *Emission Trading Markets Pilots Policy (2007)*, *Guidelines for Green Credit issued by the China Banking Regulatory Commission (2012)*, and *Guiding Opinions on Further Promoting Compensable Use and Pilot Tests of Emissions Trading (2014)*). Meanwhile, the government also increased its environmental pollution treatment investments by over 600 billion yuan over the ten-year period to 2017.[17] As a result, compared with polluters, cleaner enterprises with successful GTI tend to be more sustainable.

Furthermore, several scholars emphasise the potential impact of foreign direct investment (FDI) on green technology adoption and carbon emissions (Yu et al., 2021). They argue that FDI can enhance green innovation capabilities through knowledge spillover and the transfer of low-emissions technologies (Yu et al., 2021). However, as the primary target for foreign enterprises is rent seeking but not green development, the expected green benefits are hardly achievable, not to say that enterprises from developed countries may use this opportunity to transfer their highly polluted operations to bypass regulatory control (Luo et al., 2021; Shahbaz et al., 2018).

[17] Data is collected from China Statistical Yearbook 2019.

Additionally, studies also suggest that enterprises could be pressurised to become greener through educating the society (Chen et al., 2021a). With increased public awareness towards environmental protection, enterprises would be forced to invest more in green innovation to demonstrate their determination (Lee and Lee, 2022). However, such a strategy can be time-consuming, and the result is hard to be predicted. Last but not least, industrialisation is also identified to impact green technologies and CO_2 emissions but the rapid industrialisation in China has always been criticised for its lack of environmental considerations and limited green innovation (Wu et al., 2020; Lin and Ma, 2022). It has therefore been argued that unlike the environmental regulations which impose hard orders on enterprises' CO_2 emissions targets, the effects of FDI, public education, and industrialisation are largely contingent upon their effective interaction with environmental regulations (Tang et al., 2020). In other words, environmental regulations may create constraints as well as incentives that may shape the path of green technological development (Kleer, 2010). This has therefore made a thorough understanding of the transmission channel among environmental regulations, green innovation and emissions reduction more prominent.

As a result, this chapter provides empirical evidence for the Porter Hypothesis (PH) based on the sample of the world's biggest developing economy. In particular, the chapter aims to investigate how local environmental regulations moderate the relationship between green innovation and CO_2 emissions reduction in China. It is aware that enterprises react to different types of governmental regulations differently. Consequently, two types of environmental regulations are used, CER, the commend-based environmental regulations (e.g. programmatic guidance on environmental regulatory objectives), and MER, the market-based environmental regulations. The latter can be further categorised into expenditure- (EER) and investment-type environmental regulation (IER) based on their different impacts on enterprises' R&D capacity (Böhringer et al., 2012). EER may induce costs for enterprises to meet emissions targets, such as paying pollution discharge fees while IER may stimulate enterprises to make long-term investments to build up long-term competence in green innovation (Yuan, 2019; Tian and Feng, 2022). These different types of regulations would work together to shape enterprises' behaviours.

Therefore, it seems that the transition to a green economy cannot be achieved without innovation and the enforcement/motivation of appropriate policies. To test the above relationship empirically, this chapter employs a panel data of 30 Chinese provinces from 2003 to 2019 and applied a series of models including the fixed effect regression models, the system Generalized Method of Moments (SYS-GMM), and the difference-in-difference (DID) model. In particular, the following research questions are investigated: firstly, how are the three factors including environmental regulations, green innovation and CO_2 emissions reduction, acting on each other? Or in other word, what is the transmission mechanism among these three factors? Does tougher regulation guarantee additional green investments and whether these additional investments will lead to further CO_2 emissions reduction? Secondly, do different types of environmental regulations and green innovation have different impacts on the transmission mechanism? Thirdly, given different levels of economic development and environmental governance in different regions, are there regional heterogeneities?

The novelty of this chapter is reflected in the following three aspects. First, the results provide empirical evidence for the validation of the PH. More specifically, as the concepts of environmental protection, technology innovation, and CO_2 emissions reduction were initiated in Western countries, most discussions about the PH are based on the sample of developed economies. However, developing countries are the biggest contributors to newly generated emissions today. As the world's biggest developing country, China's development model has always been criticised and the country has tried hard to balance its economic growth and the resulting pollution over the past decade. The Chinese government has initiated policies to regulate enterprises' behaviours, on the one hand, while stimulating the innovation of greener technologies, on the other hand. Then, an interesting question is how the country is performing now after the implementation of all these policy initiates. If China's reform has been indeed successful, these ‘best practices’ can then be generalised to other emerging economies. This will help improve energy efficiency at the global level and assist more economies to achieve sustainable development.

Secondly, this chapter investigates how environmental regulations moderate the influence of GTI on CO_2 emissions. While most of the studies focusing on the relationship between environmental regulations and technology innovation or green innovation and emissions reduction, few research has linked all three together to investigate the transmission mechanisms in between. It is proved empirically that the market-based regulation tools work better and this should be pleased by the government as China is trying hard to transform into a market-based economy. To maximise the benefits of the market, the country should continue relying more on such market-based mechanisms in guiding and enforcing enterprise behaviours. Such an experience could also be shared with other developing countries to reduce red tapes and unnecessary resource wastes.

Last but not least, this chapter provides diverse explanations for the relationship between GTI and carbon emissions and also takes regional heterogeneity into consideration. Both the short-term (GPI) and long-term (GKI) environmental impacts of GTI are explored respectively to capture enterprises’ different innovation incentives. It is confirmed that different regulatory tools (CER, EER and IER) have different levels of enforcement power in shaping the path of green technological development. Meanwhile, the diversified economic development stage and demographical characteristics of different regions are also confirmed of capable of impacting the tested results. This chapter has therefore contributed to research on the heterogeneity effect of environmental regulations.

The rest of this chapter is organised as the following. Section 2 undertakes the literature review and develops the hypotheses. Section 3 describes the variables and methodology. Section 4 discusses the empirical results. Finally, Section 5 presents the conclusions of this chapter.

3.2. Literature Review and Hypothesis Development

3.2.1. Green Technological Innovation and Carbon Emissions

In recent decades, a growing body of literature has examined the drivers of carbon emissions reduction. The natural resource-based view suggests that GTI can be a valuable enterprise resource for establishing the competitive advantage and beneficial for the natural environment (Hart and Dowell, 2011). This is verified by recent studies on the role of green innovation in facilitating the relationship between high-quality economic development and environmental sustainability across different countries and regions (Ganda, 2019; Shao et al., 2021). Ganda (2019) shows that expenditure on R&D reduces CO_2 emissions. Shao et al. (2021) find GTI and renewable energy can help mitigate the consumption base CO_2 emissions in N-11 countries in the long rather than the short run.

However, evidence on the impact of green technological innovation and carbon emissions is also mixed. As suggested by Rennings and Rammer (2011), the market itself may not be able to effectively promote GTI. Enterprises may need sufficient incentives or penalties to increase their willingness to engage in green innovation. This reiterates the important role played by government regulations. Further, Mongo et al. (2021) find that there is an indirect 'rebound effect' of green technological innovation: as the green innovation improves, both the output and energy consumption levels increase.

3.2.2. Green Technological Innovation, Environmental Regulations, and Carbon Emissions

The seminal works of Porter (1991) and Porter and Van Der Linde (1995) suggest that stringent but properly designed environmental regulations may stimulate green innovation that could offset compliance costs and enhance enterprises' productivity. This can create a win-win situation that enables the enterprise to increase profitability and simultaneously achieve emissions reduction targets.[18] The PH provides a new dynamic perspective to understand the impact of environmental regulations on enterprises' innovation behaviour and its subsequent impacts on emissions reduction. Since then, a number of studies were conducted to test the hypothesis empirically. Specifically, Studies based on neoclassical economics hold that environmental regulations induce higher costs such as pollution charges, and divert valuable capital from promising innovative projects to ones that concentrate on emissions reduction only (Xie et al., 2017; Wei et al., 2022). The 'compensation effect' view suggests that under a well-functioning environmental regulation system, the benefits from the environmental efficiency of resource utilisation can exceed the offset effect caused by the internalisation of environmental costs (Luo et al., 2021). Using data on manufacturing sectors of 17 European countries, Rubashkina et al. (2015) find a positive relationship between the environmental regulation and innovation outputs. Others show that such technological progress can improve green competitiveness in the long run and strengthen the innovation performance of enterprises (Wen et al., 2021). Shao et al. (2021) show the importance of implementing environmental regulations, such as carbon pricing or taxation policies, for countries that highly rely on imported non-renewable energy sources for consumption demand.

As aforementioned, GTI may have an indirect and uncertain impact on carbon emissions (Lin and Ma, 2022). Environmental regulations are designed to deal with the negative externalities of environmental degradation, which can justify regulatory intervention and promote the effectiveness of technological innovation. Given the uncertain nature of innovation activities and the substantial capital investments required,

[18] For example, when an enterprise achieves the technological innovation that meets the requirements of environmental regulations, it can apply for patent protection. Under the context of strict environmental regulations, this behaviour can encourage other enterprises to purchase its innovation, which will bring high profits to the enterprise (Porter, 1991).

it is argued that appropriate regulations are needed to incentivise or force enterprises to invest continuously in innovation to reduce CO_2 emissions (Xie et al., 2019b). Therefore, this chapter proposes the following hypothesis:

Hypothesis 1a. *Environmental regulation positively moderates the impact of GTI on CO_2 emissions reduction.*

As for GPI, previous studies suggest that it could be further divided into two categories: GPI and GKI. The former generally focuses on optimising the production process to reduce energy consumption (Song et al., 2020), while the latter refers to the eco-innovation-related knowledge capital endowment, such as the production of green patents (Zhang et al., 2017b; Wang and Zhu, 2020). The two types of green innovation have their respective focus on prompting sustainable development. With limited supplementary inputs, GPI focuses on transforming the process to reduce emissions and is used as a 'shortcut' by enterprises to bypass potential punishments (Liu et al., 2020a). Meanwhile, GKI is acting as an internal driving force for green innovation activities as it may provide the knowledge and technological foundations for such activities. Therefore, the adoption of GKI could be said of creating a 'dual externality', improving knowledge spillover on one hand, while inspiring other types of green innovation activities on the other (Wang and Li, 2022).

Therefore, compared with GPI, GKI represents an advanced innovation which requires more capital and time inputs but also has the potential to generate more sustained long-term positive impacts related to environmental protection. Under the pressure from environmental regulations, enterprises are likely to make discretionary decisions based on their own conditions, exhibiting heterogeneous self-selection behaviours of technological innovation modes. To consider the heterogeneity of these two types of innovation, this chapter proposes the following hypotheses:

Hypothesis 1b. *Environmental regulation positively moderates the impact of GPI on*

CO_2 emissions reduction.

Hypothesis 1c. *Environmental regulation positively moderates the impact of GKI on CO2 emissions reduction.*

3.2.3. Green Innovation and Carbon Emissions: Different Types of Environmental Policy Instruments

Environmental policy instruments can be categorised into different types, such as CER, EER, and IER. Iraldo et al. (2011) show that the type of environmental regulations may be as important as its stringency in determining the nature of its relationship with economic performance. Thus, while evaluating the impact of environmental policy instruments on green innovation, different types of policy tools and the diversified institutional background is considered accordingly (Frondel et al., 2008).

CER is the government regulation which regulates both the amount and process by which enterprises should comply with. This regulation affects a wide range of aspects (Tian and Feng, 2022), including market access, product standards, product bans, and technology knowledge dissemination, etc. As environmental protection and emissions reduction are generally long-term oriented, the ultimate goal of CER is to help enterprises develop effective long-term emissions reduction technologies (Li et al., 2019). Therefore, one may expect that under regulatory requirements, enterprises are more likely to develop advanced green innovation to achieve both financial benefits and environmental benefits. Therefore, this chapter proposes the following hypotheses:

Hypothesis 2a. *CER does not positively moderate the impact of GPI on CO_2 emissions reduction.*

Hypothesis 2b. *CER positively moderates the impact of GKI on CO_2 emissions reduction.*

In many cases, excessive emissions are punishable by the discharge fee. Through the introduction of the discharge fee system, EER seeks to change enterprises' behaviour by imposing charges for non-compliance. When investments in technology innovation exceed the costs of paying the discharge fee, enterprises will have little incentive to innovate, and vice versa (Sun et al., 2021). In China, this situation has become even more complicated due to the deficiencies of the discharge fee system (Shen et al., 2020). Considering the flaws of EER and investments needed for green innovation, this chapter proposes the following hypotheses:

Hypothesis 3a. *EER does not positively moderate the impact of GPI on CO_2 emissions reduction.*

Hypothesis 3b. *EER does not positively moderate the impact of GKI on CO_2 emissions reduction.*

IER aims to promote green innovation and environmental performance by reallocating financial resources and influencing the enterprises' financing costs (Zhang, 2021). Unlike EER which may trigger enterprises to adopt countermeasures to bypass financial punishments, IER is expected to incentivise enterprises to develop green technologies, such as encouraging credit for green business. Therefore, this type of market-based mechanism strengthens the legitimate motives of enterprises to promote green technologies for more sustained growth, and hence, generate a larger positive impact on the whole society (Sun et al., 2021). To attract more sustainable green investments, compared with GPI, enterprises are more likely to develop relatively advanced GKI to build a competitive advantage and gain higher market status. Therefore, this chapter proposes the following hypotheses:

Hypothesis 4a. *IER does not positively moderate the impact of GPI on CO_2 emissions reduction.*

Hypothesis 4b. *IER positively moderates the impact of GKI on CO_2 emissions reduction.*

3.3. Methodology and Variables

3.3.1. Data and Variables

This chapter adopts panel data of 30 Chinese provinces and municipalities (except Tibet and Hong Kong, Macao, and Taiwan due to lack of comparability) over the period 2003–2019 with a total of 510 observations. This thesis selects 2019 as the endpoint for the sample period, primarily to mitigate the impacts of the COVID-19 pandemic. Firstly, the pandemic delivered a substantial shock to the global economy, including China's, and utilising data from 2020 onwards might introduce bias into the empirical results due to this external impact. Secondly, in response to the pandemic, China, along with many other countries, implemented respective lockdown measures and fiscal stimulus policies. These policies influenced the economic behaviours of firms and individuals, potentially rendering the economic data during the pandemic incomparable to preceding data. For these reasons, 2019 has been established as the cut-off point for the sample period.

As described in Table 1, the data used are collected from various sources. For the dependent variable, following Zhao et al. (2022), this chapter uses CO_2 emissions (CE) as the dependent variable and calculates it as the logarithm of annual CO_2 emissions (LnCE) for each province. Figure 3.1 displays the CO_2 emissions of various regions in China. It shows that total carbon emissions have been rising consistently across all regions, with the eastern region exhibiting the highest increase.

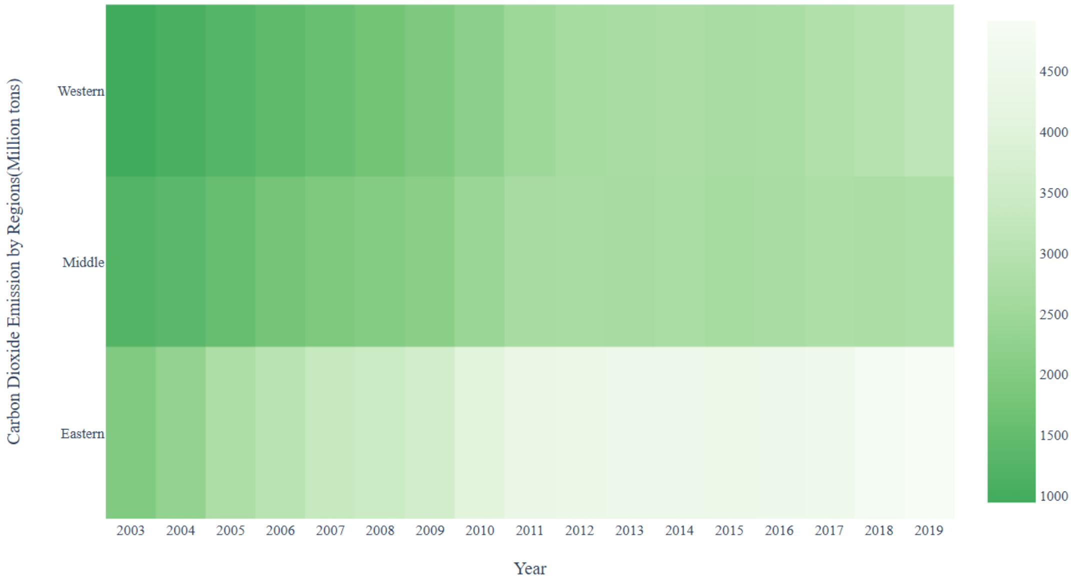


Figure 3.1 The CO_2 emissions of different regions in China, by year

Note: This figure shows CO_2 emissions of different regions in China from 2003 to 2019. For each region, the CO_2 emissions of each year is the sum of provinces located in this region.

Following Böhringer et al. (2012) and Tian and Feng (2022), this chapter considers two types of regulations: CER and MER, with MER is further divided into EER and IER. CER entails stringent regulations imposed by the government that all manufacturers must adhere to. This tool can influence environmental laws across an array of fields, including market access, product standards, product bans, and technology knowledge dissemination (Shen et al., 2020). Since environmental protection and emission reduction are generally oriented towards long-term goals, CER ultimately aims to compel enterprises to adopt effective measures to achieve long-term sustainable emission reduction targets (Huang and Zhai, 2021). In the context of EER, this tool anticipates modifying enterprises' behaviour by imposing higher charges for non-compliance. Consequently, when investments in technological innovation surpass the costs of discharge fees, enterprises may find little incentive to innovate, and vice versa (Sun et al., 2021). In China, the situation has grown increasingly complex due to deficiencies in the discharge fee system, such as limited levy scope and low standard requirements (Shen et al., 2020). Regarding IER, its aim is to foster green innovation and environmental performance by providing investment and influencing enterprises' financing and operational processes (Zhang, 2021). IER is expected to incentivise enterprises to develop green technologies for emissions reduction and to reap the benefits from green investment over an extended period. Thus, this tool is anticipated to provide a significantly stronger incentive for enterprises to promote green technologies for more sustained growth, thereby generating a substantially broader positive impact on society as a whole (Sun et al., 2021).

In prior studies, CER is mainly measured by the number of environmental protection personnel, enactment of environmental protection regulations, or promulgation of environmental protection legislation. However, these indicators fail to provide a comprehensive measurement of the strength of different types of CERs. Instead, the provincial government work report may be a better proxy (Chen and Chen, 2018). The report is more like a programmatic document, that guides the government's work in all aspects including environmental laws, market access, technology innovation, etc. As a result, the frequency of environment-related words used in such report could be considered as a good proxy to capture the overall picture of the government's attitude towards environmental protection. Hence, following the study of Chen and Chen (2018), this chapter uses the ratio of environmental-related word frequency to total word frequency in government reports as the measure of CER.

As for EER, a cost measure, it is generally measured by payment for discharge fee (Tian and Feng, 2022). Therefore, for a region, it can be calculated as the ratio of pollutant discharge fees to the total GDP of that region (Luo et al., 2021).

IER can be proxied by the green credit level (Böhringer et al., 2012), as it represents the volume of financial resources and investments flowing into non-heavy polluting enterprises (Zhang et al., 2021a). It can also be interpreted as a market signal which guides more investments towards environmentally friendly industries and promotes the rapid advancements of green technologies (Zhang et al., 2021a). To estimate the scale of green credit, the level of interest expenses is chosen as a good proxy (Hu et al., 2020b). Numerically, IER is calculated as the ratio of interest expense of non-six high energy-consuming industries to the total industrial interest expense of a region.

Regarding the overall intensity of environmental regulation, this chapter adopts the Entropy-TOPSIS method to estimate the ER variable. A larger value of Entropy-TOPSIS index represents stricter environmental regulation (Lin and Zhou, 2022).

Figure 3.2 shows the evolution of the environmental regulation intensity over the sample period. Interestingly, the regulations have become stringent on average over time, with the only exception of EER. Furthermore, as shown in Graph 3.1, mapping environmental regulation indicators for different provinces reveals the regional variation in environmental regulation intensity. For the eastern and southern regions, they tend to have stronger environmental regulations, showing the role of regional economic development level played in enforcing environmental regulations.

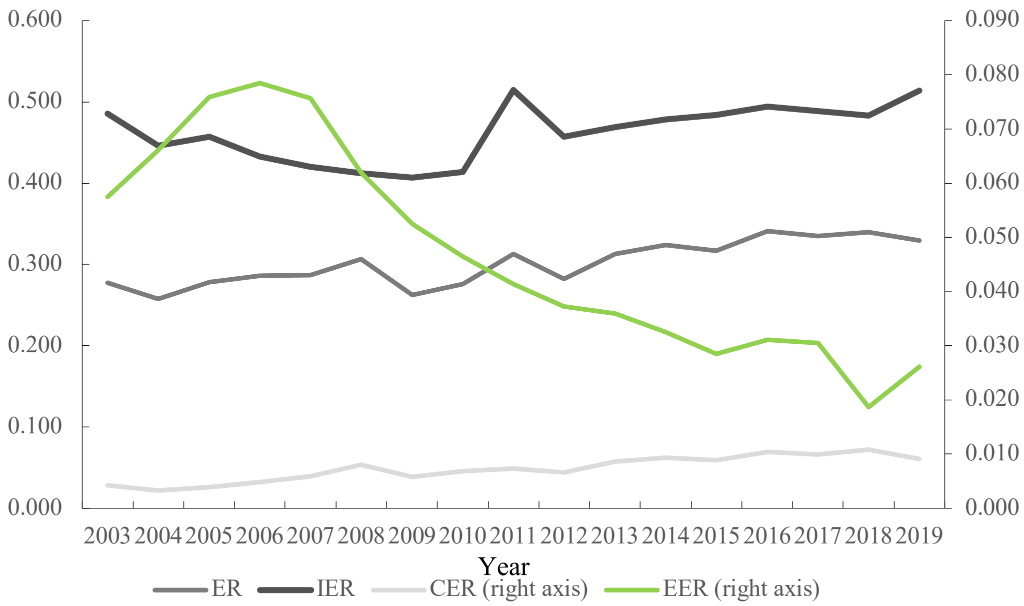
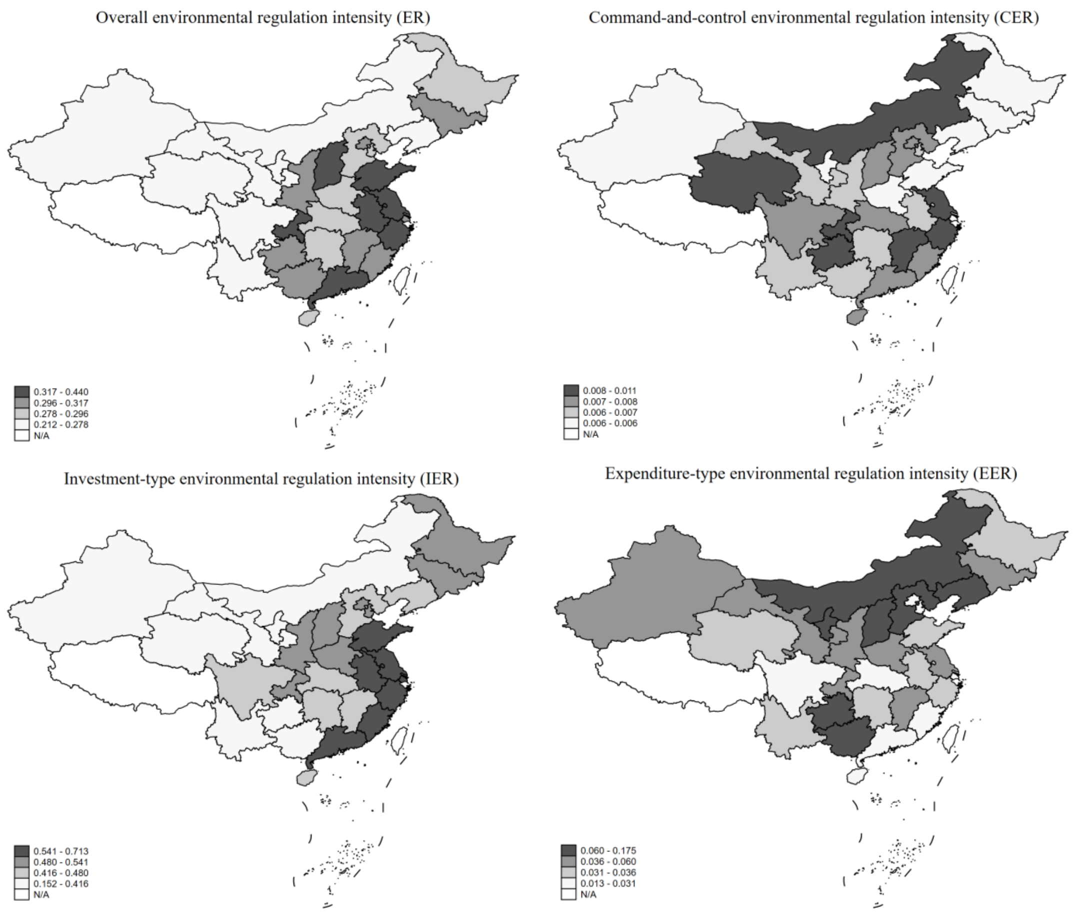


Figure 3.2 The average intensity of environmental policy instruments in China, by year

Note: This figure shows the average intensity of the four proxies for environmental regulations (ER, CER, EER and IER) in China from 2003 to 2019. The average intensity of ER and IER is show in the left axis, and the average intensity of CER and EER is show in the right axis.



Graph 3.1 The average intensity of environmental policy instruments in China, by province

Note: This graph depicts the average intensity of the four proxies for environmental regulations (ER, CER, EER and IER) for different provinces in China. For each province, the average intensity of each proxy is calculated as its simple average value across the sample period.

For GTI, this chapter also classifies it into two categories, GPI and GKI. The former is measured as the ratio of technical transformation investment to the total industrial output value added of a region (Feng and Chen, 2018). While for GKI, following Zhang et al. (2017b), it is proxied by the logarithm of the total green patent count. For GTI, it is measured by the Entropy-TOPSIS method.

This chapter also includes the following control variables in the benchmark analysis: (1) Foreign direct investment (FDI) measured by the ratio of FDI to GDP in a province (Chen et al., 2021a); (2) Rate of industrialisation (INDR) calculated by the ratio of industrial value-added to regional GDP (Wang et al., 2017b); (3) Education level (EDU) measured by $EDU_i = p_{i1} \times 6 + p_{i2} \times 9 + p_{i3} \times 12 + p_{i4} \times 16$, where p_{i1}, p_{i2}, p_{i3}, and p_{i4} denote the ratio of employees in province i graduated from primary school, junior high school, senior high school, and university or above, respectively, weighted by corresponding schooling years (Xie et al., 2017); and (4) Population (POP) estimated by the logarithmic value of the total regional population at the end of the year (Peng, 2020).

Different economic development levels may also lead to regional heterogeneity in the relationships between environmental regulations, technology innovation, and emissions reduction capacities (Frondel et al., 2008; Iraldo et al., 2011). To consider this regional heterogeneity in China, this chapter classifies China's 30 provincial regions into two groups, the Eastern and other less developed regions, according to the classification criteria of the National Bureau of Statistics.[19]

Table 3.1 summarises the key variables. All price variables are adjusted by the price level of 2003. Table 3.2 reports the correlation matrix between variables. Pairwise correlations are calculated by the covariance between the pairwise variable scaled by the standard deviations of the two variables (Bofinger et al., 2022). Notably, most variables can significantly impact CO_2 emission, suggesting the appropriateness of variable selection.

[19] The economically more advanced eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; and relatively less developed other regions includes the middle (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan) and western regions (Inner Mongolia, Chongqing, Sichuan, Guizhou, Yunnan, Guangxi, Tibet, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang) regions. http://www.stats.gov.cn/tjsj/zxfb/201701/t20170120_1455967.html

Table 3.1 Descriptive Statistics of Variables

Type	Variables	Explanation	Obs.	Mean	Std. Dev.	Min	Max	Data Source
Dependent Variable	LnCE	Logarithm of CO_2 Emissions	510	9.96	0.80	7.351	11.448	A, F
Independent Variables	ER	Environmental Regulation	510	0.30	0.06	0.129	0.648	B, C, D, E, K
	CER	Command-and-control Environmental Regulation	510	0.01	0.00	0.000	0.018	K
	EER	Expenditure-type Environmental Regulation	510	0.05	0.04	0.002	0.460	B, D, E, G
	IER	Investment-type Environmental Regulation	510	0.46	0.14	0.094	0.808	C
	GTI	Green Technology Innovation	510	0.26	0.12	0.037	0.891	B, C, G, I
	GPI	Green Process Innovation	510	2.33	1.81	0.111	11.641	B, C
	GKI	Green Knowledge Innovation	510	7.01	1.70	1.386	10.934	I
Control Variables	FDI	Foreign Direct Investment	510	0.42	0.50	0.048	5.705	A, H, J
	INDR	Rate of Industrialisation	510	0.38	0.09	0.111	0.592	A, C
	EDU	Education Level	510	2.16	0.11	1.798	2.548	A, H
	POP	Population	510	8.17	0.75	6.280	9.352	A, H

Note: The data come from different statistical yearbooks and databases; abbreviations are as follows: A: China Statistical Yearbook; B: China Environmental Yearbook; C: China Industry Statistical Yearbook; D: China Taxation Yearbook; E: China City Statistical Yearbook; F: Carbon Emission Accounts & Datasets for emerging economies; G: China Statistical Yearbook of Environment; H: Easy Professional Superior; I: Chinese Research Data Services; J: China Trade and External Economic Statistical Yearbook; and K: Report on the Work of the Government for each region.

Table 3.2 Pearson Correlation Coefficients

Variables	LNCE	ER	CER	EER	IER	GTI	GPI	GKI	FDI	INDR	EDU	POP
LNCE	1											
ER	0.324***	1										
CER	0.175***	0.536***	1									
EER	-0.00900	0.297***	-0.247***	1								
IER	0.349***	0.555***	-0.0210	-0.228***	1							
GTI	0.0120	-0.000	-0.311***	0.380***	-0.00700	1						
GPI	-0.148***	-0.131***	-0.424***	0.459***	-0.147***	0.958***	1					
GKI	0.638***	0.432***	0.438***	-0.436***	0.557***	-0.140***	-0.387***	1				
FDI	-0.229***	0.080*	-0.0650	-0.184***	0.299***	-0.082*	-0.093**	0.107**	1			
INDR	0.466***	0.108**	-0.136***	0.234***	0.117***	0.0320	0.0550	0.0140	-0.202***	1		
EDU	0.228***	0.334***	0.256***	-0.307***	0.467***	-0.207***	-0.354***	0.632***	0.344***	-0.196***	1	
POP	0.757***	0.191***	-0.0200	-0.0690	0.389***	0.145***	0.00800	0.525***	-0.205***	0.356***	-0.0680	1

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.3.2. Regression Models

First, the panel fixed-effect model is applied to test the moderating effects of environmental regulations on GTI and CO_2 emissions. Then, considering the spatial impact of CO_2 emissions, Spatial Durbin Model (SDM) is employed for the robustness test. Lastly, to mitigate endogenous problems and investigate the validity of results obtained using alternative measurements, the system generalised method of moments (SYS-GMM) and the Difference-in-Difference (DID) model are applied, respectively.

3.3.2.1. The Two-way Fixed-effect Model

The two-way fixed-effect model is applied to estimate the moderating effect of environmental regulations on green innovation and CO_2 emissions reduction. This model is represented by the following equations (1)–(6).

$$LnCE_{i,t} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 GTI_{i,t} + \beta_3 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (1)$$

$$LnCE_{i,t} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 GTI_{i,t} + \beta_3 ER_{i,t} \times GTI_{i,t} + \beta_4 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (2)$$

$$LnCE_{i,t} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 GPI_{i,t} + \beta_3 GKI_{i,t} + \beta_4 ER_{i,t} \times GPI_{i,t} + \beta_5 ER_{i,t} \times GKI_{i,t} + \beta_6 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (3)$$

$$LnCE_{i,t} = \beta_0 + \beta_1 CER_{i,t} + \beta_2 EER_{i,t} + \beta_3 IER_{i,t} + \beta_4 GPI_{i,t} + +\beta_5 GKI_{i,t} + \beta_6 ERs_{i,t} \times GPI_{i,t} + \beta_7 ERs_{i,t} \times GKI_{i,t} + \beta_8 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (4\text{-}6)$$

i and t refer to the province and year, respectively. $LnCE_{i,t}$ measures the CO_2 emissions. $ER_{i,t}$ represents ER, $CER_{i,t}$ represents CER, $EER_{i,t}$ represents EER, and $IER_{i,t}$ represents IER. $ERs_{i,t}$ represents CER (equation (4)) or EER (equation (5)) or IER (equation (6)). $GTI_{i,t}$ represents GTI, $GPI_{i,t}$ represents GPI, and $GKI_{i,t}$ represents GKI.

To investigate the moderating effect, a series of mean-centred interaction terms of environmental regulations and green innovation are constructed (Hasan et al., 2018). A negative coefficient of the interaction term represents a positive moderating effect of environmental regulations on the relationship between green innovation and CO_2 emissions reduction, and vice versa (Wu et al., 2020). Here, $ER \times GTI_{i,t}$ represents the interaction term of environmental regulation and GTI of province i in year t. $ERs \times GPI_{i,t}$ ($CER \times GPI_{i,t}$ or $EER \times GPI_{i,t}$ or $IER \times GPI_{i,t}$) and $ERs \times GKI_{i,t}$ ($CER \times GKI_{i,t}$ or $EER \times GKI_{i,t}$ or $IER \times GKI_{i,t}$) represents the cross-terms between the respective types of environmental regulations and green innovation. $X_{i,t}$ is the vector for control variables, including FDI, INDR, EDU, and POP. u_i and v_t refer to the individual and time fixed-effects, respectively, and $\varepsilon_{i,t}$ represents the random error.

3.3.2.2. Spatial Durbin Model

Besides the direct influence of environmental regulations, Wang and Zhu (2020) argue that the emissions reduction of one region can be affected by policies applied in its neighbouring regions as well. A closer geographical location tends to be associated with a stronger relationship. To verify the potential spatial impact of adjacent geographical regions, the Moran's I index is calculated for the following application of the spatial autocorrelation test (Peng, 2020).[20]

Then this chapter adopts the spatial econometric model, which incorporates the spatially autoregressive process in the regression equation, to investigate the relationship between environmental regulations, GTI, and CO_2 emissions (Jia et al., 2021). Among the three types of commonly used spatial models, the Spatial

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[20] Moran's I index is calculated based on the following function: $Moran's\ \mathrm{I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i-\bar{X})(X_j-\bar{X})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij})\sum_{i}^{n}(X_i-\bar{X})^2}$.
Where X_i and X_j are the spatial data of region i and j, respectively. W_{ij} is the spatial weight matrix. The Moran's I index generally takes the value of [-1,1].

Autoregressive Model (SAR), the Spatial Error Model (SEM), and SDM, the last one is considered to be a more general form as it can be transformed into SAR and SEM under certain conditions (Jia et al., 2021). Therefore, SDM is employed in the chapter and can be illustrated by the following equations (7)–(12):

$$LnCE_{i,t} = \rho \sum_{j=1}^{N} W_{i,j} LnCE_{j,t} + \beta_1 ER_{i,t} + \varphi_1 \sum_{j=1}^{N} W_{i,j} ER_{j,t} + \beta_2 GTI_{i,t} + \varphi_2 \sum_{j=1}^{N} W_{i,j} GTI_{j,t} + \beta_3 X_{i,t} + \varphi_3 \sum_{j=1}^{N} W_{i,j} X_{j,t} + u_i + \nu_t + \varepsilon_{i,t} \quad (7)$$

$$LnCE_{i,t} = \rho \sum_{j=1}^{N} W_{i,j} LnCE_{j,t} + \beta_1 ER_{i,t} + \varphi_1 \sum_{j=1}^{N} W_{i,j} ER_{j,t} + \beta_2 GTI_{i,t} + \varphi_2 \sum_{j=1}^{N} W_{i,j} GTI_{j,t} + \beta_3 ER_{i,t} \times GTI_{i,t} + \varphi_3 \sum_{j=1}^{N} W_{i,j} ER_{i,t} \times GTI_{i,t} + \beta_4 X_{i,t} + \varphi_4 \sum_{j=1}^{N} W_{i,j} X_{j,t} + u_i + \nu_t + \varepsilon_{i,t} \quad (8)$$

$$LnCE_{i,t} = \rho \sum_{j=1}^{N} W_{i,j} LnCE_{j,t} + \beta_1 ER_{i,t} + \varphi_1 \sum_{j=1}^{N} W_{i,j} ER_{j,t} + \beta_2 GPI_{i,t} + \varphi_2 \sum_{j=1}^{N} W_{i,j} GPI_{j,t} + \beta_3 GKI_{i,t} + \varphi_3 \sum_{j=1}^{N} W_{i,j} GKI_{j,t} + \beta_4 ER_{i,t} \times GPI_{i,t} + \varphi_4 \sum_{j=1}^{N} W_{i,j} ER_{i,t} \times GPI_{i,t} + \beta_5 ER_{i,t} \times GKI_{i,t} + \varphi_5 \sum_{j=1}^{N} W_{i,j} ER_{i,t} \times GKI_{i,t} + \beta_6 X_{i,t} + \varphi_6 \sum_{j=1}^{N} W_{i,j} X_{j,t} + u_i + \nu_t + \varepsilon_{i,t} \quad (9)$$

$$LnCE_{i,t} = \rho \sum_{j=1}^{N} W_{i,j} LnCE_{j,t} + \beta_1 CER_{i,t} + \varphi_1 \sum_{j=1}^{N} W_{i,j} CER_{j,t} + \beta_2 EER_{i,t} + \varphi_2 \sum_{j=1}^{N} W_{i,j} EER_{j,t} + \beta_3 IER_{i,t} + \varphi_3 \sum_{j=1}^{N} W_{i,j} IER_{j,t} + \beta_4 GPI_{i,t} + \varphi_4 \sum_{j=1}^{N} W_{i,j} GPI_{j,t} + \beta_5 GKI_{i,t} + \varphi_5 \sum_{j=1}^{N} W_{i,j} GKI_{j,t} + \beta_6 ERs_{i,t} \times GPI_{i,t} + \varphi_6 \sum_{j=1}^{N} W_{i,j} ERs_{i,t} \times GPI_{i,t} + \beta_7 ERs_{i,t} \times GKI_{i,t} + \varphi_7 \sum_{j=1}^{N} W_{i,j} ERs_{i,t} \times GKI_{i,t} + \beta_8 X_{i,t} + \varphi_8 \sum_{j=1}^{N} W_{i,j} X_{j,t} + u_i + \nu_t + \varepsilon_{i,t} \quad (10\text{-}12)$$

Where $W_{i,j}$ represents the spatial weight matrix. Following Zhang et al. (2017a), the adjacent weight matrix for China's 30 provincial administrative regions is constructed as follows:

$$W_{ij} = \begin{cases} 1 \; if \; provinces \; i \; and \; j \; are \; adiacent \\ 0 \; if \; provinces \; i \; and \; j \; are \; not \; adjacent \end{cases} \quad (13)$$

3.3.2.3. The System Generalised Method of Moments

Considering the issue of endogeneity, the SYS-GMM model is applied for the robustness test. It overcomes the estimation problem in single-equation and ordinary panel regressions and suits well for the dynamic panel data model as it not only avoids the autocorrelation problem, but also considers the impact of the explained variable lag on the current period. In the estimation process, the different transformation method is employed to eliminate the individual heterogeneity that does not change over time. This combines differential and horizontal GMM estimation methods to improve the efficiency of parameter estimation. The general form of the SYS-GMM model is expressed as follows:

$$LnCE_{i,t} = \beta_0 + \beta_1 LnCE_{i,t-1} + \beta_2 ER_{i,t} + \beta_3 GTI_{i,t} + \beta_4 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (14)$$

$$LnCE_{i,t} = \beta_0 + \beta_1 LnCE_{i,t-1} + \beta_2 ER_{i,t} + \beta_3 GTI_{i,t} + \beta_4 ER_{i,t} \times GTI_{i,t} + \beta_5 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (15)$$

$$LnCE_{i,t} = \beta_0 + \beta_1 LnCE_{i,t-1} + \beta_2 ER_{i,t} + \beta_3 GPI_{i,t} + \beta_4 GKI_{i,t} + \beta_5 ER_{i,t} \times GPI_{i,t} + \beta_6 ER_{i,t} \times GKI_{i,t} + \beta_7 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (16)$$

$$LnCE_{i,t} = \beta_0 + \beta_1 LnCE_{i,t-1} + \beta_2 CER_{i,t} + \beta_3 EER_{i,t} + \beta_4 IER_{i,t} + \beta_5 GPI_{i,t} + +\beta_6 GKI_{i,t} + \beta_7 ERs_{i,t} \times GPI_{i,t} + \beta_8 ERs_{i,t} \times GKI_{i,t} + \beta_9 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (17\text{-}19)$$

Where β_1 is a hysteresis multiplier capturing the effect of the previous period's CO_2 emissions reduction, $LnCE_{i,t-1}$, which is the lagged variable of $LnCE_{i,t}$. The meaning of other parameters is the same as those in equations (1)–(6).

3.4. Empirical Results

3.4.1. Benchmark Model Regression Results

This chapter reports the benchmark regression results in Table 3.3. Columns (1) and (2) report the moderating effect of environmental regulation and its interaction term, respectively, on GTI and CO_2 emissions. Meanwhile, columns (3)–(6) report the results for different types of environmental regulations and GTI.

Table 3.3 Regression Results for the Benchmark Model

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
ER	-0.219 (-0.84)	-0.119 (-0.44)	-0.605** (-2.39)			
CER				0.875 (0.19)	1.442 (0.45)	2.087 (0.63)
EER				-0.199 (-0.77)	1.430 (1.54)	-0.171 (-0.54)
IER				-0.332** (-2.60)	-0.460*** (-3.15)	-0.408** (-2.72)
GTI	0.010 (0.09)	-0.016 (-0.15)				
GPI			-0.006 (-1.06)	-0.005 (-0.98)	-0.000 (-0.05)	-0.004 (-0.86)
GKI			0.130*** (3.30)	0.117*** (2.92)	0.119*** (2.85)	0.114*** (2.93)
ER*GTI		-1.985 (-1.52)				
ER*GPI			-0.130* (-1.73)			
ER*GKI			-0.428*** (-2.84)			
CER*GPI				-0.273 (-0.12)		
CER*GKI				-8.887** (-2.68)		
EER*GPI					0.184 (1.35)	
EER*GKI					1.202*** (2.90)	
IER*GPI						-0.066 (-1.64)
IER*GKI						-0.193** (-2.68)
FDI	-0.037* (-1.72)	-0.038* (-1.72)	-0.028* (-1.97)	-0.045*** (-3.07)	-0.034* (-1.88)	-0.017 (-1.02)
INDR	0.815*** (3.81)	0.827*** (3.86)	0.592** (2.46)	0.534** (2.19)	0.605** (2.14)	0.606** (2.32)
EDU	0.060 (0.10)	0.041 (0.07)	-0.271 (-0.52)	-0.176 (-0.35)	-0.258 (-0.49)	-0.355 (-0.65)
POP	-0.503 (-0.96)	-0.525 (-1.00)	-0.289 (-0.63)	-0.275 (-0.61)	-0.264 (-0.58)	-0.209 (-0.44)
R-squared	0.857	0.858	0.879	0.884	0.887	0.880
Observations	510	510	510	510	510	510
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Column 1 shows that neither ER, GTI, nor their interaction term have significant effects on carbon emissions. Thus, hypothesis 1a is not supported. Meanwhile, when this chapter considers the heterogeneity of green innovation, the interaction terms of environmental regulations with both GKI and GPI significantly negatively affect carbon emissions. Thus, hypotheses 1b and 1c are supported. Notably, the interaction term for GKI is much stronger than that for GPI. This indicates that enterprises may be more willing to invest their limited capital into more advanced and sustainable innovation (GKI) to reduce CO_2 emissions. Similarly, Yuan (2019) finds that different types of environmental regulations may have a synergistic effect on innovation and emissions reduction. For instance, the two types of regulations considered by Yuan (2019)–CER and MER–can be complementary to each other, enabling enterprises to respond flexibly and cost-efficiently to promote advanced green innovation and achieve emissions reduction targets. This chapter also observes this synergistic effect in the benchmark model, as ER positively moderates the impact of GPI and GKI on CO_2 emissions reduction. However, this result is contrary to Du et al.'s (2019) finding that green innovation can only help enterprises in developed economies to reduce CO_2 emissions. Thus, the experience of China offers valuable insights for less developed economies, especially in terms of environmental regulation design and green technology advancement.

Regarding different types of environmental regulations, CER has no (a significant positive) moderating effect on the relationship between GPI (GKI) and CO_2 emissions reduction. These results support hypotheses 2a and 2b. This may be because although GPI may assist enterprises in meeting government environmental regulations over the short term, tougher regulations may have forced enterprises to undertake more advanced green investments in the form of GKI to build up emissions reduction capacity over the longer term. This finding aligns with prior literature, which highlights that enterprises are more inclined to foster more efficient and advanced green innovation to secure a sustained competitive advantage (Shen et al., 2020). Although earlier studies also find a negative impact of CER on technology development and pollution mitigation (Li et al., 2019), this may be primarily due to the proxy chosen to measure CER. As environmental fine is selected by most of the earlier studies, it is not surprising that it impairs enterprises' innovation capacity as only the punitive aspect of the government regulation is considered.

Similar to CER, EER has no significant moderating effect on the relationship between GPI and CO_2 emissions reduction. Meanwhile, when EER is combined with GKI, this can lead to increased carbon emissions. As enterprises are trying hard to minimise costs, when the cost of the discharge fee is less than the cost of developing GKI, enterprises may choose not to invest in GKI, and thus, CO_2 emissions reduction. This is especially true in China, as the discharge fee of the country has low environmental standards, narrow scope of levies, and weak enforcement strength (Shen et al., 2020). As GKI is relatively costly, paying the discharge fees is more economical for enterprises. Meanwhile, as GPI is not as expensive, some enterprises may choose to refine the production process for potential emissions reduction. However, the number of such enterprises is limited. In general, EER might encourage the opportunism behaviour of enterprises, damaging the long-term emissions reduction capacity of enterprises, and these results are consistent with prior research (Shen et al., 2020; Luo et al., 2021) and support hypotheses 3a and 3b.

Finally, IER has a significant positive (no significant) moderating effect on the relationship between GKI (GPI) and carbon emissions reduction. These results are consistent with hypotheses 4a and 4b. IER is designed to stimulate enterprises' long-term investments in green technologies. Therefore, when combined with more advanced green innovation, GKI, its moderating effect on carbon emissions reduction is positive. However, for GPI, as it only involves some adjustments/alterations in the existing process but does not require significant investments (Shen et al., 2020; Wang et al., 2021), the tested moderation effect is insignificant. Therefore, under IER, enterprises are stimulated to invest heavily in more advanced green technologies for emissions reduction, represented by GKI, rather than GPI. These findings are consistent with earlier research, suggesting that enterprises are more inclined to foster advanced and superior green innovation to attract greater capital investment (Wang et al., 2022b). This can help enterprises build up a long-term competitive advantage and gain the firstmover advantage in future development. Furthermore, when enterprises perform well in green innovation, they are more likely to be granted additional investments and this can further strengthen their innovation capacity (Wang et al., 2022b). This reinforces the positive moderating effect of IER on GKI for emissions reduction.

Regarding control variables, only FDI has a significant negative impact on CO_2 emissions in most cases. This is consistent with Xie et al.'s (2017) finding that FDI generally involves the transfer of advanced technologies and managerial experiences to investee enterprises, which can directly promote emissions reduction. The rate of industrialisation has a significant positive impact on CO_2 emissions, suggesting that regions with a higher level of industrialisation are more polluted. This is consistent with research showing that the extravagant growth model adopted by the Chinese government in the early days has led to severe pollution (Wu et al., 2020). While several policies have been adopted to restructure the economy over the past decade, the impact of the earlier production model remains (Zhang et al., 2017b).

Meanwhile, both educational level and population size have no significant impact on CO_2 emissions. This finding is consistent with the literature (Lee and Lee, 2022). Theoretically, these two factors are important in influencing CO_2 emissions levels. However, empirical results are mixed (Lee and Lee, 2022). This may be because a higher level of educational level does not necessarily lead to more green innovation or a higher level of environmental awareness. Similarly, a higher level of population agglomeration may not lead to higher CO_2 emissions.

3.4.2. Robustness Test – Spatial Durbin Model Results

Next, the chapter calculates the Global Moran's I index values of CO_2 emission over 2003 to 2019, and summarise the results in Table 3.4. The significant positive results suggest that CO_2 emission shares a significant positive spatial correlation. That is, if the two geographical locations are closer to each other, their CO_2 emission are strongly correlated. Therefore, the relationship between environmental regulations, GTI, and CO_2 emission should be further investigated considering spatial factors. To further examine this spatial correlation, this chapter applies the SDM and reports the results in Tables 3.5a and 3.5b. This chapter reruns the six regressions of the baseline model by incorporating spatial factors. The results are reported in columns (1) to (6).

Table 3.4 Global Moran's I Results of CO_2 Emissions

Year	I	E(I)	sd(I)	z	p-value
2003	0.196	-0.034	0.123	1.876	0.030
2004	0.198	-0.034	0.123	1.894	0.029
2005	0.224	-0.034	0.120	2.151	0.016
2006	0.214	-0.034	0.121	2.056	0.020
2007	0.218	-0.034	0.121	2.091	0.018
2008	0.223	-0.034	0.121	2.132	0.017
2009	0.207	-0.034	0.121	1.991	0.023
2010	0.214	-0.034	0.122	2.042	0.021
2011	0.191	-0.034	0.122	1.847	0.032
2012	0.182	-0.034	0.122	1.781	0.037
2013	0.174	-0.034	0.122	1.714	0.043
2014	0.175	-0.034	0.122	1.717	0.043
2015	0.170	-0.034	0.122	1.677	0.047
2016	0.156	-0.034	0.122	1.564	0.059
2017	0.124	-0.034	0.122	1.294	0.098
2018	0.141	-0.034	0.122	1.442	0.075
2019	0.123	-0.034	0.122	1.293	0.098

Note: The global autocorrelation test result

Table 3.5a Regression Results for SDM

	(1)			(2)			(3)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Variables	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
ER	-0.072 (-0.29)	0.291 (0.41)	0.219 (0.27)	0.027 (0.10)	0.305 (0.42)	0.332 (0.40)	-0.335 (-1.58)	0.105 (0.31)	-0.230 (-0.72)
GTI	0.034 (0.30)	0.648 (1.60)	0.682 (1.58)	-0.006 (-0.05)	0.548* (1.83)	0.542* (1.68)			
GPI							-0.005 (-0.86)	0.034** (2.22)	0.029* (1.87)
GKI							0.156*** (4.62)	0.023 (0.28)	0.180** (2.19)
ER*GTI				-2.139 (-1.43)	-3.949 (-0.56)	-6.089 (-0.78)			
ER*GPI							-0.149* (-1.79)	-0.424** (-2.02)	-0.573** (-2.34)
ER*GKI							-0.320*** (-2.66)	-0.504** (-2.13)	-0.824*** (-3.48)
rho	0.012 (0.09)			0.002 (0.02)			-0.196** (-2.23)		
sigma2_e	0.014*** (4.76)			0.014*** (4.99)			0.010*** (5.90)		
LR-lag	34.07***			36.27***			82.73***		
LR-sem	34.30***			36.71***			77.76***		
Control Variables	YES			YES			YES		
Province F.E.	YES			YES			YES		
Year F.E.	YES			YES			YES		
Observations	510	510	510	510	510	510	510	510	510
Log likelihood	370			373.9			436.7		

Note: Robust z statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.5b Regression Results for SDM

	(4)			(5)			(6)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Variables	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
CER	3.798 (0.91)	0.311 (0.04)	4.108 (0.45)	5.697* (1.89)	-4.455 (-0.54)	1.242 (0.14)	4.921 (1.56)	-3.502 (-0.55)	1.419 (0.20)
EER	-0.139 (-0.63)	1.050 (1.38)	0.911 (1.29)	0.961 (1.23)	2.808*** (3.11)	3.769*** (3.94)	-0.084 (-0.31)	1.557** (1.98)	1.473** (1.97)
IER	-0.256** (-2.21)	-0.393 (-1.36)	-0.649*** (-2.63)	-0.372*** (-2.95)	-0.479 (-1.57)	-0.850*** (-3.23)	-0.330*** (-2.70)	-0.125 (-0.57)	-0.455** (-2.08)
GPI	-0.004 (-0.81)	0.040** (2.38)	0.036** (2.22)	-0.001 (-0.17)	0.035** (2.16)	0.034** (2.15)	-0.002 (-0.40)	0.042*** (2.85)	0.041*** (2.75)
GKI	0.140*** (4.46)	0.003 (0.03)	0.143* (1.72)	0.146*** (4.94)	0.086 (1.06)	0.232*** (3.08)	0.140*** (4.45)	0.045 (0.57)	0.186** (2.40)
CER*GPI	-0.539 (-0.26)	0.802 (0.20)	0.264 (0.07)						
CER*GKI	-6.745*** (-2.75)	-6.264* (-1.75)	-13.009*** (-3.00)						
EER*GPI				0.209* (1.94)	0.104(0.38)	0.313 (1.02)			
EER*GKI				0.910*** (2.79)	1.119*(1.84)	2.030*** (3.25)			
IER*GPI							-0.077* (-1.88)	-0.163 (-1.62)	-0.239* (-1.96)
IER*GKI							-0.136** (-2.54)	-0.261 (-1.51)	-0.396** (-2.45)
rho	-0.174** (-2.12)			-0.260*** (-3.01)			-0.234*** (-3.09)		
sigma2_e	0.010*** (5.38)			0.010*** (5.49)			0.010*** (6.14)		
LR-lag	71.89***			88.08***			97.24***		
LR-sem	68.21***			76.06***			92.33***		
Control Variables	YES			YES			YES		
Province F.E.	YES			YES			YES		
Year F.E.	YES			YES			YES		
Observations	510	510	510	510	510	510	510	510	510
Log likelihood	441.7			456.9			447.4		

Note: Robust z statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

First, the test models are validated. The spatial rho, representing the existence of the spatial effect, is significant in almost all models except for regressions (1) and (2), suggesting that the SDM fits well for regressions (3) to (6). Hence, this chapter focuses on these four regressions. This chapter also applies the likelihood ratio (LR), calculated by the maximum likelihood estimation (MLE), to decide the best fit model from SAR, SEM, and SDM (Wang and Zhu, 2020). All statistical values of the LR tests are significant, implying that the SDM model is the best fit for the sample. Moreover, to address the potential endogeneity problem caused by the inclusion of lag terms of the dependent variables in SDM, this chapter applies the MLE method based on the conditional log-likelihood function. This method is regarded as an appropriate estimation approach for the SDM and has been widely used in the literature (Jia et al., 2021). Lastly, referring to the literature, when interpreting the results generated by the SDM, this chapter divides them into direct and indirect effects (Jia et al., 2021). The former refers to the impact of independent variables in one province on the CO_2 emissions of the same province, while the latter is the influence of independent variables in one province on the CO_2 emissions of its neighbouring provinces. The total effect is the sum of the direct and indirect effects (Wang and Zhu, 2020).

This chapter finds significant direct and indirect moderating effects of ER on the impact of GKI on CO_2 emissions reduction in local and neighbouring regions. This is consistent with Hypothesis 1b. In China, each local government has certain powers in setting up local policies, and local businesses are responsive to local authorities and follow these policies. Hence, in line with Peng (2020), the environmental regulations set up by the local government are more likely to be followed by the local business due to enforcement power at the local level, resulting in a significant direct effect. Meanwhile, good local practices could also be diffused and adopted by other regions. This positive spillover effect on neighbouring regions may explain the significant indirect effects (Wu et al., 2020).

Moreover, this chapter finds significant positive moderating effects of ER on GPI and carbon emissions reduction as well. However, this effect is relatively smaller compared with GKI, as observed in the benchmark regression results. This is as expected as more advanced GKI is preferred by the government as it may lead to long-term sustained environmental protection. For enterprises, GKI is also preferred over GPI as it may assist enterprises in earning additional profits. For example, enterprises can apply for green patent protection for those that have CO_2 emissions reduction effect. Then, other enterprises may buy its green innovation, which can benefit the innovating enterprise (Porter, 1991). Through GPI, the transformation of technology and equipment in the production process can help CO_2 emissions reduction in the short-term; however, the upgraded equipment will be depreciated over time. Then, the capital input in this process cannot generate more profits for enterprises over the long-term period. Therefore, under strict environmental regulations, enterprises are more likely to promote GKI to achieve long-term sustained economic growth.

Regarding the different combinations of regulatory policies and green innovation, the results are similar to those for the benchmark model (regressions 4–6). For CER, its positive moderation effect on GKI and CO_2 emissions reduction is significant for the direct effect and the indirect effect. When enterprises are required to reach certain emissions reduction targets, they may weigh the costs and benefits of different types of green innovation. The more advanced GKIs are preferred by enterprises for the creation of long-term competitive advantages (Zhang et al., 2017b; Wang and Li, 2022). Then, these moderating effects of CER appear in local and neighbouring regions due to the demonstration and spillover effects in different regions.

Meanwhile, EER has significant negative moderating effects on the impact of GKI on carbon emissions reduction for direct, indirect, and total effects. Significant negative direct, but not indirect and total effects, are observed for GPI. Overall, these results are in line with the benchmark regression results that EER rather promotes carbon emissions. These findings are unsurprising, as deficiencies have been documented in the Chinese EER system. The implementation of EER is not strong enough to promote green innovation for carbon emissions reduction as enterprises can easily settle the punishment by paying an insignificant amount of the discharge fee.

Lastly, for IER, its moderation effects on GKI and CO_2 emissions reduction remain significantly positive in direct and total effect models. To seek for more sustained investments, enterprises are more willing to advance superior green innovation, thereby meeting the emissions reduction targets. However, these effects only exist in the local province. Even though the coefficient *IER*GPI* is significantly negative, the smaller coefficient and less significant level indicate that enterprises prefer investments in GKI, especially cash-strapped ones which need to use their capital effectively.

3.4.3. Additional Robustness Test – SYS-GMM Results

Next, this chapter applies the SYS-GMM to address endogeneity concerns. This chapter performs the SYS-GMM estimation of dynamic panel data in China including the eastern, central, and western areas. During the SYS-GMM estimation, it is necessary to test the adequacy of the model and the validity of instrument variables. The test includes two aspects: First, the difference method is used to test the suitability of the model, and the null hypothesis that there is no sequence related and subjected to asymptotic distribution (Zhou and Xu, 2022). Second, the Sargan estimation is used to test whether the instrumental variables are over-identified. If this is not true, the asymptotic chi-square distribution will be obeyed. The difference between the number of instrumental variables and parameters is the degree of freedom (Yuan, 2019). The results of the dynamic SYS-GMM estimation are summarised in Table 3.6.

Table 3.6 Regression Results for SYS-GMM

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
L.LnCE	0.918*** (19.62)	0.908*** (19.19)	0.884*** (14.32)	0.863*** (15.54)	0.850*** (20.18)	0.867*** (15.69)
ER	-0.095 (-0.82)	-0.009 (-0.08)	-0.199 (-1.19)			
CER				-3.540 (-0.98)	-1.670 (-0.68)	-2.480 (-0.78)
EER				-0.042 (-0.28)	0.835*** (2.90)	-0.032 (-0.28)
IER				-0.106 (-1.28)	-0.116 (-1.53)	-0.052 (-0.65)
GTI	-0.058 (-0.64)	-0.064 (-0.82)				
GPI			-0.005 (-1.16)	0.003 (0.65)	0.003 (0.69)	-0.001 (-0.18)
GKI			-0.005 (-0.25)	0.007 (0.29)	0.004 (0.22)	0.008 (0.47)
ER*GTI		-0.204 (-0.23)				
ER*GPI			0.000 (0.01)			
ER*GKI			-0.091* (-1.72)			
CER*GPI				1.701 (0.79)		
CER*GKI				-2.995* (-1.88)		
EER*GPI					-0.022 (-0.29)	
EER*GKI					0.437** (2.64)	
IER*GPI						0.024 (0.70)
IER*GKI						-0.036* (-1.88)
Control Variables	YES	YES	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
Observations	480	480	480	480	480	480
AR (1) p-value	0.00494	0.00573	0.00390	0.00447	0.00678	0.00368
AR (2) p-value	0.165	0.106	0.0858	0.226	0.136	0.180
Sargan p-value	0.425	0.621	0.296	0.627	0.802	0.296

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To ensure the validity of the model, the p-values of AR (1) and AR (2) are tested and they indicate no serious second-order sequence correlation, confirming the appropriateness of the GMM approach (Zhou and Xu, 2022). Moreover, the Sargan tests indicate that the null hypothesis that all instrumental variables used in the GMM estimations are effective could not be rejected (Yuan, 2019). This indicates that the dynamic panel model is set properly. Again, the statistical results obtained are in general consistent with previous findings. Notably, the *ER*GKI* still outperforms the *ER*GPI* combination in reducing CO_2 emissions (Column 3), but the interaction term of environmental regulation and GPI becomes insignificant (columns 3 and 6).

Table 3.7 SYS-GMM Regression Results for the Eastern Region

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
L.LnCE	0.943*** (34.00)	0.944*** (35.29)	0.933*** (36.74)	0.945*** (64.26)	0.927*** (55.09)	0.949*** (65.87)
ER	-0.145 (-1.42)	-0.116 (-1.03)	-0.015 (-0.15)			
CER				1.276 (0.58)	-3.165 (-1.31)	-1.257 (-0.54)
EER				0.483 (1.56)	0.297 (1.21)	0.458 (1.54)
IER				-0.048 (-1.26)	-0.068** (-2.25)	0.002 (0.07)
GTI	0.073 (0.74)	0.063 (0.59)				
GPI			-0.000 (-0.09)	0.003 (0.85)	0.004 (0.90)	-0.001 (-0.34)
GKI			-0.010 (-1.43)	-0.003 (-0.26)	0.007 (0.65)	0.001 (0.06)
ER*GTI		-0.425 (-0.26)				
ER*GPI			0.031 (0.65)			
ER*GKI			-0.104* (-2.09)			
CER*GPI				2.532** (2.53)		
CER*GKI				-1.117 (-0.99)		
EER*GPI					-0.151 (-1.31)	
EER*GKI					0.318** (2.88)	
IER*GPI						0.009 (0.29)
IER*GKI						-0.037* (-2.19)
Control Variables	YES	YES	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
Observations	176	176	176	176	176	176
AR (1) p-value	0.0123	0.0102	0.0113	0.0111	0.0147	0.0137
AR (2) p-value	0.133	0.0956	0.130	0.127	0.190	0.166
Sargan p-value	0.243	0.332	0.312	0.268	0.373	0.338

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

This chapter also considers the regional heterogeneity, and the results are reported in Tables 3.7 and 3.8. For the eastern region, the findings for ER with different types of green innovation are consistent with findings at the national level. However, CER does not promote carbon emissions reduction. This may be because the eastern region has more enterprises with foreign investments, who may possess relatively advanced technologies (Su et al., 2022). Therefore, they are not that sensitive to CER and EER as the enterprises may have already met the emissions reduction targets. Instead, some may even expand their production, thereby generating more pollution up to their emissions allowance. Nevertheless, when the investment-based regulation is considered, it is found to be able to play a positive moderation effect on the impact of GKI on CO_2 emissions reduction (Column 6). This is as expected as the investment-type regulations tend to be long-term focused and could assist enterprises to build up their sustained competitive advantages, which is in line with the findings of Zhou and Xu (2022). Thus, the synergistic effect of the investment-type regulation and advanced green innovation on CO_2 emissions reduction is clear in the eastern region, as evidenced by the robust results for *IER*GKI*.

Table 3.8 SYS-GMM Regression Results for the Middle and Western Regions

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
L.LnCE	0.853*** (9.65)	0.858*** (9.69)	0.883*** (10.45)	0.831*** (11.14)	0.853*** (18.21)	0.883*** (13.04)
ER	-0.023 (-0.23)	0.007 (0.04)	-0.014 (-0.06)			
CER				1.965 (0.39)	1.471 (0.38)	-1.085 (-0.33)
EER				0.125 (0.83)	1.287** (2.54)	0.038 (0.25)
IER				0.005 (0.02)	-0.008 (-0.06)	0.008 (0.06)
GTI	-0.045 (-0.83)	-0.040 (-0.56)				
GPI			-0.000 (-0.10)	-0.001 (-0.18)	-0.000 (-0.03)	-0.004 (-0.79)
GKI			0.024 (0.92)	-0.002 (-0.08)	-0.016 (-0.63)	0.026 (1.21)
ER*GTI		-0.134 (-0.19)				
ER*GPI			0.002 (0.04)			
ER*GKI			0.004 (0.06)			
CER*GPI				2.502 (0.81)		
CER*GKI				-2.891 (-1.39)		
EER*GPI					0.055 (0.59)	
EER*GKI					0.689** (2.56)	
IER*GPI						0.010 (0.39)
IER*GKI						-0.033 (-0.83)
Control Variables	YES	YES	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
Observations	304	304	304	304	304	304
AR (1) p-value	0.0181	0.0216	0.0268	0.0274	0.0411	0.0247
AR (2) p-value	0.0315	0.0242	0.0163	0.144	0.0842	0.0233
Sargan p-value	0.417	0.667	0.485	0.781	0.935	0.693

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

This chapter observes a different picture for the middle and western regions. Almost all tested moderating effects are insignificant or negative, suggesting that regulations in these regions may not effectively influence the impact of green innovation on emissions reduction. This does not come as a surprise. Compared with the more economically developed eastern region, enterprises in the western and middle regions tend to be less developed and are governed by local authorities with weaker enforcement power. This can reduce the effectiveness of CER. The findings for EER remain consistent with those observed before: it does not reduce carbon emissions. When the cost of the discharge fee is less than the cost of developing green innovation, enterprises may choose not to invest in green innovation and CO_2 emissions reduction (Wang et al., 2019). Moreover, with limited capital available, enterprises in the middle and western regions tend to accept green innovation passively, and the results are in line with Tang et al. (2020). This could be evidenced by the insignificant moderation effect of IER on the relationship between green innovation and emissions reduction.

3.4.4. Robustness Test – Alternative Measures and DID Analysis Results

Based on the empirical results of previous sections, it can be seen that IER is most effective tool among different environmental regulations. Therefore, the chapter conduct robustness test by replacing measurement (*IER2*) to ensure the accuracy of the results. However, different measurements have been adopted to measure green credit. Besides the continuous variable measurements used in sections 3.4.1–3.4.3, policy variable measurements have been widely adopted (Wen et al., 2021; Hu et al., 2021; Song et al., 2021). According to the 2012 Green Credit Guideline (GCG), financial institutions in the banking sector must strengthen their auditing and tracking of enterprise environmental performance and establish an information sharing mechanism to develop green credit (Zhang, 2021; Wang et al., 2022).

Following Nunn and Qian (2011) and Kim and Valentine (2021), this chapter uses GCG as an alternative proxy for IER and employs the DID model with continuous grouping variables to test the fundamental hypotheses as follows:

$$LnCE_{i,t} = \beta_0 + \beta_1 CER_{i,t} + \beta_2 EER_{i,t} + \beta_3 GPI_{i,t} + \beta_4 GKI_{i,t} + \beta_5 IER2_t \times GPI_{i,t} + \beta_6 IER2_t \times GKI_{i,t} + \beta_7 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (20)$$

where $IER2_t$ is a policy year dummy variable measuring the impact of GCG, which equals one if the year is after 2012, and zero otherwise. $IER2_t \times GPI_{i,t}$ and $IER2_t \times GKI_{i,t}$ are the interaction terms of IER and different types of green innovation. Similar to the moderation analysis, this model does not stipulate dummy variables of the controlled and treated groups as the explanatory variables GPI and GKI are not dichotomous. That is, as the chapter presumes that the policy to affect CO_2 emission reduction with different green innovation, the higher level of such factors the region has, the more likely it is classified as the treated group (Kim and Valentine, 2021; Xing et al., 2021; Nunn and Qian, 2011; Qian, 2008). Therefore, the chapter introduces the policy effect (*IER2*) and construct interaction terms with types of green innovation to examine their impacts on CO_2 emissions reduction. Since the chapter focus on IER, the key to validating hypotheses 4a and 4b is β_5 and β_6, respectively. The chapter also utilises a two-way fixed-effects regression strategy to control the unobservable characters of individuals and increase measurement accuracy (Kang et al., 2019). Thus, as time is fixed, *IER2* is not added alone in the equations because of the perfect collinearity.

The chapter also undertakes time trend analysis and placebo test. The most important requirement for employing the DID method is the parallel trends assumption (time trend analysis). That is, the treatment and control groups should be similar before the intervention; otherwise, the result estimated via the DID method may be biased (Kim and Valentine, 2021; Xing et al., 2021; Wang et al., 2022). The regression equation for testing the parallel trends assumption is shown in equation (21).

$$lnCE_{i,t} = \beta_0 + \beta_1 CER_{i,t} + \beta_2 EER_{i,t} + \beta_3 GPI_{i,t} + \beta_4 GKI_{i,t} + \sum_{k=-8}^{7} \gamma_k GPI_{i,t} \times$$

$$Year_{k_t} + \sum_{k=-8}^{7} \alpha_k \, GKI_{i,t} \times Year_{k_t} + \beta_5 X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (21)$$

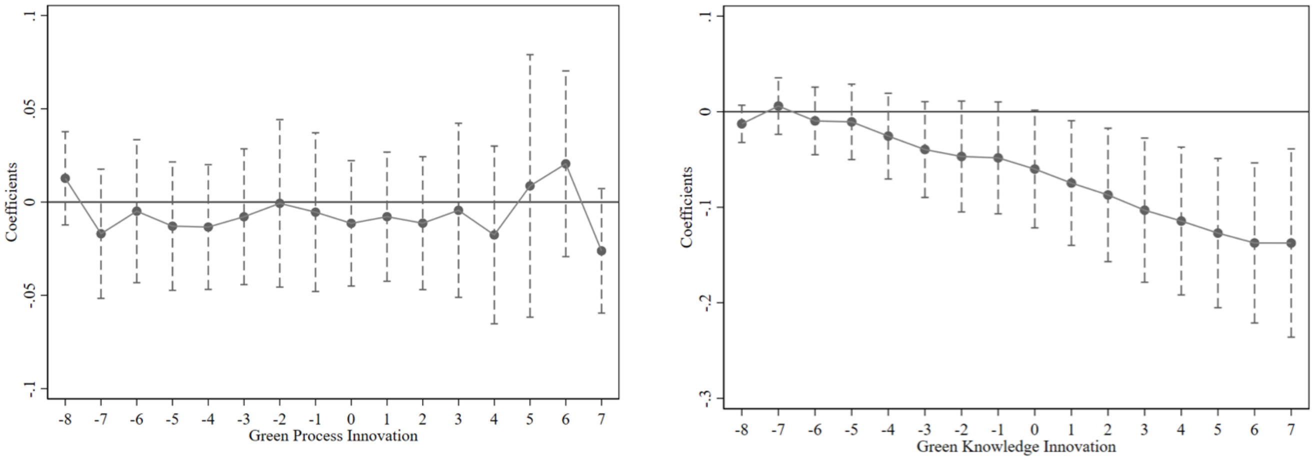
Here, $Year\_k_t$ is a list of dummy variables which equal one if the time is (2012 + k) year. Therefore, γ_k and α_k are the time trend effects; that is, the effects of GCG and different green innovation on CO_2 emissions reduction in (2012 + k) year. Following Xing et al. (2021), the chapter selects the first year, 2003, as the benchmark, and hence, γ_{-9} and α_{-9} are excluded from the equations. If the parallel trends assumption holds, then $\gamma_{-8} - \gamma_{-1}$ and $\alpha_{-8} - \alpha_{-1}$ should be insignificant. If GCG can stimulate green innovation to reduce CO_2 emission, $\gamma_0 - \gamma_7$ and $\alpha_0 - \alpha_7$ should be significantly positive.

Furthermore, to test whether the observed policy effect is indeed caused by GCG, following Li et al. (2022), the chapter assumes 2010 (or 2011) as GCG's implementation year and conduct a placebo test. If the coefficient of *IER2*GKI* is insignificant, then the policy effect observed is indeed caused by the GCG (Li et al., 2022).

Table 3.9 Regression and Placebo Results for the DID Model

	(1)	(2)	(3)
Variables	LnCE	LnCE	LnCE
IER2*GPI	-0.012 (-0.93)	-0.015 (-0.70)	-0.024 (-0.89)
IER2*GKI	-0.088*** (-3.25)	-0.009 (-0.51)	-0.025 (-1.15)
R-squared	0.891	0.907	0.909
Observations	510	270	270
Control Variables	YES	YES	YES
Province F.E.	YES	YES	YES
Year F.E.	YES	YES	YES

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Only interaction terms are presented here due to space limit, full table can be requested from authors.



(1) (2)

Figure 3.3 Parallel Trends Assumption Results for the DID model (GPI and GKI)

The results are summarised in Table 3.9. Column (1) shows the results of DID model, whereas columns (2) and (3) present the placebo test results for the years 2010 and 2011, respectively. The coefficient of *IER2*GKI* is negative and statistically significant, indicating that IER together with GKI can reduce CO_2 emissions. This finding is consistent with conclusions reached in earlier sections.

The chapter then interprets the coefficients of equation (21) into Figure 3.3. Consistent with the above findings, all coefficients of $\gamma_{-8} - \gamma_{-1}$ and $\alpha_{-8} - \alpha_{-1}$ are insignificant (all 90% confidence intervals in Figure 3.3 include zero before *Year_0*). Therefore, the parallel trends assumption is supported because all the interactions before 2012 are insignificant. The coefficients are significantly negative (zero is excluded in the confidence intervals in Figure 3.3 (1) after *Year_0*). This indicates that when IER is combined with GKI (i.e. the more advanced green innovation), it positively affects carbon emissions reduction; that is, IER has a positive moderating effect on the relationship between GKI and carbon emissions reduction.

The results of placebo tests show that when the chapter assumes 2010 or 2011 as the implementation year of the IER policy GCG, all coefficients of *IER2*GKI* are insignificant. This provides supporting evidence that the positive moderating effect is indeed caused by the IER, thereby further supporting hypothesis 4b.

3.5. Conclusion and Policy Implications

3.5.1. Conclusion

Resource scarcity and climate change have been the core of the economic and political debate during the last decades. Environment-related technical progress brings about opportunities to create a more sustainable low-carbon future. However, green innovation is a complicated and dynamic process. Enterprises' willingness and ability to conduct green innovation are conditioned by the financial rewards from doing so and the resource available. Interventions from the government are considered useful in correcting market failure to maximise the environmental and economic benefits brought about by green innovation.

This chapter contributes to growing concerns about the effectiveness of environmental regulations in promoting green innovation and the achievement of emissions reduction. Based on panel data of 30 Chinese provinces from 2003 to 2019, a series of carefully chosen models were applied for this analysis. First of all, the Panel Fixed-effect model is applied for the benchmark analysis. Through controlling for individual and time fixed effects, it reduces omitted variable bias, enhances estimation accuracy and leads to the high R-squared values estimated across all models (Hasan et al., 2018). Then the SDM is adopted to capture the spatial factors to verify the robustness of the empirical findings (Jia et al., 2021). The validation tests all confirm the presence of spatial effects, e.g. coefficients of LR-lag and LR-sem are 34.07 and 34.30, respectively, and are both significant at the 1% level. Thirdly, to mitigate the endogeneity problem and improve parameter estimation efficiency, the SYS-GMM model is conducted (Zhou and Xu, 2022). The instrumental variables are strictly selected according to the Sargan tests estimation to ensure the effectiveness of tested results (all Sargan-p values are larger than 0.1) (Yuan, 2019). Lastly, the DID model is applied to further verify the robustness of the results. Further, the key values of placebo tests confirm that the positive moderation effect found in this chapter is indeed caused by the IER.

The chapter concludes with the following main findings. First, the environmental outcomes of GKI can be efficiently promoted by environmental regulations, as evidenced by the change of sign, from 0.130 to -0.428, of the coefficient of GKI in the benchmark model. However, the effect of GPI is unstable. GKI is typically more advanced than GPI and has the potential to bring sustained competitive advantages to enterprises. Therefore, the results suggest that in China, the synergistic effect of environmental regulations performs well but is only stable in promoting the emissions reduction effect of more advanced green innovation. Second, regarding the effectiveness of different types of environmental regulations, both CER and IER promote the CO_2 emissions reduction effect of GKI significantly (e.g. in benchmark results, both coefficients of CER*GKI (-8.887) and IER*GKI (-0.193) are significant at 5% level). In particular, stimulated by IER, enterprises are more likely to invest heavily in more advanced GKI, enabling them to achieve a higher emissions reduction target. However, a different picture emerges for EER. It has a significant negative moderating effect on the relationship between GKI and emissions reduction. As enterprises are profit-oriented, when paying the discharge fee becomes more economical, they may reduce efforts in green innovation and CO_2 emissions control. Although this may bring short-term benefits to enterprises, it may damage their reputation and growth potential over the long run.

All these findings remain robust when considering spatial factors and regional heterogeneity. ER is confirmed to be effective in moderating the relationship between green knowledge innovation and CO_2 emissions reduction among both local and neighbouring regions, as suggested by the estimated coefficients of ER*GKI (direct effect: -0.320, significant at 1% level and indirect effect: -0.504, significant at 5% in Table 3.3a). This is consistent with the spillover and positive demonstration effects. GKI remains the most effective type of green innovation chosen by enterprises for carbon emissions reduction as it may benefit enterprises over the long-term period. Meanwhile, regarding regional heterogeneity, the ER is found to be effective in promoting the impact of GKI on CO_2 emissions reduction for the relatively well-developed eastern region only (e.g. the coefficients of ER*GKI (-0.104) and IER*GKI (-0.037) are both significant at 10% level for the eastern region but insignificant when middle and western regions are under investigation). This is as expected. With large amounts of FDI and a well-developed economic infrastructure, it is unsurprising that investment-led policies will further stimulate enterprises' innovation capacity, leading to the development of more advanced green technologies, and hence, carbon emissions reduction. However, in other regions, environmental regulations fail to positively moderate the impact of green innovation on CO_2 emissions reduction.

The main contribution of this chapter lies in the following aspects. First, the chapter provides empirical evidence in support of the PH in an emerging market. Through comprehensive analysis of the relationship between environmental regulations, green innovation, and CO_2 emissions in the Chinese market, it identifies the importance of environmental regulations in shaping more advanced and long-term green innovation. Moreover, the chapter analyses the heterogeneity of environmental regulations, green innovation and regions, which will be helpful for better understanding the efficiency of different policy instruments in the Chinese context and supplementing the PH under different scenarios. Consequently, successful practices can be generalised to other developing countries, accelerating the process of carbon neutrality globally.

3.5.2. Policy Implications

Overall, the empirical analysis suggests that current environmental regulations are effective in moderating the emissions reduction effect of green innovation to some extent, especially for more advanced innovation. The Chinese government should effectively use different environmental policy tools in combination to stimulate their synergistic effects. As the country is moving towards the market economy, the government should make the market-based regulatory instrument play a more dominant role in directing enterprise behaviours. In this case, IER should be more widely adopted as the main regulatory tool for CO_2 emissions reduction. The further development of the Chinese green finance system is necessary to complement the effectiveness of such policy instruments. Meanwhile, the government should limit the use of expenditure-type environmental regulations, especially for less developed regions, as it may encourage short-termism and opportunistic behaviours of enterprises.

Further, knowledge-based green innovation may assist enterprises in achieving long-term sustained growth, while process innovation may be only temporary or window dressing. Effective mechanisms can be designed to facilitate the collaboration of green innovation among big enterprises, and/or research institutions. This can facilitate information dissemination, and reduce costs and risks faced by all participants. Simultaneously, more stringent laws and regulations on intellectual property protection should be implemented by the Chinese government to protect the legitimate rights of innovators and increase market confidence. As the environmental regulation system matures and improves gradually, the positive effects of green innovation in reducing CO_2 emissions are more likely to strengthen in the future. Therefore, reform efforts and innovation incentives should be continuously initiated. The green sustainable and enterprise development goals should also be coordinated to further leverage the positive effect of environmental regulations and green innovation on CO_2 emissions reduction.

3.5.3. Limitations and Possible Future Work

Due to the data availability, currently it is difficult to obtain adequate data of other greenhouse gas (GHG) emissions in Chinese market, for example, nitrous oxides. Therefore, when data becomes accessible, a more comprehensive measurement of GHG emissions could be constructed to testify to the effectiveness of different policy instruments. Also, this would facilitate the drawing of more useful experiences to assist the green transformation process among China and other economies.

Chapter 4: The Impact of Green Credit Guideline on Green Innovation Performance: Evidence from China

4.1. Introduction

Over the past decades, issues related to global warming caused by environmental pollution has triggered wide debate (Bergek and Mignon, 2017; Mealy and Teytelboym, 2022). As one of the largest polluters, China sacrifices approximately 10% of its GDP to tackle environmental pollution-induced problems every year (Ge et al., 2020). With the country's continued economic expansion, this high-pollution growth model may not be unsustainable. In response, the Chinese government proposed a few targets, such as achieving carbon peak before 2030 and carbon neutrality before 2060, to manifest the country's willingness and determination to achieve sustainable development (Zhang et al., 2022b). In particular, there is increasing focus on the green transition of the heavily polluting enterprises (HPEs) (Zhou et al., 2019b; Hu et al., 2021).

To meet these targets, a series of regulatory measures were implemented by the Chinese environmental protection department.[21] These mainly include command-, market- and voluntary-based measures. Notably, by using the market as a means to reduce environmental pollution, the market-based environmental regulation (MER) is now playing an increasingly important role given their flexibility, autonomy, and strong economic efficiency (Tchórzewska et al., 2022; Tian and Feng, 2022; Chang et al., 2023). One such typical market-based regulation instrument introduced by China is the Green Credit Guideline (GCG), which was originally designed to encourage banks to channel cheaper loans to green businesses while restraining funding for heavily polluters. The aim was to stimulate green innovation, and assist the country in achieving

[21] Currently, China mainly has command- (e.g. *Atmospheric Pollution Prevention and Control Law (2015 Revision)*), market- (e.g. *Emission Trading Markets Pilots Policy (2007)* and *Guidelines for Green Credit issued by the China Banking Regulatory Commission (2012)*), and voluntary-based environmental regulation.

wider-scale economic restructuring and green transition (Lu et al., 2022; Tan et al., 2022). China's economic and financial strategies wield significant global influence (Tian and Feng, 2022). The country's green finance policies and implementations could serve as benchmarks for other nations and regions worldwide (Su et al., 2022). Such referential value is crucial for the global pursuit of carbon neutrality and the green transition of the economy.

Green innovation refers to an innovation in technology, product, service, or management to achieve sustainable development (Vasileiou et al., 2022). On the one hand, they may mitigate the negative human impact on the environment (Rennings, 2000; Walker er al., 2015). On the other hand, they can assist enterprises to gain competitive advantages via positive publicity, government support, and technological leadership (Gupta and Barua, 2018).[22] Therefore, one may argue that the emission reduction policies should promote green technology innovation for the achievement of these positive impacts (Bergek et al., 2014; Stern and Valero, 2021).

Regarding the connection between environmental regulations and green innovation, the Porter Hypothesis (PH), proposed by Porter (1991), posits that flexible environmental regulations can indeed effectively enhance the environmental advantages of innovation. Consequently, this chapter offers empirical evidence supporting the PH, drawing from samples in the world's largest developing economy. Owing to its flexibility and efficacy, the GCG, grounded in market mechanism strength, has emerged as a central environmental regulation in China's environmental governance (Yao et al., 2021). When faced with GCG, HPEs are typically the most impacted due to the financial constrain and their needs for more substantial profit gains (Hu et al., 2021). Also, GEs can also be largely impacted and promoted to continue investing in green innovation to maintain their competitive edge. Furthermore, existing studies primarily focus on the

[22] For example, when an enterprise achieves technological innovation that meets the requirements of environmental regulations, it can apply for patent protection. In the context of strict environmental regulations, this behaviour can encourage other enterprises to purchase its innovation, which can bring high profits to the enterprise (Porter, 1991).

effects of single policy on enterprises' business behaviours and innovation activities (Tang et al., 2020; Xu and Li, 2020; Su et al., 2022), neglecting the synergistic impact of different environmental regulations. However, the synergistic effect of various environmental regulations is a vital component of practices of the PH, and the findings from such research will be significant for China and other economies with similar economic and social characteristics in shaping effective environmental policies.

Given the significance of such research objectives, this chapter empirically tests the relationship between GCG and green innovation using panel data on Chinese listed enterprises from 2007 to 2019. In particular, the goal is to investigate whether GCG promotes green innovation among HPEs under heterogeneous conditions. Further, China has implemented different types of environmental regulations and these policies may have a synergistic effect. Then, understanding how these policy instruments affect the relationship between GCG and green innovation may be worthwhile. The chapter also explores: what are the impacts of GCG on GEs? Are these impacts consistent with those on HPEs?

This chapter contributes to the literature in the following aspects. First, while most studies focus on investigating the impact of GCG on the performance of HPEs (Yao et al., 2021; Cui et al., 2022; Peng et al., 2022) or enterprises' green innovation in general (Lu et al., 2022), little is known about the impacts of such policy on GEs. While they are less polluting, GCG can also incentivise GEs to consolidate their competitiveness. Nevertheless, their reactions can differ under different types of regulatory initiatives and when they choose different types of green innovation. By conducting a comparative study on HPEs and GEs, this research provides valuable insights for setting future policies.

Second, this chapter examines the heterogeneity in the relationship between the GCG and green innovation by dividing the green innovation performance into green innovation quality and green innovation increment.[23] In particular, this chapter explores which type of innovation is preferred by enterprises and the underlying reasons for these choices. Furthermore, this chapter examines whether enterprises with different ownership structures and different degree of reliance on external finance exhibit different behaviours.

Third, as an important market-based environmental regulation tool, GCG plays a crucial role in environmental governance in the Chinese market. However, studies show that different types of regulation tools may have a synergistic effect on enterprises' innovation and emission reduction (Yuan, 2019). Therefore, this chapter also investigates the moderating effects of command- and voluntary-based regulatory tools on the relationship between the GCG and green innovation.

Fourth, while assessing the comprehensive impact of GCG on green innovation, changes in internal factors (e.g. efficiency of green capital utilisation) should also be considered besides external factors (e.g. intensity of various regulatory instruments). However, studies have not explored the internal mechanisms through which GCG affects green innovation. This chapter fills this gap by revealing that the efficiency of green capital utilisation is one such mechanism.

Fifth, this chapter employs the Word Embedding model as a novel method to quantify variables, thus enhancing the accuracy of variable measurements and the robustness of empirical results. When measuring certain variables, it is often essential to utilise different words with similar semantics, as individual words frequently capture only a portion of the information specific to the variables' feature. A common approach is to manually identify synonyms to broaden the word set (Loughran and McDonald, 2011). However, comprehensively and accurately measuring text features using this method is

[23] Green innovation quality focuses more on the quality of green innovation and is more related to newly created inventions (Zhang et al., 2023). While green innovation increment focuses more on the quantity if green innovation and tends to build on existing technologies or products (Wang and Li, 2022).

challenging and involves a high degree of subjectivity, leading to a potentially biased set of words. The Word Embedding model in machine learning effectively overcomes this limitation (Li et al., 2021). Specifically, the model employs a neural network to deeply parse a large amount of financial text, building a word similarity model from which similar words can be trained. The similarity dictionary constructed by this model enables comprehensive and objective variable measurements (Li et al., 2021). Consequently, this chapter uses the Word Embedding model to measure the variables for incentive-based environmental regulation and green investment.[24]

The rest of this chapter is organised as follows. Section 2 provides an overview of the literature and develops the hypotheses. Section 3 describes the variables and methodology. Section 4 discusses the empirical results. Finally, section 5 presents the conclusions of this chapter.

4.2. Literature Review and Hypothesis Development

4.2.1. Theoretical Background

The Porter Hypothesis (PH) suggests that stringent but properly designed environmental regulations can stimulate enterprise innovation, especially green innovation (Porter and Linde, 1995). To comply with the regulatory requirements while building up sustained competitive advantages over the longer term, enterprises can be pressurised/incentivised to invest in green technologies and adjust their competitive strategies accordingly (Farooq et al., 2021). To ensure the appropriate functioning of the environmental regulation system, it should have the following characteristics: broad coverage: it should provide the largest potential space for enterprise innovation; continuity: it should stimulate continuous innovation; flexibility: it should allow enterprises to implement the policies in stages with certain level of discretionary power;

[24] Here, the variables Incentive-based Environmental Regulation (CER_Incentive) and Green Investment (GreenInv) are constructed using the Word Embedding model.

and enforceability: it should be able to control and enforce enterprise behaviours effectively with a well-designed appraisal mechanism and encourage government-enterprise collaboration (Porter and Linde, 1995).

Many studies have demonstrated the validity of PH (Zhao et al., 2015; Ouyang et al., 2020). For instance, enterprises can create new market opportunities by developing greener products (Ouyang et al., 2020), which can motivate enterprises to invest more in green innovation.[25] Over the longer term, investments in green technology may be fully compensated by the potential gain from reduced costs in pollution control, increased productivity, and positive publicity. This can be especially true when enterprises face greater environmental regulation intensity, which can accelerate green innovation processes and lead to the development of an environmental-friendly industry (Zhao et al., 2015). However, green investments also require strong financial support. As such, GCG can help in this respect by easing financing constraints, thereby complementing environmental regulations and promoting green innovation activities.

Recent research has started to leverage environmental policies as quasi-natural experiments to investigate the PH and mitigate the potential endogeneity issues, such as the introduction of the carbon emissions trading system (Hu et al., 2020a). For instance, Hu et al. (2020a) discover that the carbon emissions trading market has had a significant positive impact on both the volume and quality of innovation amongst Chinese enterprises. As a significant tool in environmental regulation, the role of the GCG in environmental governance has received increased attention in recent years (Yao et al., 2021). Certain studies have found that the enactment of the GCG resulted in reduction in bank loans and the scale of investments in HPEs, leading ultimately to a decrease in these enterprises' operational performance and total factor productivity (Liu et al., 2019). Liu et al. (2019), using the announcement of the GCG as a quasi-natural

[25] The innovation compensation effect of PH posits that during the dynamic process of economic development, environmental regulations can stimulate enterprises to innovate their production modes, improve economic efficiency, and offset the effect of circular cost (Ouyang et al., 2020).

experiment, demonstrate that the debt financing capacity of HPEs has decreased significantly. Moreover, the negative net effect of debt financing is more pronounced in state-owned enterprises and those located in regions with weaker financial ecosystems.

However, according to the PH, the effectiveness of an environmental regulation policy in influencing innovation serves as a crucial measure of a successful green transition (Pizer and Popp, 2008). It is evident that the primary goal of the GCG is to mitigate environmental pollution, not to undermine enterprise competitiveness. Recently, Li et al. (2018) build a green loan theory using quantitative models to support the GCG's role in promoting clean production innovation. Nevertheless, the exact influence of China's GCG on green innovation remains ambiguous, especially regarding its impact on diverse enterprises in practical scenarios. These questions are significant in verifying the applicability of the PH in China. Furthermore, existing research exploring the synergistic effect of other environmental regulations in conjunction with the GCG is limited. Neglecting this facet may lead to an incomplete estimation of the PH's validity (Zefeng et al., 2018). Therefore, this chapter addresses this research gap and expands upon the PH by considering the synergistic effect of various environmental regulations.

4.2.2. Green Credit Guideline

China's GCG aims to achieve two interrelated targets through financial mechanisms: environmental protection and economic development. Instead of punishing enterprises, it aims to achieve a balanced or harmonised development between the external environment and enterprise behaviours (Sun et al., 2019). The GCG implemented in China has had substantial impacts, and the balance of green credit in China is rising annually (Figure 4.1). According to the GCG, all commercial banks must strengthen the management of enterprise environmental performance and establish an information sharing mechanism to develop green credit (Yao et al., 2021).[26] It aims to establish a powerful database to assess the environmental performance when enterprises apply for credit, track their follow-up activities, and share this information with other government institutions for coordinated management and control (Zhang et al, 2021a; Yao et al., 2021).

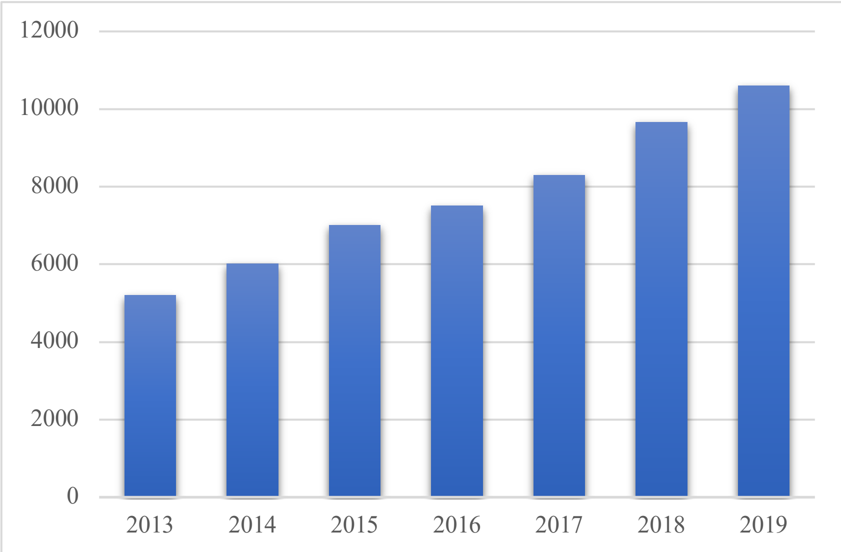


Figure 4.1 The green credit balance of China, by year

Note: The green credit balance of China from 2013 to 2019. The volume (¥bn) of green credit is show on the left axis. Data source: CSMAR.

4.2.3. Green Credit Guideline and Green Innovation Performance

Here, the goal of providing green credit is to promote green innovation performance via the development of technologies or approaches that contribute to energy savings, emissions reduction, and environmental protection, among others (Chen et al., 2006).

[26] The main points of the GCG are as follows. First, a strict access mechanism requires credit-granting financial institutions to consider not only the economic performance and risks of enterprises but also their environmental performance and potential environmental risks. Credit to enterprises with poor environmental performance is curtailed. Second, information communication and dynamic tracking mechanisms must be established for enterprises that have obtained loans after thorough examination and approval, and their credit should be terminated if environmental problems occur. Third, stronger coordination and cooperation must be established with government and environmental protection departments. Information sharing must be improved to link environmental protection and financial credit (Yao et al., 2021; Zhang et al., 2021c).

Similar to other types of general innovation, green innovation can help the technological advancement of enterprises, empowering them to develop more innovative services and products (Aldieri et al., 2020). The green characteristics of such innovation also benefit the environment (Huang and Li, 2017). Therefore, green innovation may help achieve the dual targets of environmental protection and economic development simultaneously (Ganda, 2019; Shao et al., 2021). Thus, green innovation fits well within the scope of GCG.

Over the past decades, many HPEs are keen to structurally transform themselves to continue to access and attract stable capital inflow from financial institutions. Therefore, achieving qualified environmental and sewage performance has become particularly important for these HPEs (Berrone et al., 2013). For Chinese enterprises, despite extensive capital market reforms, loans remain the primary financing resource, especially for HPEs (Xing et al., 2020). Due to the GCG, HPEs that want to secure financial support may be motivated to cut emissions, including via green innovation, as they must fulfil GCG requirements to access loans from financial institutions (Shi et al., 2022). This also helps HPEs build good relationships with the local government because they can demonstrate commitment to environmental sustainability (Hu et al., 2021). Based on the above discussion, the first hypothesis is proposed as follows:

Hypothesis 1. GCG improves the green innovation performance of HPEs.

4.2.4. The Moderating Effect of Environmental Regulations

Environmental regulations may change the behaviour of enterprises through various channels, such as encouraging them to invest more in green innovation or cultivating a green culture in the enterprise (Kesidou and Demirel, 2012). In general, apart from MER, ERs also consist of two categories: command-and-control (CER) and voluntary environmental regulations (VER). The former is mainly based on government command (Tang et al., 2020) and comprises environmental law enforcement, administrative penalties, and government subsidies (Carrión-Flores et al., 2013). VER refers to enterprises' voluntary environmental information disclosure (Jiang et al., 2020). These disclosures can effectively reduce information asymmetry between financial institutions and enterprises, increasing enterprises' accessibility of green credit.

4.2.4.1. Command-and-control Environmental Regulation

Due to its relatively strong enforcement power, CER remains an important environmental regulation in developing countries. CERs, especially penalty-based regulations (CER_Penalty), can inhibit the environmental pollution behaviours of enterprises. However, CER_Penalty has been criticised for their penalty costs, low operational efficiency, and deviation from the original targets of promoting technological innovation among enterprises (Joshi et al., 2001). Further, Hotte and Winer (2012) point out that as CER_Penalty often fails to consider the substantial cost differences among enterprises, it may actually impede the technology adoption rate, especially among small enterprises. Since penalties can only be applied to certain measurable targets, regulations structured based on them may not prevent all types of pollution activities effectively (Shevchenko, 2021). When enterprises possess more information than the regulators, this situation can become even worse.

Therefore, the inherent inferiorities of CER_Penalty have made it a less efficient alternative than the incentive-based regulations (Lin and Xie, 2023). Instead of stimulating increased green innovation funded by favourable GCG, CER_Penalty may impose additional financial burden on HPEs, worsening their financing situation while sending bad signals to the market (Requate and Unold, 2003). Consequently, green innovation efforts may have less funding. Moreover, the long-term financing capacity of enterprises may be further restrained. Based on the discussion, this chapter proposes the following hypothesis:

Hypothesis 2a. CER_Penalty does not positively moderate the relationship between GCG and green innovation performance among HPEs.

Among various types of CERs, government subsidy actually shares some incentive-based characteristics; that is, it is an incentive-based CER (CER_Incentive). In China, it effectively acts as a free transfer of funds from local governments to enterprises (Huang et al., 2019), while restraining the use of fund to certain purposes like green investments (Zhang, 2022). CER_Incentive acts as a direct substitute for debt financing, providing a viable alternative to HPEs for their innovative green transformations (Horbach et al., 2012). Furthermore, CER_Incentive also signifies government's support for the enterprise, enabling it to bypass the restrictions imposed by debt financing (Zhang, 2022). In other words, CER_Incentive can assist enterprises to diversify the risks involved in green innovation to some extent, thereby increasing their willingness to invest into such activities (Bai et al., 2019). Moreover, to nurture the long-term relationship with the government, HPEs tend to be more strongly motivated to improve their environmental performance via green innovation. Therefore, this chapter proposes the following hypothesis:

Hypothesis 2b. CER_Incentive can positively moderate the relationship between GCG and the green innovation performance of HPEs.

4.2.4.2. Voluntary Environmental Regulation

Compared with CER and MER, VER is considered as the 'third generation' of tools for controlling pollution (Tietenberg, 1998). The disclosure of pollutant emissions, such as the environmental information disclosure of listed enterprises in China are good examples of this (Jiang et al., 2020). By reducing the costs and improving the time efficiency in providing, processing, and disseminating related information, VER reduces the information asymmetry between enterprises and financial institutions (Lundqvist, 2001). This can help establish a long-run trusted relationship between the two, which can help improve overall organisational performance (Huang and Chen, 2015). Therefore, considering the positive impact of VER on enterprise performance and its signalling effect, this chapter proposes the following hypothesis:

Hypothesis 3. VER can positively moderate the relationship between GCG and the green innovation performance of HPEs.

4.3. Methodology and Variables

4.3.1. Data and Sample Selection

The sample includes data on China's A-share listed enterprises from 2007 to 2019. 2007 is the sample's starting year because new accounting standards were implemented in China in this year. Meanwhile, 2019 is set as the ending year to mitigate the impact of the COVID-19 pandemic. HPEs are defined according to the '*Guidelines for the Industry Classification of Listed Enterprises*' revised by the China Securities Regulatory Commission in 2012 and '*Guidelines for Environmental Information Disclosure of Listed Enterprises (Draft for Soliciting Opinions)*' published by the China Environmental Protection Administration in 2010 (hereafter, Draft) (Shi et al., 2022). The sample is filtered as follows: (1) excluding financial and ST enterprises; (2) removing enterprises with missing key variables; (3) winsorising all continuous variables at the 1% and 99% levels to mitigate the effect of outliers; and (4) removing enterprises which changes their status between heavily and non-heavily polluting industries over the sample period. All data are collected from the China Stock Market and Accounting Research (CSMAR) database, Chinese Research Data Services (CNRDS) database, annual reports, and corporate social responsibility (CSR) reports of respective listed enterprises.

4.3.2. Models

Following Zhang et al. (2021a) and Shi et al. (2022), this chapter constructs the following models to explore the effect of GCG on green innovation.

$$LnGI_{i,t} = \beta_0 + \beta_1 DID_{i,t} + \beta_2 X_{i,t} + u_p + \nu_t + \gamma_s + \lambda_q + \varepsilon_{i,t} \quad (22)$$

$$LnGI_{i,t} = \beta_0 + \beta_1 DID_{i,t} + \beta_2 ERs_{i,t} + \beta_3 DID_{i,t} \times ERs_{i,t} + \beta_4 X_{i,t} + u_p + \nu_t + \gamma_s + \\ + \lambda_q + \varepsilon_{i,t} \quad (23)$$

$LnGI_{i,t}$ measures enterprise green innovation. $DID_{i,t}$ is the interaction between Treat × Post and it captures the difference-in-difference (DID) effect. $ERs_{i,t}$ represent CER and VER. $X_{i,t}$ represents the set of control variables. u_p, ν_t, γ_s, and λ_q denote the enterprise, industry, year, and region fixed effects, respectively.[27] The original rough time and treat variables are not included since the enterprise and year fixed effects are considered. This can effectively alleviate endogeneity problems, such as omitted variable bias, to a certain extent (Meyer, 1995; Shi et al., 2022).

4.3.3. Variables

4.3.2.1. Dependent Variables

Following Rong et al. (2017) and Hu et al. (2021), this chapter uses the natural logarithm of the sum of 1 and the number of overall green patent applications of firm i in year t to proxy green innovation (GI). The green patent data are collected from CNRDS database.

4.3.2.2. Independent Variables

The independent variables are the treated group (Treat) and policy implementation

[27] The study constructs the fixed effect panel data regression to evaluate policy performance. Considering that samples' time, regions and industries are generally different in economic development and population level, according to Liu and Wang (2023), the study also introduces fixed effect variables.

(Post). Treat is a dummy variable equalling 1 if the enterprise is an HPE and 0 otherwise. Post is a dummy variable that equals 1 if the GCG has been implemented, or within the period of 2012–2019. According to the model construction, the interaction Treat × Post (DID) is the key variable and should be significant if the DID effect exists (Wang and Li, 2022).

4.3.2.3. Moderating Variables

CER is mainly divided into two types: CER_Penalty and CER_Incentive. CER_Penalty refers to the penalties imposed by the government on listed enterprises with environmental issues (Ma et al., 2022). It is proxied by whether the enterprise has had the environmental violation noted in the year. CER_Incentive is mainly related to the green subsidies granted by the government.[28] To capture various types of sponsorships initiated by the government, this chapter uses the Word Embedding model from machine learning to construct the green subsidy dictionary and then obtains the green subsidy data by examining the notes to the annual reports of enterprises using this dictionary.[29] After filtering, the logarithm of the sum of the amount green subsidy items detected is used to construct the CER_Incentive indicator.

Traditional text analysis method often relies on the manual identification of synonyms to expand the word set (Loughran and McDonald, 2011). However, this method entails a high degree of subjectivity and may introduce bias into the word set. Consequently, this thesis employs the Word Embedding model to construct the CER_Incentive indicator. The model utilises a neural network to deeply parse a substantial volume of financial texts, thereby building a word similarity model from which similar words are trained. The similarity dictionary, crafted by this model, enables a comprehensive and objective variable measurement, thus enhancing the accuracy of variable measurement

[28] To avoid potential bias caused by the decrease in total observations, this chapter also uses the logarithm of government subsidy (CER_Incentive1) to conduct a robustness test. The results are reported in Appendix 1.
[29] The model and data source of the Word Embedding model are from www.wingodata.com.

and the robustness of empirical results (Li et al., 2021).

VER is measured by the pollutant emission disclosure level of an enterprise. In China, the disclosure of environmental liabilities is voluntary, and thus, its intensity can be reflected by the environmental regulation pressure faced by the enterprise and its willingness to disclose environmental information voluntarily (Huang and Chen, 2015). Specifically, if an enterprise chooses to disclose the pollutant emission information, measured here by six indicators, voluntarily, that indicator is assigned a value of 1, and 0 otherwise. Then, the values of different indicators are aggregated to obtain the VER.[30]

4.3.2.4. Control Variables

The following control variables are considered to control for the influence of enterprise-specific characteristics.

4.3.2.4.1 Profitability

Enterprise profitability is measured by the return on assets (ROA) (Zhang et al., 2022c). This should enhance enterprises' innovation capacity as a higher profit margin allows enterprises to accumulate more retained earnings for R&D investments (Hu et al., 2021). While others argue that as innovation can be costly and risky, managers of those enterprises with high ROA may be reluctant to invest financial resources in green innovation. This may have led to the inconsistent relationship between profitability and innovation (Zhang et al., 2022c).

4.3.2.4.2 Enterprise Size (Size)

[30] The environmental liabilities database of CSMAR constructs an index of voluntary disclosure of enterprise environmental pollutants, which include wastewater emission, COD emission, SO_2 emission, CO_2 emission, soot and dust emissions, and industrial solid waste emission. The index can appropriately reflect the VER level of enterprises (Huang and Chen, 2015).

The natural logarithm of the enterprise's total assets is used to measure enterprise size (Size) (Hu et al., 2021; Zhang et al., 2022c; Albitar et al., 2023). An enterprise's size has always been one of the most important factors affecting its technological innovation capabilities. A scale expansion, such as through merger and acquisition, may facilitate innovation resource sharing, and hence, enhancing an enterprise's innovation capacity (Wang and Li, 2022). Larger enterprises also find it easier to get additional financial support from external sources, allowing them to invest more in R&Ds. Therefore, this chapter expects a positive relationship between enterprise size and green innovation.

4.3.2.4.3 Leverage

Leverage is measured by the ratio of liabilities to total assets (Zhang et al., 2022c; Wang and Li, 2022). A higher leverage may increase the financial risks for enterprises. In response, enterprises may cut R&D investments to reduce uncertainties and/or use the current resources more efficiently for more innovation outputs. Hence, the resulting impact is hard to predict and varies under different scenarios (Zhang et al., 2022c, Lu et al., 2022). Therefore, this chapter considers the effect of leverage on green innovation to be uncertain.

4.3.2.4.4 Listing Years (Age)

The natural logarithm of numbers of years the enterprise has been listed plus one to measure enterprise maturity (Hu et al., 2021).[31] As stock listing may allow enterprises to access a larger funding pool and enhance their public image, enterprises that have been listed for a longer period may be more innovative. However, others argue that stock listing is not a necessary condition for increased green innovation as enterprises may pursue other business objectives after listing (Zhang et al., 2022c). Therefore, this chapter considers the relationship between age and green innovation to be uncertain.

[31] Since the listed age is zero when an enterprise goes public in its first year, taking the natural logarithm of 0 (Ln0) has no mathematical meaning.

4.3.2.4.5 Enterprise Governance Measures (INST and Inden)

This chapter considers two important enterprise governance variables: the shareholding ratio of institutional investors (INST) and proportion of independent directors on the board (Inden) (Hu et al., 2021; Zhang et al., 2022c; Wang and Li, 2022). As important board members, institutional investors may play a key role in influencing an enterprise's capital allocation.

However, due to weak public awareness and insufficient supervision towards environmental problems over the past decades, institutional investors may fail to capture green transition issues due to opportunistic and short-sighted behaviours (Wang and Li, 2022). Consequently, a negative relationship is expected between INST and green innovation. While independent directors play an important role in enterprise governance, their ability to influence enterprise decision-making remains doubtful (Zhang et al., 2022c). Thus, the relationship between Inden and green innovation is expected to be uncertain.

4.3.2.4.6 Corporate Social Responsibility

CSR is proxied by a dummy variable which equals 1 if enterprises disclose their CSR reports, and 0 otherwise (Hu et al., 2021). Enterprises that care about their social impact may take a more active attitude towards green technology innovation (Baker et al., 2021). Therefore, a positive relationship is assumed between disclosing CSR reports and green innovation.

After the variable construction, in the next section, this chapter first examines the effect of GCG on green innovation among HPEs using a DID model. Next, a series of tests, such as parallel trend analysis and propensity score matching-DID (PSM-DID), are conducted to ensure the robustness of the benchmark results. The chapter then conducts the heterogeneity analysis, incorporating factors including types of green innovation, ownership structure of enterprises, and degree of external finance dependence, to explore the relationships under different scenarios. Further, to identify enterprises' response to different types of environmental regulations, this chapter investigates the moderating effect of CERs and VERs on the relationship between GCG and green innovation in HPEs. Finally, to comprehensively understand the effects of GCG, this chapter explores the relationship between GCG and green innovation for GEs.

4.4. Empirical Results

4.4.1. Descriptive Statistics and Correlation Analysis

Table 4.1 presents the descriptive statistics for the main variables. Among the 14,789 samples from 2007 to 2019, the minimum and maximum values of GI are 0 and 3.829, respectively, indicating substantial variations in green innovation levels among the sample enterprises. DID's mean value is 0.152, suggesting that approximately 15.2% of the sample enterprises are affected by the GCG. The results for other variables are consistent with the literature and fall within a reasonable range. Table 4.2 reports the correlation matrix between variables. All variables can significantly impact green innovation performance, suggesting the appropriateness of variable selection (Zhang et al., 2020).

Table 4.1 Descriptive statistics[32]

Variable	Explanations	Obs.	Mean	Std. Dev.	Min	Max	Data Source
GI	Green innovation	14789	0.425	0.839	0.000	3.829	A
DID	The interaction term of Treat × Post	14789	0.152	0.359	0.000	1.000	B
ROA	Profitability	14789	0.044	0.050	-0.165	0.192	C
Size	Enterprise size	14789	22.230	1.308	19.890	26.069	C
Leverage	Leverage	14789	0.421	0.201	0.048	0.845	C
Age	Listing years	14789	2.145	0.785	0.000	3.258	C
INST	Shareholding ratio of institutional investors	14789	0.466	0.241	0.003	0.910	C
Inden	The proportion of independent directors	14789	0.372	0.053	0.308	0.571	C
CSR	Corporate social responsibility	14789	0.295	0.456	0.000	1.000	D

Notes: The data come from different databases; data sources are as follows: A: CNRDS database; B: 'Guidelines for the Industry Classification of Listed Enterprises' and Guidelines for Environmental Information Disclosure of Listed Enterprises (Draft for Soliciting Opinions) published by China Environmental Protection Administration in 2010; C: CSMAR database; D: CSR reports of enterprises.

[32] One observation is dropped in the benchmark regression, which leads to a minor difference in the total observations between the benchmark model and descriptive statistics because this chapter controls enterprise-level fixed effect and uses the command 'reghdfe' in Stata to regress linear models. Maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Hence, the 'reghdfe' package now automatically drops singletons (Correia, 2015).

Table 4.2 Pearson correlation coefficients

	GI	DID	ROA	Size	Leverage	Age	INST	Inden	CSR
GI	1								
DID	0.097***	1							
ROA	0.020**	-0.105***	1						
Size	0.270***	0.092***	-0.041***	1					
Leverage	0.107***	0.015*	-0.367***	0.533***	1				
Age	0.060***	0.084***	-0.176***	0.418***	0.388***	1			
INST	0.061***	-0.061***	0.146***	0.433***	0.247***	0.183***	1		
Inden	0.030***	-0.005	-0.047***	0.059***	-0.001	-0.016**	-0.065***	1	
CSR	0.203***	0.081***	0.061***	0.454***	0.150***	0.228***	0.218***	0.019**	1

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.4.2. Benchmark Results

First, based on Eq. (22), this chapter examines the effect of GCG on HPEs' green innovation. The results are lists in Table 4.3. Columns 1 and 2 shows the results for all sampled enterprises, while columns 3–4 show the results when green enterprises are excluded (i.e. for HPEs) mainly due to concerns about estimation bias (Zhang et al., 2022c). Columns 1 and 3 only includes the DID variable, while columns 2 and 4 also include additional control variables. The coefficients of DID are significantly positive regardless the inclusion of other control variables and green enterprises. Therefore, GCG significantly improves HPEs' green innovation among HPEs. Hence, hypothesis 1 is supported. To obtain more capital from financial institutions and maintain their competitiveness, HPEs are incentivised to make the best of the existing funding to build up their green innovation capability. Hu et al. (2021) find a similar result.

Following Su and Moaniba (2017), Hu et al. (2021), Filiou et al. (2023), the thesis also employs some additional tests to re-test hypothesises of chapter 4 and 5. When the Green Investment (GreenInv) and previous GI are included in the model respectively, the empirical results are still basically consistent with previous findings (results can be found in appendix 4 and 5). The results are still consistent when the $GI_{(t+1)}$ is considered (results can be found in appendix 6). Although some results show differences when the negative binomial model is adopted (results can be found in appendix 7), the preliminary OLS analysis of benchmark model is still reliable due to the thesis uses the logarithm of green patents (Zhang et al., 2022a).

Table 4.3 Benchmark Regression

	(1)	(2)	(3)	(4)
Variables	GI	GI	GI	GI
DID	0.090**	0.108***	0.107**	0.123***
	(2.08)	(3.22)	(2.42)	(3.58)
ROA		0.128		0.136
		(1.03)		(0.78)
Size		0.138***		0.140***
		(5.20)		(6.60)
Leverage		-0.060		-0.062
		(-1.03)		(-0.83)
Age		0.028		0.023
		(0.57)		(0.43)
INST		-0.181***		-0.215***
		(-3.20)		(-3.94)
Inden		-0.120		-0.082
		(-0.98)		(-0.95)
CSR		0.095**		0.093**
		(2.71)		(2.86)
Constant	0.461***	-2.555***	0.409***	-2.643***
	(79.66)	(-5.11)	(60.83)	(-6.44)
Enterprise F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Observations	16,814	16,814	14,788	14,788
R-squared	0.689	0.692	0.677	0.682

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Regarding control variables, only Size, INST, and CSR significantly impact green innovation, in line with prior studies (Hu et al., 2021; Wang and Li, 2022). Compared with smaller enterprises, only large enterprises may have sufficient financial capital and experiences in R&D activities. This translates into increased green innovation outputs. Meanwhile, to maintain their leadership in their respective industries, large enterprises are also under pressure to achieve continuous technological advancements (Wang and Li, 2022). Next, the shareholding ratio of institutional investors has a significant negative relationship with enterprises' green innovation outputs, consistent with expectations. Institutional investors tend to be relatively risk-averse. However, as R&D

investments are highly risky, enterprises with more institutional investors may find it hard to gain the board's approval/support for such investments (Wang and Li, 2022). Lastly, enterprises disclosing CSR reports may care more about their social perception and are more likely to engage actively in green innovation.

Among other control variables with insignificant results, having higher profitability and a longer listing period does not necessarily guarantee more green innovation outputs as enterprises' R&D decisions may be affected by a series of complicated factors. Further, although enterprises with higher leverage level may be subject to stricter lending restrictions and increased financial risks, this does not necessarily restrain their green innovation. (Zhang et al., 2022c). Finally, independent directors' influence on enterprise decision making may be limited.

4.4.3. Robustness Tests

An important assumption of the DID model is that the trends of the treated and controlled groups are similar before policy implementation.[33] This chapter uses the event study method to test this assumption (Zhang et al., 2021a). Following Lu et al. (2022), year dummies are constructed to track the effect of GCG in 2012. Post_-4 to Post_-1 are dummy variables that equal 1 if the observation year is 2008 to 2011, respectively, and 0 otherwise. Post_0 to Post_7 are dummy variables that equal 1 if the observation year is 2012 to 2019, respectively, and 0 otherwise. Post_-4 to Post_7 are respectively multiplied with Treat to obtain 12 dummy variables (DID_-4 to DID_7). Then, Eq. (1) is re-estimated with DID_-4 to DID_7 to examine the parallel trends assumption. The coefficients of DID_-4 to DID_7 are presented in Figure 4.2, corresponding to points -4 to 7. All coefficients are insignificant (all confidence intervals include zero), suggesting that all interactions before 2012 are insignificant. Therefore, the parallel trend assumption is supported and the DID model can be used.

[33] If a significant difference is observed in the green innovation between HPEs and other enterprises before the implementation of the GCG, then the results may not be caused by GCG (Yao et al., 2021).

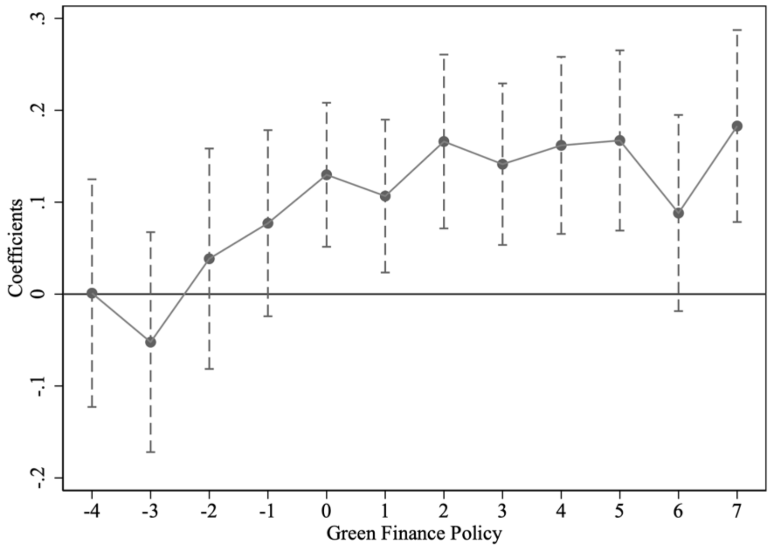


Figure 4.2 Parallel trend analysis

To reduce the potential endogeneity problems caused by self-selection bias, this chapter employs the PSM method to match the treatment and control groups, and reports the results in Table 4.4. Following Cui et al. (2022), this chapter selects the control variables ROA, Size, Leverage, Age, INST, Inden, and CSR as the covariates to run a logit regression to obtain the propensity score of enterprises in the treatment group and then matches enterprises in the control groups with similar characteristics using the neighbour match method. This method can effectively solve the initial difference between the treatment and control groups, thus making the estimation results more accurate (Zhang and Jiang, 2022). The balance tests of PSM show that the bias between two groups is below 10%, suggesting the self-selection bias is also markedly reduced. The results of PSM indicate a strong positive relationship between independent and dependent variables. Related results are presented in the appendix 8. After performing the PSM, the unmatched observations are deleted and the estimations are repeated. The results shown in column 1 are consistent with the main findings of the benchmark model.[34]

[34] The PSM-DID model has passed the balanced test, the results are available upon request.

Table 4.4 Other tests for the benchmark model

Variables	(1) PSM-DID	(2) 2008–2015	(3) Delete2008&2009	(4) Delete Provinces
DID	0.123***	0.101***	0.101***	0.132**
	(3.56)	(3.10)	(3.17)	(2.66)
Constant	-2.650***	-2.974***	-2.392***	-2.924***
	(-6.47)	(-5.66)	(-6.08)	(-6.49)
Control Variables	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Observations	14,778	9,010	13,182	12,385
R-squared	0.682	0.728	0.700	0.660

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

As the inclusion of a long sample period after the implementation of GCG may lead to biased estimations, the sample period is shortened to 2008–2015 (Wang et al., 2022b).[35] The coefficient of DID remains significantly positive in column 2. However, other events during the sample period, such as the great financial crisis (2008 to 2009) and the Beijing Olympics (2008), may also affect the estimation results as these events may have disrupted normal business activities (Zhang et al., 2022c). To remove the potential effects of the great financial crisis, this chapter drops the observations during 2008 and 2009, and reruns the regression. The results in column 3 are consistent with the benchmark results. Regarding the Beijing Olympics, a series of new initiatives were introduced during this period, including the ‘Green Olympics’ concept, and the implementation of blue-sky and green-water projects in Beijing and surrounding regions. In addition, in 2015, with the introduction of the Outline of the Plan for the Coordinated Development of Beijing-Tianjin-Hebei, issues related to environmental protection had become very important. Therefore, following Tang et al. (2020), this chapter drops the related regions and reruns the benchmark model. The findings in

[35] For example, the regression results may be influenced by other policies (Wang et al., 2022b).

column 4 remain robust.[36]

Thus, the DID model employed here is a good fit for the sample, and for both heavily polluting and green enterprises. Overall, GCG emerges as an important factor which affects enterprises' innovation outputs. In the following heterogeneity analysis, although the inclusion of green enterprises did not affect the estimated results in the benchmark model, only HPEs are included to minimise the estimation bias.

4.4.4. Heterogeneity Analysis

4.4.4.1. Heterogeneity Analysis by the Types of Green Innovation

It is suggested that regulations may stimulate different types of green innovation differently due to the investments needed, risks involved, and regulatory intensity (Jaffe and Palmer, 1997). To comprehensively investigate GCG's impact on different types of green innovation, this chapter divides green innovation into green innovation quality performance (GI_qua), and green innovation increment performance (GI_inc). Firstly, the variables GI_qua and GI_inc inherently differ, as Wang and Li (2022) note, GI_qua is more related to newly created inventions, while GI_inc tends to build on existing technologies or products. Given that the GCG is instituted to foster the development and application of green technologies, scrutinizing its impacts on two distinct types of innovation facilitates a more comprehensive understanding. Secondly, from the perspective of enterprises, developing GI_qua and GI_inc entails distinct difficulties and costs. GCG might exert diverse impacts on enterprises' decisions to pursue technological innovation. Compared with GI_inc, GI_qua requires more resource inputs and faces higher uncertainties. Hence, it should be affected more by the GCG. Therefore, examining the effects on these two types of innovation separately enables stakeholders to acquire a more profound understanding of the policy's specific

[36] Regions include Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, and Liaoning.

influences and its repercussions on enterprises' behaviour.

GI_qua is measured by the natural logarithm of one plus the number of green invent patent applications of firm i in year t (Zhang et al., 2023). GI_inc is measured by the natural logarithm of one plus the number of green utility patent applications of firm i in year t (Wang and Li, 2022). Meanwhile, diversified ownership categories of enterprises indicate that green patents are not only an internal research activity but an inter-enterprise cooperative activity (Liu and Wang, 2023). Patent applications can be divided into independent and joint green innovation.[37] Considering the variation of the dependent variable GI, this chapter also considers different green patent indicators. Therefore, considering that both GI_qua and GI_inc comprise independent and joint green innovation, we have GI_qua_ind, GI_qua_joi, GI_inc_ind, and GI_inc_joi (Liu and Wang, 2023).[38] The results are reported in Table 4.5.

Table 4.5 Heterogeneity analysis for green innovation

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI_qua	GI_inc	GI_qua_ind	GI_inc_ind	GI_qua_joi	GI_inc_joi
DID	0.069**	0.124***	0.048*	0.096***	0.032*	0.029**
	(2.25)	(5.08)	(2.09)	(5.71)	(2.04)	(2.23)
Constant	-2.408***	-1.379***	-2.005***	-1.185***	-0.736**	-0.415
	(-6.14)	(-3.83)	(-5.12)	(-4.50)	(-2.97)	(-1.69)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,788	14,788	14,788	14,788	14,788	14,788
R-squared	0.656	0.637	0.624	0.619	0.525	0.503

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

[37] Joint green innovation refers to an application with green invention and/or green utility patents by two or more legal entities, whereas there is only one entity for independent green innovation.

[38] These are independent green innovation quality performance (GI_qua_ind), joint green innovation quality performance (GI_qua_joi), independent green innovation increment performance (GI_inc_ind), and joint green innovation increment performance (GI_inc_joi).

The interaction item, DID, significantly stimulates all types of green innovation, regardless of the variables used. Notably, the coefficient of GI_inc is more significant than that of GI_qua (GI_qua: 0.069, significant at 5% level and GI_inc: 0.124, significant at 1% in Table 4.5), in line with expectations and prior research (Wang and Li, 2022). To attract funding sponsored by GCG, HPEs are keen to advance their green performance to meet the loan requirements. Then, increasing the number of patents is easier than improving their quality (Zhang et al., 2022c). This may be particularly true for enterprises with limited green innovation experiences and operating in heavily polluting industries. Similar conclusions hold for either independent or joint green innovation, as shown in columns 3–6. These results indicate that GCG not only motivates HPEs to improve their own green innovation capabilities, but also enables them to value cooperation with other enterprises.

4.4.4.2. Heterogeneity Analysis by Ownership Structure of Enterprises

Table 4.6 Heterogeneity analysis for the property rights structure

	(1)	(2)	(3)	(4)	(5)	(6)
	SOE			Non-SOE		
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.181**	0.117*	0.161***	0.037*	-0.008	0.074***
	(2.96)	(2.00)	(5.20)	(1.88)	(-0.41)	(5.26)
Constant	-2.337***	-2.142***	-1.055***	-3.027***	-2.658***	-1.842***
	(-5.00)	(-3.69)	(-5.12)	(-6.30)	(-6.18)	(-3.81)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,674	6,674	6,674	7,870	7,870	7,870
R-squared	0.734	0.710	0.684	0.630	0.598	0.586

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Next, this chapter explores the influence of the ownership structure of enterprises on the relationship between GCG and HPEs' green innovation performance by dividing the sample into state-owned enterprises (SOEs) and non-SOEs (Yao et al., 2021). The results are presented in Table 4.6.

The coefficients of DID in columns 1–3 are significantly positive and greater than those in columns 4–6. GCG promotes both the quality and quantity of green innovation for SOEs (GI_qua: 0.117, significant at 10% level and GI_inc: 0.161, significant at 1% in Table 4.6), but only the quantity for non-SOEs. This is unsurprising as compared with non-SOEs, SOEs tend be favoured by bank credit, enabling them to participate in high-quality green innovation (Ouyang et al., 2020). In addition, the close relationship between SOEs and governments also suggests that the former may also have more pressure to meet state-mandated emission reduction requirements (Wang et al., 2022b). This can force them to make the best use of the required funding for more green innovation. Nevertheless, for both SOEs and non-SOEs, incremental green innovation remains the key focus mainly because the sample is comprised of heavily polluters only. For instance, any adjustments/small amendments to existing green technologies may help them achieve significant emission reduction. However, non-SOEs are neither capable nor incentivised enough to engage in more advanced green quality innovation.

4.4.4.3. Heterogeneity Analysis by External Finance Dependence

The essence of GCG's design is linking the availability of bank credit with the environmental performance of enterprises. Therefore, enterprises that rely heavily on external financing are more likely to be affected by the GCG (Sun et al., 2019). To measure the extent of enterprises' reliance on external capital, following Sun et al. (2019), this chapter constructs an external finance dependence (EFD) index and then classifies enterprises into two categories high-EFD and low-EFD according to their reliance.[39] A high index underscores the enterprise's pronounced reliance on external

[39] EFD = (Capital expenditures − Cash flow from operations) / Capital expenditures. Enterprises are classified as high-EFD if the index value is above the median (0.216), and low-EFD otherwise.

financing to bolster its investment activities. This could stem from the enterprise's operational activities not generating sufficient cash or perhaps due to the enterprise embarking on large-scale investment activities that necessitate substantial capital expenditure. Conversely, a low index suggests that the enterprise can predominantly depend on the cash flow produced from its own operational activities to fund its investments. The results are reported in Table 4.7.

Table 4.7 Heterogeneity analysis for external finance dependence

	(1)	(2)	(3)	(4)	(5)	(6)
	High-EFD			Low-EFD		
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.127***	0.080**	0.122***	0.111**	0.049	0.114***
	(3.76)	(2.86)	(6.38)	(2.69)	(0.96)	(8.04)
Constant	-2.808***	-2.317***	-1.817***	-3.026***	-2.448***	-2.121***
	(-4.57)	(-3.68)	(-4.31)	(-4.24)	(-4.82)	(-3.28)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,748	4,748	4,748	4,723	4,723	4,723
R-squared	0.716	0.682	0.682	0.769	0.750	0.738

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

The results for both high- and low-EFD enterprises in columns 1–6 are consistent with earlier findings. However, as shown in columns 1–3, GCG has a larger effect on the green innovation performance of high-EFD HPEs, consistent with prior studies (Sun et al., 2019). When the government advocates green development, it will adjust credit policies to restrict the inflow of bank loan to heavily polluting activities accordingly (Wang and Li, 2022). This forces the HPEs with high-EFD to enhance their green innovation performance, signifying their determination of achieving sustainable growth to secure banking credit. Notably, GCG significantly improves both the quality and quantity of green innovation in the high-EFD group, but only the quantity in the low-EFD group. This could be attributed to the fact that high-EFD enterprises are more inclined to boost advanced green innovation performance to ensure future green credit availability from banks. However, as they are less reliant on external finance, low-EFD enterprises might be reluctant to assume higher risks associated with advanced green innovation. In contrast, low-EFD enterprises tend to enhance their GI_inc primarily to comply with the environmental protection mandates of relevant regulations.

4.4.5. Moderation Effects Analysis

Table 4.8 Moderation effects analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.112***	0.067**	0.110***	0.129*	0.083	0.095***	0.085**	0.038	0.101***
	(3.39)	(2.25)	(5.57)	(2.06)	(1.43)	(3.58)	(2.91)	(1.52)	(5.31)
CER_Penalty × DID	0.050	0.079	0.084						
	(0.25)	(0.89)	(0.40)						
CER_Penalty	-0.121***	-0.193***	0.018						
	(-3.14)	(-3.22)	(0.66)						
CER_Incentive × DID				0.031**	0.022***	0.027*			
				(2.74)	(9.87)	(2.12)			
CER_Incentive				-0.001	-0.002	-0.001			
				(-0.36)	(-0.80)	(-0.41)			
VER × DID							0.023***	0.026***	0.008**
							(4.72)	(8.86)	(2.19)
VER							0.005	-0.000	0.005*
							(1.28)	(-0.01)	(1.95)
Constant	-2.500***	-2.337***	-1.280***	-3.109***	-2.931***	-1.954***	-2.573***	-2.417***	-1.299***
	(-6.01)	(-5.66)	(-4.23)	(-8.75)	(-10.21)	(-13.31)	(-6.16)	(-5.87)	(-4.33)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,064	14,064	14,064	4,779	4,779	4,779	14,064	14,064	14,064
R-squared	0.693	0.670	0.650	0.696	0.666	0.669	0.694	0.670	0.651

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

The CERs and VERs play a key role in the green transformation process (Horbach et al., 2012; Huang and Chen, 2015). By enacting different environmental regulations, a synergistic effect is anticipated, consequently facilitating the development of green innovation. Here, additional tests are conducted to investigate the moderating effect of other environmental regulations on the relationship between the GCG and green innovation among HPEs. To capture the diverse impact of different types of environmental regulations, CERs and VERs are analysed separately. The results are reported in Table 4.8.

As a commend-based regulatory instrument, CER_Penalty has a negative relationship with GI and GI_qua (Columns 1–3). This is unsurprising as CER_Penalty represents additional environmental cost to HPEs, reducing the capital available for R&D activities. In some extreme cases, enterprises could be suspended for rectification due to environmental violations (Ma et al., 2022). Regarding the moderation effect, CER_Penalty has no significant impact on the relationship between GCG and green innovation. Thus, hypothesis 2a is supported. This may be because GCG is more of a market mechanism but CER_Penalty is more of a policy instrument. They tend to function on enterprises' innovation behaviours differently. Notably, as only 47 enterprises, or 0.5% of observations, are fined over the sample period. Thus, the CER_Penalty is used more like a demonstrating mechanism to showcase the government's intention. The results are basically consistent when GreenInv and previous GI are included in the model respectively (results can be found in appendix 4 and 5). Although there is a different picture when the $GI_{(t+1)}$ is considered, the limited number of penalties received by enterprises shows the ineffectiveness of this regulation tool (results can be found in appendix 6). Also, the results are still consistent when the negative binomial model is adopted (results can be found in appendix 7).

CER_Incentive has a significantly positive moderation effect (e.g. the coefficient of DID in column 4 of Table 4.8 (0.031) is significant at 5% level). Thus, hypothesis 2b is supported. However, it is unable to significantly affect enterprises' green innovation on its own. Consistent with Huang et al. (2019), if a HPE can access state subsidies, it can favourably position itself to secure additional green credit from banks. With sufficient funding, high quality green innovation is more likely to be delivered. Meanwhile, to attract future government funding continuously, enterprises are also motivated to fulfil the requirements of the government and financial institutions with the highest possible quality. This may enhance their green innovation efficiency. This may be why the moderation effect of CER_Incentive is more significant in the case of green innovation quality rather than the simpler incremental green innovation. Although the situation shows differences when the GreenInv and previous GI are included in the model respectively due to the decrease of data sample, the results become better and consistent with previous findings when the CER_Incentive1 is considered (results can be found in appendix 4 and 5). In addition, the results are still consistent when the $GI_{(t+1)}$ is considered (results can be found in appendix 6). Even though some results show differences when the negative binomial model is adopted (results can be found in appendix 7), the preliminary OLS analysis of benchmark model is still reliable due to the thesis uses the logarithm of green patents.

The moderation effect of VER is significantly positive for all types of green innovation measures (Columns 7–9) (e.g. the coefficient of DID in column 7 of Table 4.8 (0.023) is significant at 1% level). The higher intensity of VER shows the green transition determination of HPEs and their motivation to engage more in green innovation activities (Huang and Chen, 2015). Furthermore, this positive impact is more prominent for green innovation quality than increment (Columns 8–9). To achieve a more thorough green transformation, HPEs try to produce high-quality green innovation (Bu et al., 2020). However, due to the lack of core green technologies and green capital, HPEs also invest part of their financial resources in green innovation increment to meet the compliance requirements of financial institutions and the government. Thus, hypothesis 3 is supported. When the GreenInv and previous GI are included in the model respectively, the empirical results are still basically consistent with previous findings (results can be found in appendix 4 and 5). The results are still consistent when the $GI_{(t+1)}$ is considered (results can be found in appendix 6). Also, the results are still consistent when the negative binomial model is adopted (results can be found in appendix 7).

Thus, CER_Incentive and VER can positively moderate the relationship between GCG and green innovation in most cases. However, CER_Penalty tends to be ineffective. Meanwhile, green quality innovation is more significantly promoted by the CER_Incentive and VER than incremental innovation, as enterprises are more motivated to build long-term competitive advantages in their green transition.

4.4.6. Channel Analysis for Enterprise Green Investments

Table 4.9 Channel analysis of enterprise green investment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	GreenInv	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc
GreenInv			0.010***		0.005***		0.007**
			(4.22)		(3.59)		(2.78)
DID	0.080	0.160***	0.160***	0.102***	0.102***	0.174***	0.173***
	(0.62)	(7.17)	(6.92)	(8.49)	(8.30)	(22.14)	(21.64)
Constant	-2.443	-1.063***	-1.039***	-1.167***	-1.154***	-0.312	-0.294
	(-0.89)	(-3.50)	(-3.27)	(-6.38)	(-6.41)	(-1.20)	(-1.25)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,045	3,045	3,045	3,045	3,045	3,045	3,045
R-squared	0.651	0.729	0.729	0.719	0.719	0.702	0.702

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

This chapter explores how GCG influences the green innovation performance of enterprises. Specifically, this chapter focuses on the efficiency of green capital utilisation (GreenInv) in HPEs. The data of GreenInv is collected manually from the notes of 'projects under construction' in the annual report of enterprises (Lu, 2021). Specifically, this chapter uses the Word Embedding model to construct a green investment dictionary and then extracts the GreenInv data based on this dictionary. After data cleaning, the amount of different green investment items is aggregated to create the GreenInv variable. The results are reported in Table 4.9.

GCG and GreenInv have an insignificant relationship, while GreenInv and green innovation are significantly related. Thus, while GCG does not affect the green investment made by HPEs (Column 1), it can significantly enhance their green innovation performance (Column 3). Similar results are found for green innovation quality and increment (Columns 5 and 7). This may be because as the implementation of GCG may further constrain the capital inflow to HPEs, they may be motivated to improve their innovation efficiency given the limited funding. This may be the only viable way for such cash-strapped enterprises to transform themselves for long-term sustained development. Yan et al. (2022) find similar results in their study of green finance and enterprise investment efficiency. Consequently, GCG imposes added compliance obligations and elevates social reputational pressure on HPEs, compelling these enterprises to augment their green innovation output. GCG also reflects societal concern, pressing enterprises to boost their innovation efficiency either to secure green capital in the future or to prevent falling behind competitors.

4.4.7. The Impact of GCG on Green Enterprises

Since the GCG affects both HPEs and GEs simultaneously, a comparative study is conducted here to test the robustness of the findings. According to Al-Tuwaijri et al. (2004) and Wang et al. (2020), GEs refer to enterprises whose main business involves environmental-friendly products. Based on annual reports and the industry classification of the listed enterprises developed by Tonghuashun Finance and Economic, this chapter manually analyses the main business of every enterprise to determine whether it can be classified as a green enterprise.[40] Furthermore, this chapter

[40] https://www.10jqka.com.cn/

checks the selection results of GEs with the Hexun, one of the most famous financial and economic platforms, to ensure the accuracy of the results.[41] Then, the chapter replaces the treated group with GEs.[42] Specifically, Treat is a dummy variable equalling 1 if the enterprise is a GEs. Post is another dummy variable that equals 1 if the GCG has been implemented, or the samples are within the 2012–2019 period. The interaction Treat × Post (DID) should be significant if the DID effect exists (Wang and Li, 2022). The results are reported in Table 4.10.

Table 4.10 Results of green innovation for GEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	GI	GI_qua	GI_inc	GI_qua_ind	GI_inc_ind	GI_qua_joi	GI_inc_joi
DID	0.104***	0.098***	0.107***	0.045*	0.040**	0.077***	0.080***
	(3.25)	(4.19)	(4.84)	(1.81)	(2.43)	(13.60)	(5.09)
Constant	-2.626***	-2.247***	-1.529**	-1.863***	-1.198**	-0.782*	-0.579*
	(-4.47)	(-4.45)	(-2.74)	(-4.31)	(-2.77)	(-2.12)	(-2.03)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,496	13,496	13,496	13,496	13,496	13,496	13,496
R-squared	0.698	0.672	0.648	0.654	0.637	0.481	0.480

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

[41] https://www.hexun.com/?from=rongshuxia; Specifically, this chapter uses Python to crawl the main business content of listed enterprises from Tonghuashun Finance and Economic, and Hexun, and then manually judges related information.

[42] Furthermore, this chapter drops HPEs from the regression sample to avoid potential research bias.

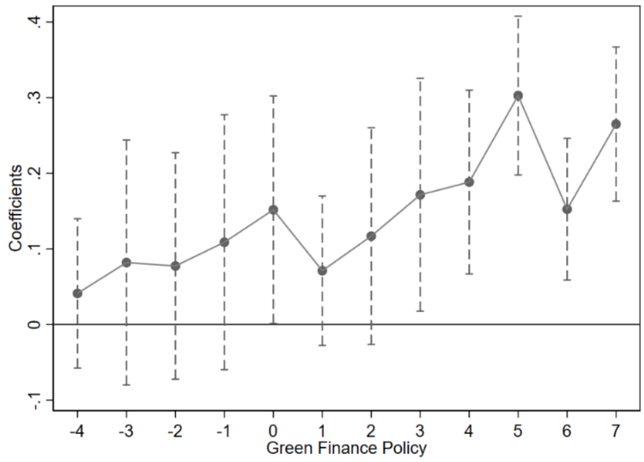


Figure 4.3 The Parallel trend analysis of green enterprises

Similar to HPEs, GCG can significantly promote green innovation among GEs (Column 1).[43] To maintain market competitiveness, GEs are also under the pressure to enhance their innovation capacity to deliver better green products and services (Xu and Li, 2020). Further, GCG promotes the green innovation quality and increment of GEs (Columns 2–7). Notably, the promotional effect of GCG on green innovation quality is greater for GEs than that in HPEs.[44] This is as expected as GEs tend to have a better foundation in green innovation.[45] Therefore, they are more likely to concentrate more on those high-quality green innovation to build their long-term competitive strength.

This chapter then applies similar tests to capture the impact of ownership structure, external finance dependence, and the moderating effect of environmental regulations among GEs.

[43] The parallel trend analysis also shows the adoption of DID model is rational, as shown in Figure 4.3.
[44] The coefficient of DID on GI_qua is 0.098 for GEs at the 1% level, whereas it is 0.069 for HPEs at the 5% level.
[45] The average green innovation performance of GEs is higher than that of HPEs, see Appendix 2.

Table 4.11 Heterogeneity analysis of the property right structure for GEs

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.142***	0.118***	0.100***	0.009	0.034	0.066
	(4.10)	(3.97)	(3.75)	(0.24)	(1.30)	(1.60)
Constant	-1.795	-1.678	-0.709	-3.362***	-2.709***	-2.281***
	(-1.44)	(-1.38)	(-1.11)	(-5.67)	(-5.32)	(-3.89)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,897	5,897	5,897	7,378	7,378	7,378
R-squared	0.732	0.708	0.666	0.677	0.649	0.637

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries, robust t statistics are enclosed in parentheses.

In terms of the impact of ownership structure (Table 4.11), in general, the conclusions for HPEs hold. The GCG has a greater effect on green innovation among SOEs, especially for the green innovation quality performance. However, GCG has no effects for non-SOE green enterprises. This finding is different than that for non-SOE heavily polluting enterprises. Hu et al. (2021) reach similar conclusions. Unlike HPEs, GEs are not that cash-strapped. Further, the non-SOE green enterprises are not largely influenced by government policies but are more likely to follow their own green development pace.

Table 4.12 Heterogeneity analysis of the external financing dependence for GEs

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.094*	0.081**	0.099**	-0.058**	0.002	-0.025
	(1.89)	(2.62)	(2.49)	(-2.20)	(0.06)	(-1.27)
Constant	-2.984***	-2.340***	-1.884***	-2.026***	-1.469***	-1.719***
	(-3.88)	(-3.67)	(-3.20)	(-3.11)	(-3.01)	(-3.05)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,347	4,347	4,347	4,348	4,348	4,348
R-squared	0.752	0.735	0.712	0.781	0.751	0.743

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries, robust t statistics are enclosed in parentheses.

With regard to the impact of external finance dependence (Table 4.12), GEs that depend heavily on external finance are more willing to improve green innovation performance to secure future funding, whereas those with low-EFD tend to care little about continuous green innovation outputs. This is in line with Sun et al. (2019). Compared with HPEs, GEs tend to already have a sound level of green innovation. Therefore, they may not experience serious difficulties in accessing funding directly from banks and other financial institutions (Peng et al., 2022).

Table 4.13 Moderation effects analysis for GEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.093**	0.093***	0.094***	0.108***	0.120***	0.052	0.082**	0.081***	0.093***
	(2.49)	(3.68)	(3.81)	(3.05)	(5.75)	(1.37)	(2.31)	(3.29)	(4.11)
CER_Penalty × DID	0.278	0.231	0.274						
	(1.36)	(1.71)	(1.48)						
CER_Penalty	-0.083**	-0.135***	0.018						
	(-2.46)	(-7.26)	(0.55)						
CER_Incentive × DID				0.019	0.020**	0.025			
				(0.80)	(2.76)	(1.01)			
CER_Incentive				0.002	0.002	0.002***			
				(0.80)	(0.85)	(3.40)			
VER × DID							0.042***	0.047***	0.006
							(8.35)	(29.82)	(0.54)
VER							0.006	0.003	0.005
							(1.45)	(0.80)	(1.17)
Constant	-2.542***	-2.203***	-1.444**	-2.789***	-2.682***	-2.045***	-2.576***	-2.242***	-1.447**
	(-4.35)	(-4.25)	(-2.58)	(-4.12)	(-4.21)	(-3.42)	(-4.50)	(-4.42)	(-2.64)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,852	12,852	12,852	4,435	4,435	4,435	12,852	12,852	12,852
R-squared	0.711	0.686	0.663	0.730	0.715	0.697	0.711	0.687	0.663

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries, robust t statistics are enclosed in parentheses.

Regarding the moderating effect of other environmental regulations (Table 4.13), CER_Penalty still fails to positively moderate the effect of the GCG on green innovation for GEs. This is unsurprising as GEs tend to have better environmental performance and fewer environmental violations than HPEs. [46] Regarding CER_Incentive, the significant moderating effect is only present in the case of green innovation quality performance. Given that GEs possess strong green innovation capabilities, additional financial support from the government may encourage these enterprises to pursue more advanced innovation, driving the overall industrial structural

[46] The mean value of environmental violation for HPEs is 0.0079, which is nearly twice higher than that for green enterprises at 0.0041.

upgrading. Finally, the VER only significantly promotes the positive relationship between GCG and GI or GI-qua. This is consistent with earlier findings. Adhering to VER often demands a substantial allocation of resources, including time and finances. Consequently, GEs might opt to channel these resources into advanced green innovation instead of dispersing them across multiple projects (Huang and Chen, 2015).

Table 4.14 Channel analysis of enterprise green investment for GEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	GreenInv	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc
GreenInv			0.013***		0.005**		0.011*
			(3.32)		(2.85)		(2.10)
DID	-0.067	0.144**	0.145**	0.207***	0.207***	0.105**	0.106**
	(-0.66)	(2.65)	(2.65)	(4.46)	(4.45)	(2.49)	(2.47)
Constant	-4.536*	-1.502	-1.444	-2.032	-2.009	-0.545	-0.494
	(-1.82)	(-1.09)	(-1.07)	(-1.68)	(-1.67)	(-0.49)	(-0.46)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,969	2,969	2,969	2,969	2,969	2,969	2,969
R-squared	0.651	0.751	0.751	0.736	0.736	0.713	0.714

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries, robust t statistics are enclosed in parentheses.

Lastly, the channel analysis results for GEs are consistent with those for HPEs (Table 4.14). Overall, the GCG is playing a more active role in stimulating green innovation efficiency among listed green enterprises in China (Xu and Li, 2020).

4.5. Conclusion and Policy Implications

4.5.1. Conclusion

China's 12^{th} Five-Year-Plan (2011–15) reported for the first time that the country was facing severe environmental degradation, showing the government's interest in considering these issues. Indeed, various policy initiatives were initiated to rebalance the economy for environmental protection and sustained development, including the GCG. The GCG can be regarded as a valuable market-based regulatory instrument designed to mitigate environmental pollution and provide more funding for green activities (Lu et al., 2022). This chapter empirically investigates the influence of GCG on green innovation using panel data on Chinese listed enterprises from 2007 to 2019. A DID model is employed for the benchmark test, and then a series of tests, such as the parallel trend analysis and PSM-DID, are conducted to ensure the robustness of the results. Next, this chapter explores heterogeneous impacts of various factors, including types of green innovation (green quality innovation and green incremental innovation), ownership structure of enterprises (SOEs and non-SOEs), and the degree of external finance dependence.

Overall, the results shows that GCG can enhance the green innovation performance of both heavily polluting (e.g. the coefficient of DID in column 4 of Table 4.3 (0.123) is significant at 1% level) and green enterprises (e.g. the coefficient of DID in column 1 of Table 4.10 (0.104) is significant at 1% level). Compared with green enterprises, heavily polluters tend to pay more attention on the green innovation increment due to their limited green innovation experiences and financial resources (GI_qua: 0.069, significant at 5% level and GI_inc: 0.124, significant at 1% in Table 4.5). Incremental green innovation is easier and more feasible for them to meet government regulatory requirements while achieving a certain degree of green transformation. Meanwhile, compared to HPEs, with the support of GCG, green enterprises have stronger capability in delivering green quality innovation and this may help them build up long-term competitive advantages. SOEs are also better motivated by the GCG to deliver high-quality green innovation, given their closer relationship with the government. Compared with non-SOEs, SOEs tend be favoured by banking credit but are also under more pressure to meet state-mandated emission reduction requirements (Wang et al., 2022b). Lastly, enterprises that need more external financial support are more likely to be affected by the GCG as they are forced to deliver superior performance to meet the borrowing conditions.

Given the close connection among other environmental regulations, the GCG, and enterprise innovation, this chapter further investigates the moderation effects of different types of environmental regulations, including CERs and VERs. The penalty-based regulation, CER_Penalty, has no significant moderation effect, while the incentive-based regulation (CER_Incentive) can promote the relationship between the GCG and green innovation for HPEs significantly (e.g. the coefficient of DID in column 4 of Table 4.8 (0.031) is significant at 5% level). Similar conclusion is also reached for the VER (e.g. the coefficient of DID in column 7 of Table 4.8 (0.023) is significant at 1% level). Moreover, the CER_Incentive and VER have more significant positive moderation effects for higher quality green innovation, especially for green enterprises. A higher intensity of VER signifies the green transition determination of enterprises, signifying their motivation to engage more in high quality green innovation activities (Huang and Chen, 2015). Lastly, the mechanism analysis shows that the GCG can enhance green innovation performance by improving the efficiency of green investment use.

4.5.2. Policy Implications

First, more targeted green finance policy can be implemented to encourage greater bank lending to HPEs for increased green innovation. This can help accelerate overall industrial transformation. Next, stimulated by GCG, although HPEs are willing to innovate, they tend to focus more on incremental innovation due to their lack of experience and resources. Therefore, policy efforts should encourage information/knowledge sharing among enterprises of the same industry. This can help improve resource use efficiency. Meanwhile, effective performance measures should be designed to evaluate the long-term green performance of HPEs. This may encourage their management to commit valuable financial resources towards higher quality green innovation, which require more investments and longer development cycle. Lastly, the Chinese government should use different environmental policy tools effectively together to leverage their synergistic effects. Enterprises should be both pressured and motivated to engage more in high quality green innovation. This requires the further improvement of the current green finance system. As a key player, banks need to take a more proactive role in this process. They should establish comprehensive procedures to encourage promising green innovation at an early stage. Banks should also provide sufficient supervision throughout the process to encourage enterprises, especially the heavily polluters, to participate in more green innovation and socially responsible behaviours.

4.5.3. Limitations and Potential Future Work

Due to the data availability, currently it is difficult to obtain adequate data of enterprise-level CO_2 emissions in Chinese market. The disclosure of enterprise-level CO_2 emissions is very limited in the Chinese market. As data become accessible, the current research can be extended to understand the impact of policies on enterprises' emissions reduction and innovation behaviours. This can facilitate the drawing of useful experiences to assist the green transformation process among other developing economies.

Chapter 5: The Impact of Green Bond Issuance on Green Innovation Performance: Evidence from China

5.1. Introduction

In recent years, climate change caused by fossil fuel consumption and greenhouse gas emissions has become a crucial global issue (Han and Li, 2022). Countries around the world are actively exploring strategies to successfully transform to low-carbon and green economies (Wang and Fan, 2023). As one of the largest polluters, China reportedly sacrifices approximately 10% of its GDP every year to tackle environmental pollution-induced problems (Ge et al., 2020). The hope is that the country can achieve high-quality sustained growth in the near future (Li et al., 2023).

To encourage changes in enterprise behaviour along these lines, the Chinese government proposed a series of policy initiatives.[47] They mainly include the command- and market-based regulations; notably, the latter play a more significant role as they have flexibility, autonomy, and strong economic efficiency (Tian and Feng, 2022). Among these market-based tools, the development of green bonds over the past few years has attracted great attention. As shown in Figure 5.1, although developed countries continue to be the primary issuers of green bonds, developing countries have also witnessed a rapid increase in green bond issuance (GBI) in recent years. In 2022, approximately 23.28% green bonds were issued by emerging market enterprises.

[47] Currently, China mainly has command- (i.e. *Atmospheric Pollution Prevention and Control Law (2015 Revision)*), market- (i.e. *Emission Trading Markets Pilots Policy (2007), Guidelines for Green Credit issued by the China Banking Regulatory Commission (2012), and The Guidelines on the Issuance of Green Bonds issued by the National Development and Reform Commission in 2016*), and voluntary-based environmental regulations.

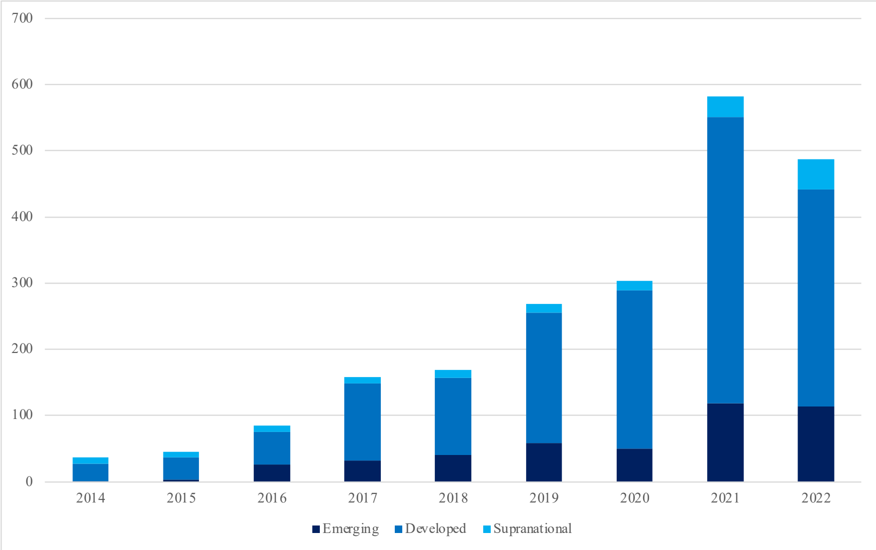


Figure 5.1 The source of green bonds, by year

Note: This figure shows the source (emerging, developed, and supranational markets) of the green bonds from 2014 to 2022. The volume ($bn) of green bonds is shown on the vertical axis. Data source: Climate Bonds Initiative, https://www.climatebonds.net/.

Besides offering the same financing functions as traditional bonds, green bonds serve as a market-based instrument designed to incentivise enterprises, rather than impose mandatory regulations, to facilitate green transformation. To promote the green development of businesses, and accelerate their transformation and upgrade, the National Development and Reform Commission of China released 'The Guidelines on the Issuance of Green Bonds' in 2016. This policy aims to encourage enterprises to raise funds through market mechanisms and specifies that the proceeds from green bonds will predominantly finance green projects during the bond term. Hence, Chinese GBI is characterised by a significant top-down policy push using the capital market mechanism to impact on enterprises' strategic choices. For enterprises, issuing green bonds to raise funds for green projects is both a financing and an environmental protection behaviour (Tang and Zhang, 2020). Since 2016, listed enterprises in China are allowed to issue green bond provided that they satisfy the following requirements: the funds raised from GBI should be allocated to compliant green projects; the issuing enterprise is required to demonstrate that the project aligns with government environmental standards; and the enterprise should regularly disclose both the usage of green bond proceeds and resulting environmental impact of these activities. As shown in Figure 5.2, China has become the second-highest green bond issuer in the world. Figure 5.3 depicts the development of green bonds in China over the period 2014–2022. Within ten years, the total green bond issuance in China has increased by $85.2 bn, reaching $85.4 bn in 2022.[48] Indeed, it is now regarded as an important funding source for enterprises' green innovation (GI).

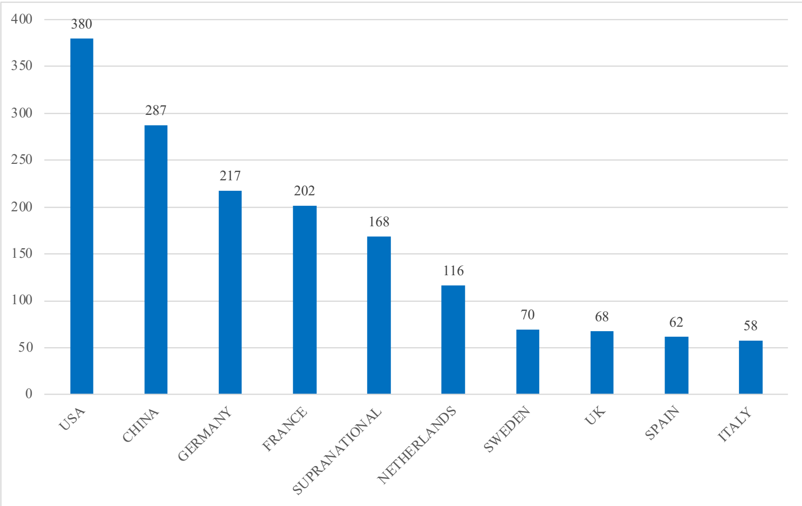


Figure 5.2 Top 10 green bond issuers in the world, until 2022

Note: This figure shows the top 10 green bond issuers in the world until 2022. The volume ($bn) of green bonds is shown on the vertical axis. Data source: Climate Bonds Initiative, https://www.climatebonds.net/.

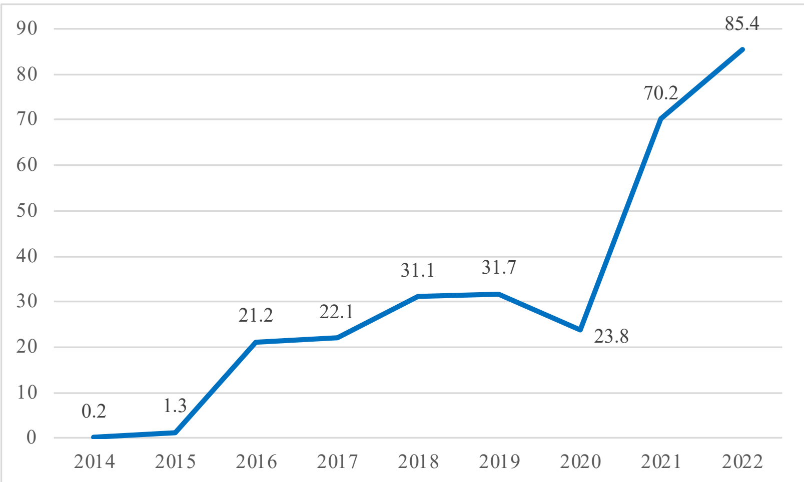


Figure 5.3 Green bonds issuance in China, by year

Note: This figure shows the issuance of green bonds in China from 2014 to 2022. The volume ($bn) of green bonds is shown on the vertical axis. Data source: Climate Bonds Initiative, https://www.climatebonds.net/.

48 https://www.climatebonds.net/

As a technological innovation activity initiated for green development and ecological environment improvement, GI is considered a meaningful way to enhance the green performance of enterprises (Wang et al., 2023). Like other types of R&D activities, GI also involves substantial capital investment, high risk of failure, and long development period. This has increased the need for establishing an effective market-based financial system which can provide the required funding support to such R&D activities (Hu et al., 2021). Green bonds are generally regarded as a response to this need (Wang et al., 2022c). On the one hand, only those enterprises who display superior green performance may gain support from the regulatory bodies and investors in the bond issuing process. On the other hand, GBI also has a demonstration effect, signifying the enterprises' intention/determination of engaging into more GI activities. This may also increase peer pressure on other competitors, thereby accelerating the entire industry's green transition (Gupta and Barua, 2018).

Given the potential positive impact of GBI in the overall economic structural transformation process and its growing importance in the Chinese market, this chapter uses panel data on Chinese listed enterprises from 2007 to 2019 to empirically examines this positive impact. The chapter asks: Whether enterprises issuing green bonds can deliver better GI performance under heterogeneous conditions? If so, what are the underlying mechanisms? Does GBI encourage peer enterprises to participate more in GI activities? The findings obtained from this chapter can provide valuable guidance to different regions in adjusting and optimising their respective environmental regulation polies. Useful experiences could also be generalised to other developing economies in achieving more sustained growth.

The chapter makes three contributions to existing literature. First, as green bond is a type of debt finance and an important component of enterprises' capital structure, most studies focus on the bond pricing or stock market reactions to GBI (Zerbib, 2019; Tang and Zhang, 2020). There is limited research examining the relationship between green bond issuance and green innovation in the Chinese market. However, understanding the impact of green bond issuance on an enterprise's green transition is of great significance. Consequently, this chapter aims to address this gap by investigating whether the issuance of green bonds has enabled enterprises to achieve superior green innovation performance.

Second, due to the positive publicity created by GBI and potential long-term benefits of GI, this chapter further expands its scope by focusing not only on enterprises issuing green bonds, but also on other enterprises operating in the same industry. By exploring the spillover effects of the GBI, this chapter broadens the understanding of PH's influence and its practical application in the Chinese market in particular.

Third, this chapter considers the heterogeneous relationship between GBI and GI considering various factors, including different supervisory mechanisms, enterprise characteristics, and regional diversification, into the analysis. Enterprises under different intensity of external supervision, different ownership structure, and located in regions with diversified economic development levels may respond differently with GBI. These findings can further supplement the PH in the Chinese market.

The rest of the article is organised as follows. Section 2 provides an overview of the literature and proposes hypotheses. Section 3 describes the variables and methodology. Section 4 discusses the empirical results. Section 5 presents the conclusions of this chapter.

5.2. Literature Review and Hypothesis Development

Environmental protection and economic development have a close connection with each other. In 1991, Porter first proposed that appropriately designed environmental regulations may alter enterprises' behaviour towards a more sustainable path (Porter, 1991). This is also known as the Porter Hypothesis (PH). Considering the growing public awareness of environmental protection and tougher government regulations, the PH was refined by further elaborating on the process by which environmental protection could enhance competitiveness through innovation.[49]

Many studies have empirically tested PH, suggesting that well-designed environmental policy stimulates innovation (Calel and Dechezlepretre, 2016; Xie et al., 2017). Ford et al. (2014) discover that regulation spurs innovation in Australia's oil and gas industry, as enterprises facing high levels of regulatory burden are more likely to introduce product and service innovation. Calel and Dechezlepretre (2016) examine the impact of the European Union Emissions Trading System on technological change and find an increase in low-carbon innovation among regulated enterprises. Some studies also investigated the PH from the perspective of heterogeneous impacts of different types of environmental policies. Xie et al. (2017) find that compared with a command-and-control policy, flexible environmental regulations, such as market-based instruments, are more conducive for promoting productivity and enterprises' innovation capability. Market-based policies provide enterprises with greater flexibility in the abatement process, allowing them to select either the most suitable technological solution or timing for the adjustment (Albrizio et al., 2017). Garcés-Ayerbe and Cañón-de-Francia (2017) argue that environmental policies should also cooperate with other regulatory or supervisory approaches. The authors believe that aligning environmental regulations with the specific condition of enterprises or/and regions can help create a win-win situation both economically and environmentally. Consequently, studies related to environmental protection should also consider other dimensional factors, such as enterprises characterises or public attention.

As an important type of market-based environmental policy instrument, green bonds

[49] A well-designed environmental regulation system should have the following characteristics: broad coverage, it should provide the largest potential space for enterprise innovation; continuity, it should stimulate continuous innovation; flexibility, the environmental policies can be implemented in stages with certain level of discretionary power been given to enterprises; enforceability, an effective appraisal system should be put in place to control and punish wrong-doings, and encourage government-enterprise collaboration (Porter and Linde, 1995).

have attracted great attention since their introduction as they are both an environmental regulatory instrument proposed by the government and a financing source welcomed by enterprises (Wang et al., 2022d; Lee et al., 2023). Most early studies focus on issues related to the pricing and yield of green bonds (Zerbib, 2019; Larcker and Watts, 2020). GBI can be used by enterprises to create a positive publicity; improve performance over the short-term; and increase their long-term value (Tang and Zhang, 2020; Flammer, 2021). This positive effect is more pronounced when the green bonds issued are underwritten by a third party and/or when the initial offering resulted in high cumulative excess returns.

Besides enhancing enterprise performance, green bonds are designed to provide financial support to enterprises' GI activities (Lin and Su, 2022). Compared with a conventional bond which has an average term to maturity of 12.2 years, the green bond has a much longer repayment period of 17 years (Roch et al., 2023). This aligns it well with the long cycle of innovation activities (Huang et al., 2022). Consequently, this ensures the provision of sustained funding for enterprises' GI (Herrera and Minetti, 2007). Meanwhile, unlike the indirect financing method of bank credit, bond financing is a direct method which does not require enterprises to pay excessive intermediary fees (Tang and Zhang, 2020; Su et al., 2023). For example, in 2022, the average interest rate for loans in China was 4.385%,[50] noticeably higher than the average interest rate for GBI during the same period at 3.286%.[51] Specifically, banks act as intermediaries in providing credit financing and bear the operational costs, such as reviewing loan applications and administering loans. These costs are transferred to the borrower in the form of higher interest rates, which is not the case in the bond market where these costs are comparatively low. Furthermore, because of their green characteristics, enterprises may issue green bonds at a lower cost than conventional bonds and easily acquire favourable policies such as tax benefits (Tang and Zhang, 2020). This has made the issuance of green bond more attractive. Finally, due to its signalling effect, green bonds

[50] https://www.ceicdata.com/en
[51] https://www.wind.com.cn

may also assist issuers to reduce information asymmetry, and thus, further lower the financing costs (Flammer, 2021). With clearly defined use of fund, enterprises that issue green bond may have a high social status and been supported by the environmentalist. This can provide enterprises with a more favourable environment for its innovation activities (Tang and Zhang, 2020; Dong et al., 2021). Based on this discussion, the chapter proposes the following hypothesis:

Hypothesis 1. GBI improves the GI performance of the issuing enterprises.

Moreover, due to the signalling effect of green bond issuing, peer pressure could be created due to industrial rivalries, stimulating a positive spillover effect (Beatty et al., 2013). Enterprises from the same industry typically learn from and imitate their peers' business decisions, thereby enhancing their value and mitigating risks (Kaustia and Rantala, 2015). This is especially the case for finance related decisions (Graham and Harvey, 2001). As the stock market reacts positively to GBI, when one enterprise issues green bond, its competitors tend to react strategically by enhancing their green performance to demonstrate that they care about the environment (Flammer, 2021). This may make the future GBI of such enterprises more attractive to investors (Lins et al., 2017; Flammer, 2021). Therefore, enterprises' GI activities are influenced not only by their organisational characteristics and resource conditions, but also by the financial behaviour of other enterprises (Flammer, 2015). In particular, as GI is crucial for enterprises to build up their core competitiveness and achieve sustainable development, the existence of a green bond pioneer within an industry may stimulate peer enterprises alike to care more about their own GI performance to meet future GBI requirements and environmental compliance thresholds (Ellison and Fudenberg, 1995; Huang and Li, 2017). This can generate a positive spillover effect within the industry (Lins et al., 2017; Xie et al., 2019a). Based on this discussion, the chapter proposes the following hypothesis:

Hypothesis 2. GBI improves the GI performance of green bond peer enterprises.

5.3. Methodology and Variables

5.3.1. Data and Sample Selection

The sample comprises panel data on China's A-share listed enterprises from 2007 to 2019. 2007 is chosen as the starting year because it is the year when new accounting standard was implemented in China. 2019 is chosen as the ending year to eliminate the influence of the pandemic. The sample is further process by: (1) excluding financial and ST enterprises; (2) removing enterprises with missing research variables; (3) excluding observations with leverage less than 0 or greater than 1; and (4) winsorising all continuous variables at 1% and 99% to exclude the outlier effect. All data are collected from the China Stock Market and Accounting Research (CSMAR) database, Chinese Research Data Services (CNRDS) database, Wind database, and annual reports and CSR reports of listed enterprises.

5.3.2. Variables

5.3.2.1. Dependent Variables

The dependent variable is the amount of enterprise green patent application. Following Xing et al. (2021) and Zhou et al. (2023), GI is proxied by the natural logarithm of the sum of one and the number of overall green patent applications of firm i in year t. The green patent data are collected from the CNRDS database. The PH posits that environmental policies can generate various types of innovation (Jaffe and Palmer, 1997). To comprehensively investigate the PH, this chapter further divides GI into GI quality performance (GI_qua) and GI increment performance (GI_inc) to investigate the impact of GBI on the GI capabilities of listed enterprises. As Wang and Li (2022) note, GI_qua is more related to newly created inventions, while GI_inc tends to build on existing technologies or products. Consequently, compared with GI_inc, GI_qua requires more resource inputs and faces higher uncertainties. GI_qua is measured by the natural logarithm of one plus the number of green invention patent applications of firm i in year t (Zhang et al., 2023). GI_inc is measured by the natural logarithm of one plus the number of green utility patent applications of firm i in year t (Wang and Li, 2022).

5.3.2.2. Independent Variables

The independent variables are the treated group (Treat) and policy implementation (Post). In the green bond issuing enterprise sample, Treat is a dummy variable which equals 1 if the enterprise issues green bonds. Post is a dummy variable that takes the value of 1 at time t and subsequent periods if an enterprise issues its first green bond in year t (Wang et al., 2022c). In the green bond peer enterprise sample, if an enterprise in a specific industry issued green bonds, other enterprises (Treat) in the same industry will be assigned a value of 1, and 0 otherwise (Beatty et al., 2013; Durnev and Mangen, 2020).[52] For the treated group, if the issuing time of the first green bond enterprise in an industry is t, the enterprises in the industry are assigned a value of 1 at time t and later (Post), and 0 otherwise. For the control group, all Post t values are 0. The interaction Treat × Post (DID) is the key and should be significant if the DID effect exists (Wang and Li, 2022).

5.3.2.3. Control Variables

(1) Profitability (ROA). Enterprise profitability is measured by the rate of return on total assets, denoted by ROA (Zhang et al., 2022c). (2) Enterprise size (Size). The chapter uses the natural logarithm of the enterprise's total assets, denoted by Size (Hu et al., 2021; Zhang et al., 2022c). (3) Leverage. It is measured by liabilities/total assets,

[52] 'Guidelines for the Industry Classification of Listed Enterprises' revised by the China Securities Regulatory Commission in 2012 is used to define different industries (Shi et al., 2022).

denoted by Leverage (Zhang et al., 2022c; Wang and Li, 2022). (4) Listing years (Age). The chapter uses the natural logarithm of enterprise listed age plus one to measure enterprise maturity (Hu et al., 2021).[53] (5) Enterprise governance measures (INST, Inden). The chapter introduces two important enterprise governance variables, Shareholding ratio of institutional investors (INST) and the proportion of independent directors relative to all board members (Inden) to measure enterprises' enterprise governance (Hu et al., 2021; Zhang et al., 2022c; Wang and Li, 2022). (6) Corporate social responsibility (CSR). It is proxied by a dummy variable which equals 1 if enterprises disclose their CSR reports, and 0 otherwise (Hu et al., 2021).

5.3.3. Models

Following Du et al. (2022), this chapter constructs the following multi-stage DID models.

$$LnGI_{i,t} = \beta_0 + \beta_1 Treat_i \times Post_t + \beta_2 X_{i,t} + u_p + \nu_t + \gamma_s + \lambda_q + \varepsilon_{i,t} \qquad (24)$$

$LnGI_{i,t}$ measures enterprise GI. The interaction between $Treat_i \times Post_t$ measures the effect of GBI on GI for the green bond issuing and green bond peer enterprises.[54] $X_{i,t}$ measures a set of control variables. u_p, ν_t, γ_s and λ_q denote the enterprise, industry, year, and region (city) fixed effects, respectively.[55] The chapter does not include the original Time and Treat variables since the enterprise and year fixed effects have been controlled. This effectively alleviates endogeneity problems, such as omitted variable bias, to a certain extent (Meyer, 1995; Shi et al., 2022).

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53 Since the listed age is 0, when an enterprise goes public in its first year, taking the natural logarithm of 0 (Ln0) has no mathematical meaning.

54 For the green bond issuing enterprise, $Treat_i \times Post_t$ is represented by DID in tables. For the green bond peer enterprise, $Treat_i \times Post_t$ is represented by Peer in tables.

55 The study constructs the fixed effect panel data regression to evaluate policy performance. Considering that samples' time, regions and industries are generally different in economic development and population level, according to Liu and Wang (2023), the study also introduces fixed effect variables.

5.4. Empirical Results

5.4.1. Descriptive Statistics and Correlation Analysis

Table 5.1 Descriptive statistics[56]

Green Bond Issuing Enterprise							
Variables	Explanations	Obs.	Mean	Std. Dev.	Min	Max	Data Source
GI	Green innovation	26071	0.358	0.772	0.000	3.689	A
GI_qua	Green innovation quality	26071	0.243	0.612	0.000	3.219	A
GI_inc	Green innovation increment	26071	0.211	0.544	0.000	2.773	A
DID	The interaction term of Treat × Post	26071	0.003	0.051	0.000	1.000	B
ROA	Profitability	26071	0.045	0.050	-0.165	0.199	C
Size	Enterprise size	26071	22.055	1.277	19.780	26.063	C
Leverage	Leverage	26071	0.412	0.200	0.049	0.844	C
Age	Listing years	26071	1.928	0.909	0.000	3.258	C
INST	Shareholding ratio of institutional investors	26071	0.468	0.258	0.004	0.979	C
Inden	The proportion of independent directors	26071	0.373	0.053	0.308	0.571	C
CSR	Corporate social responsibility	26071	0.248	0.432	0.000	1.000	D
Green Bond Peer Enterprise							
Variables	Explanations	Obs.	Mean	Std. Dev.	Min	Max	Data Source
GI	Green innovation	25820	0.352	0.763	0.000	3.689	A
GI_qua	Green innovation quality	25820	0.238	0.604	0.000	3.219	A
GI_inc	Green innovation increment	25820	0.206	0.536	0.000	2.773	A
Peer	The interaction term of Treat × Post	25820	0.120	0.325	0.000	1.000	B
ROA	Profitability	25820	0.045	0.050	-0.165	0.199	C
Size	Enterprise size	25820	22.043	1.269	19.780	26.063	C
Leverage	Leverage	25820	0.410	0.200	0.049	0.844	C
Age	Listing years	25820	1.928	0.910	0.000	3.258	C
INST	Shareholding ratio of institutional investors	25820	0.466	0.258	0.004	0.979	C
Inden	The proportion of independent directors	25820	0.373	0.053	0.308	0.571	C
CSR	Corporate social responsibility	25820	0.246	0.431	0.000	1.000	D

Notes: The data come from different databases, Abbreviations are as follows: A: CNRDS database; B: 'Guidelines for the Industry Classification of Listed Enterprises' and Guidelines for Environmental Information Disclosure of Listed Enterprises (Draft for Soliciting Opinions) published by China Environmental Protection Administration in 2010; C: CSMAR database; D: CSR reports of enterprises.

[56] Three observations are dropped in the benchmark regression, which leads to a minor difference in the total observations between the benchmark model and descriptive statistics because this chapter controls enterprise-level fixed effect and uses the command 'reghdfe' of Stata to regress linear models. Maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Due to this problem, the 'reghdfe' package now automatically drops singletons (Correia, 2015).

Table 5.1 presents the descriptive statistics for the main variables. Among the 26,071 observations in the green bond issuing group (versus 25,820 for the green bond peer enterprise group) over the period from 2007 to 2019, the minimum and maximum values of GI are 0 and 3.689 (versus 0 and 3.219 for the green bond peer group), respectively, indicating significant variations in GI levels among the sample enterprises. The descriptive statistical results for other variables are consistent with existing literature and fall within a reasonable range (Hu et al., 2021; Wang and Li, 2022).

Table 5.2a Pearson correlation coefficients

	GI	DID	ROA	Size	Leverage	Age	INST	Inden	CSR
GI	1.000								
DID	0.082***	1.000							
ROA	0.009	-0.017***	1.000						
Size	0.227***	0.077***	-0.098***	1.000					
Leverage	0.097***	0.054***	-0.374***	0.532***	1.000				
Age	-0.004	0.020***	-0.236***	0.436***	0.402***	1.000			
INST	0.041***	0.023***	0.106***	0.396***	0.226***	0.188***	1.000		
Inden	0.027***	-0.002	-0.027***	0.026***	-0.016**	-0.031***	-0.081***	1.000	
CSR	0.147***	0.036***	0.015**	0.458***	0.180***	0.256***	0.211***	0.018***	1.000

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5.2b Pearson correlation coefficients

	GI	DID	ROA	Size	Leverage	Age	INST	Inden	CSR
GI	1.000								
Peer	0.133***	1.000							
ROA	0.012*	-0.042***	1.000						
Size	0.220***	0.082***	-0.096***	1.000					
Leverage	0.090***	0.031***	-0.373***	0.528***	1.000				
Age	-0.003	0.027***	-0.237***	0.438***	0.405***	1.000			
INST	0.038***	-0.077***	0.107***	0.394***	0.223***	0.188***	1.000		
Inden	0.024***	0.001	-0.026***	0.024***	-0.018***	-0.030***	-0.084***	1.000	
CSR	0.143***	0.006	0.017***	0.455***	0.177***	0.256***	0.209***	0.017***	1.000

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Tables 5.2a and 5.2b report the correlation matrix among variables. The correlation coefficients of DID and GI, and Peer and GI are 0.082 and 0.133, respectively, and significant at 1% level. The results indicate that GBI enhances GI performance of enterprises, which preliminarily supports Hypotheses 1 and 2 (Yao et al., 2021).

Next, this chapter first examines the effect of GBI on GI among enterprises issuing green bonds and their peer enterprises based on the multi-stage DID model. Then, a series of tests, including the parallel trend analysis and propensity score matching DID (PSM-DID), are conducted to verify the robustness of the results obtained from the benchmark model. The chapter then conducts the heterogeneity analysis considering aspects like diversified external supervision environment, internal enterprises' characteristics, and regional diversities. A mediation analysis is also conducted to capture the impact of R&D on the relationship between GBI and GI performance.

5.4.2. Benchmark Results

First, based on Eq. (24), the chapter investigates the impact of GBI on GI among both green bond issuing (Columns 1–3 of Table 5.3) and peer enterprises (Columns 4–6 of Table 5.3). The coefficients of the DID and Peer variables are significantly positive, suggesting that GBI significantly enhances GI capacity among both issuer and peer enterprises. These findings align with Hypotheses 1 and 2. Furthermore, GBI not only enhances the performance of GI quality but also fosters GI increment performance. Compared with GI_inc, GI_qua is more creative, and thus, requires more resources and faces higher uncertainties due to the challenges associated with new innovation (Wang and Li, 2022). Among green bond issuing enterprises, the coefficient of GI_qua is larger and more significant than that of GI_inc, consistent with expectations and prior findings (Wang et al., 2022c). These enterprises tend to be under increased scrutiny by external stakeholders. Consequently, to demonstrate superior performance, they are more likely to engage in higher quality GI to achieve more comprehensive green transformations (Wang et al., 2022c). When the R&D and previous GI are included in the model respectively, the empirical results are still consistent with previous findings (results can be found in appendix 4 and 5). The results are still consistent when the $GI_{(t+1)}$ is considered (results can be found in appendix 6). Also, the results are still consistent when the negative binomial model is adopted (results can be found in appendix 7).

Table 5.3 Benchmark regression

	Green Bond Issuing Enterprise			Green Bond Peer Enterprise		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.434***	0.424***	0.342**			
	(3.08)	(3.64)	(2.59)			
Peer				0.106***	0.075**	0.092***
				(3.42)	(2.12)	(4.77)
ROA	0.093	0.052	0.097	0.079	0.045	0.077
	(0.94)	(0.73)	(1.43)	(0.81)	(0.64)	(1.21)
Size	0.066***	0.060***	0.029**	0.069***	0.062***	0.032**
	(3.19)	(3.46)	(2.04)	(3.39)	(3.61)	(2.30)
Leverage	-0.027	-0.020	-0.014	-0.035	-0.025	-0.022
	(-0.53)	(-0.56)	(-0.38)	(-0.74)	(-0.74)	(-0.60)
Age	0.030	0.013	0.026	0.031	0.014	0.028*
	(1.39)	(0.76)	(1.54)	(1.50)	(0.80)	(1.73)
INST	-0.136***	-0.091**	-0.076**	-0.148***	-0.100**	-0.086***
	(-2.78)	(-2.18)	(-2.52)	(-3.09)	(-2.45)	(-2.95)
Inden	0.003	-0.016	0.037	-0.004	-0.017	0.031
	(0.03)	(-0.18)	(0.50)	(-0.05)	(-0.20)	(0.43)
CSR	0.082***	0.061**	0.051***	0.082***	0.063***	0.050***
	(3.36)	(2.59)	(3.41)	(3.37)	(2.72)	(3.31)
Constant	-1.104**	-1.069***	-0.478	-1.184***	-1.124***	-0.542*
	(-2.62)	(-3.08)	(-1.55)	(-2.82)	(-3.24)	(-1.80)
Observations	26,068	26,068	26,068	25,817	25,817	25,817
R-squared	0.701	0.678	0.642	0.697	0.675	0.637
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

Meanwhile, the positive relationship between GBI and GI also has significant spillover effects, as demonstrated by the significantly positive coefficients of the 'Peer' variable on GI in Columns 4–6 of Table 5.3.

When an enterprise issues green bonds, it sends a green signal to the industry. In fear of leaving behind, other competitors may also enhance their GI capacity in preparation for future GBI (Lins et al., 2017). Meanwhile, if enterprises can achieve GI breakthroughs, they may gain competitive advantages in the market (Flammer, 2015). This also motivates other rivalries, captured by 'Peer', to imitate similar competition strategies and invest in green technologies (Cao et al., 2019). Specifically, enterprises that are peers of green bond issuers show significant positive effects on both GI_qua and GI_inc (Columns 5 and 6). This indicates that peer enterprises are willing to pursue GI_qua and GI_inc simultaneously, while paying more attention to the latter: the coefficient of GI_inc is 0.092 and significant at 1%, which is higher than that of GI_qua. This is unsurprising as green quality innovation tends to be riskier and requires more capital inputs than green increment innovation. Without sufficient financial support, enterprises which do not issue green bonds are more likely to engage in incremental GI, altering/adjusting the current practice to improve green performance gradually. In addition, when comparing the GI performance among green bond issuing enterprises and their peers, the former demonstrates much stronger innovation capacity regardless of which measure is used to proxy GI. For instance, the coefficient of DID in Column 1 is 0.434, while that of Peer in Column 4 is 0.106. Therefore, although under peer pressure, enterprises operating in industries with green bond issuers are motivated to enhance their own green performance; however, this is limited due to funding constraints. To achieve more advanced GI, particularly in higher quality ones, enterprises have to issue their own green bonds to expand their funding pool for more opportunities. When the R&D and previous GI are included in the model respectively, the empirical results are still consistent with previous findings (results can be found in appendix 4 and 5). The results are still consistent when the $GI_{(t+1)}$ is considered (results can be found in appendix 6). Also, the results are still consistent when the negative binomial model is adopted (results can be found in appendix 7).

Regarding control variables, Size, INST, and CSR significantly influence the GI activities of enterprises. On the one hand, larger enterprises are more likely to have sufficient financial resources for R&D activities, thereby enhancing their GI performance. On the other hand, to maintain their leading position within the respective industries, large enterprises are also under more pressure to achieve continuous technological advancements (Wang and Li, 2022). This again explains the significant positive relationship between enterprise size and GI capability. Meanwhile, institutional ownership (INST) has a significant negative relationship with enterprises' GI performance. Given that institutional investors tend to be relatively risk-averse and R&D activities carry high risk, enterprises with a higher proportion of institutional investors may struggle to secure board support for such investments (Wang and Li, 2022). Consequently, enterprises with a larger percentage of institutional investors on their boards tend to have lower green outputs. Lastly, enterprises that disclose CSR reports tend to care more about the social and environmental impacts of their operations. Unsurprisingly, CSR disclosure and GI have a significantly positive relationship (Hu et al., 2021).

5.4.3. Robustness Tests

To further test the validly of the results, this chapter adopts an event study method to test whether the parallel trend assumption made by the DID model holds. According to DID model, the trends of the treated and controlled groups should be parallel before policy implementation. That is, if a significant difference is observed in the GI between the treated and controlled groups before the GBI, this chapter's results may not be because of the GBI (Yao et al., 2021). The parallel trend analysis results are reported in Figures 5.4 and 5.5.

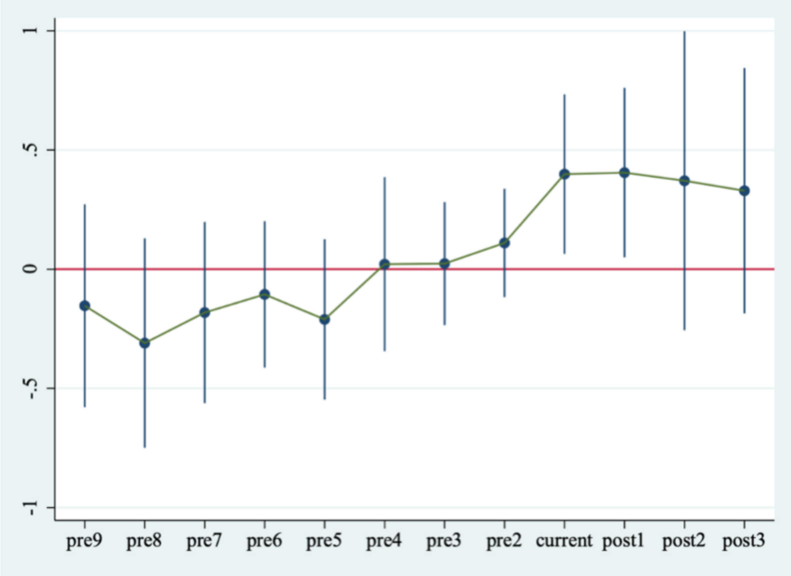

Figure 5.4 Parallel trend analysis of GI for green bond issuing enterprise

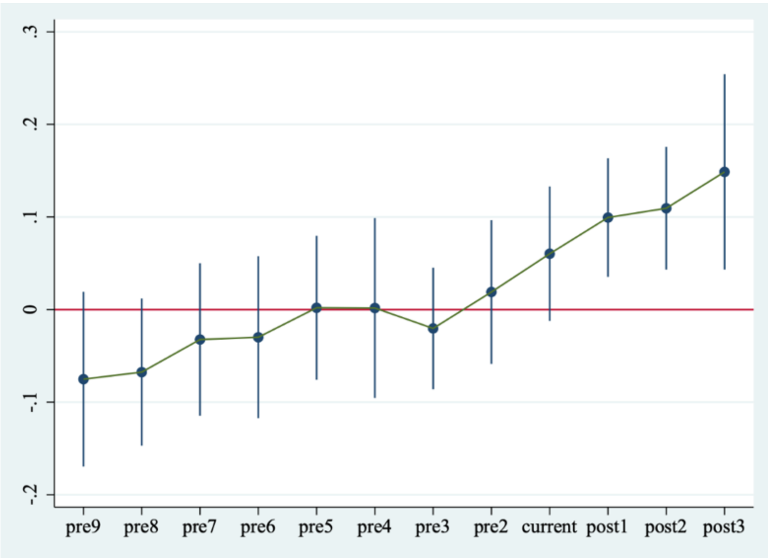

Figure 5.5 Parallel trend analysis of GI for green bond peer enterprise

Clearly, all coefficients are insignificant (all confidence intervals include zero before *Current*) (Figures 5.4 and 5.5). Therefore, the parallel trend assumption is supported because all interactions before *Current* are insignificant (Du et al., 2022). Thus, the choice of the DID model is appropriate for the sample.

Further, to reduce the potential endogeneity problems caused by self-selection bias, the chapter employs the PSM-DID method to match the treatment and control groups (Table 5.4). Several control variables are selected as the covariates to run a logit regression to obtain the propensity score of enterprises in the treatment group. Then, the treatment group is matched with the control group with similar characteristics (Cui et al., 2022). This chapter chooses the neighbour and kernel match method (Wang and Zhang, 2022). The balance tests of PSM show that the bias between two groups is below 10%, suggesting the self-selection bias is also markedly reduced. The results of PSM indicate a strong positive relationship between independent and dependent variables. Related results are presented in the appendix 8. After PSM, the unmatched observations are deleted and the examination is repeated. The results shown in Table 5.4 are consistent with the main findings of the benchmark model.

Table 5.4 Results of PSM-DID

	Green Bond Issuing Enterprise						Green Bond Peer Enterprise					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Neighbour			Kernel			Neighbour			Kernel		
	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.411***	0.402***	0.329**	0.410***	0.399***	0.329**						
	(2.85)	(3.39)	(3.39)	(2.84)	(3.36)	(2.44)						
Peer							0.106***	0.075**	0.092***	0.106***	0.075**	0.092***
							(3.42)	(2.12)	(4.77)	(3.42)	(2.12)	(4.77)
Constant	-0.999*	-0.959*	-0.506	-0.864	-0.857*	-0.437	-1.184***	-1.124***	-0.541**	-1.184***	-1.124***	-0.541**
	(-1.86)	(-2.21)	(-1.20)	(-1.61)	(-1.96)	(-1.03)	(-2.82)	(-3.25)	(-1.79)	(-2.82)	(-3.25)	(-1.79)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,660	19,660	19,660	19,221	19,221	19,221	25,807	25,807	25,807	25,807	25,807	25,807
R-squared	0.722	0.699	0.661	0.723	0.700	0.662	0.697	0.675	0.637	0.697	0.675	0.637

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

Lastly, during the sample period, other events, such as the global financial crisis (2008 to 2009), may have affected the results. To remove the potential effects of the financial crisis, the chapter drops the observation during 2008 and 2009, and reruns the regression (Zhang et al., 2022c). The results remain consistent (Columns 1–3 of Tables 5.5a and 5.5b). Next, the inclusion of a long sample period may lead to biased estimations because the regression results may be influenced by other policies (Wang et al., 2022b). Therefore, to ensure the adequacy of the sample size and mitigate the impacts of other policies simultaneously,[57] the chapter then shortens the sample period purposely to 2012–2019 for the estimation. The results remain consistent (Columns 4–6).

Table 5.5a Other tests for the benchmark model of green bond issuing enterprises

	Delete 2008 and 2009			2012–2019		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.406***	0.392***	0.326**	0.379***	0.381***	0.276**
	(2.85)	(3.36)	(2.49)	(2.70)	(3.46)	(2.01)
Constant	-0.958**	-0.960***	-0.321	-0.493	-0.467	-0.181
	(-2.53)	(-2.96)	(-1.18)	(-1.52)	(-1.51)	(-0.80)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,764	23,764	23,764	19,438	19,438	19,438
R-squared	0.714	0.697	0.654	0.754	0.743	0.694

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

[57] For example, the Green Credit Guideline was implemented in 2012.

Table 5.5b Other tests for the benchmark model of green bond peer enterprises

	Delete 2008 and 2009			2012–2019		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
Peer	0.099***	0.069**	0.088***	0.079***	0.054*	0.073***
	(3.31)	(2.02)	(4.68)	(3.17)	(1.74)	(4.48)
Constant	-1.041***	-1.019***	-0.387	-0.578*	-0.532	-0.247
	(-2.76)	(-3.11)	(-1.47)	(-1.72)	(-1.63)	(-1.12)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,537	23,537	23,537	19,256	19,256	19,256
R-squared	0.710	0.692	0.649	0.751	0.740	0.690

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

5.4.4. Heterogeneity Analysis

5.4.4.1. Heterogeneity in External Supervision

Green bonds, as a market-based environmental policy tool, facilitate green governance through green financing. However, research also indicates that the effectiveness of environmental policies can be influenced by the intensity of external supervision, government attention (GA), and media attention (MA) (Luo et al., 2021; Zhang et al., 2022d). This section explores the heterogeneous effects of these external supervisory mechanisms on the relationship between GBI and GI. Both formal and informal supervision mechanisms are considered, which are represented by GA and MA, respectively. GA, which reflects the official stance towards environmental governance, is a formal instrument of regulation in China (Chen and Chen, 2018). Meanwhile, MA reflects societal and public interest in the enterprise, serving as an informal form of monitoring.

First, GA is measured using the ratio of the frequency of environmental-related words to the total word frequency in government work reports of each city (Chen and Chen, 2018). The government work report is a programmatic document in China that guides the government's work. It may generate profound impacts on various aspects of the economy, such as environmental laws, market access, and technology innovation. Then, the frequency of environment-related words in the government work report can provide an overall picture of the government's attitude towards environmental protection (Chen and Chen, 2018). Python is used to extract environment-related words from government work reports.[58] Then, the sample is divided into High- and Low-GA groups by the median GA (Sun et al., 2019).

Second, MA is measured by the web search volume index of Chinese listed enterprises (Xu et al., 2021; Chen et al., 2022a).[59] The web search volume index aggregates data from sources, such as news and public opinion, reflecting the public attention in an enterprise's operations, environmental protection measures, and social responsibilities. It serves as a crucial metric for measuring the level of public attention focused on listed enterprises and their changes over time. Here, the index is computed by summing up the internet search values associated with Chinese listed enterprises and then applying a logarithmic transformation. Then, the sample is divided into High- and Low-MA groups by the median MA (Sun et al., 2019). The results are summarised in Table 5.6 and 5.7.

[58] For example, environment-related words include environmental protection, low-carbon, pollution, climate, SO_2, CO_2, energy consumption, ecology, COD, and energy-saving, among others.
[59] The web search volume index data is collected from CNRDS.

Table 5.6 Heterogeneity analysis of formal supervision (GA)

	Green Bond Issuing Enterprise						Green Bond Peer Enterprise					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High-GA	Low-GA	High-GA	Low-GA	High-GA	Low-GA	High-GA	Low-GA	High-GA	Low-GA	High-GA	Low-GA
Variables	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc
DID	0.363**	0.571*	0.283*	0.549**	0.354**	0.454*						
	(2.15)	(1.82)	(1.73)	(2.42)	(2.62)	(1.68)						
Peer							0.115***	0.102**	0.101***	0.055	0.088***	0.099***
							(4.34)	(2.17)	(3.16)	(1.11)	(4.02)	(3.16)
Constant	-0.978*	-1.249**	-0.860**	-1.246***	-0.478	-0.556*	-1.094**	-1.307***	-0.940**	-1.284***	-0.562	-0.613**
	(-1.93)	(-2.49)	(-2.10)	(-2.67)	(-1.21)	(-1.75)	(-2.12)	(-2.65)	(-2.26)	(-2.76)	(-1.40)	(-2.01)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,963	12,060	11,963	12,060	11,963	12,060	11,843	11,969	11,843	11,969	11,843	11,969
R-squared	0.747	0.725	0.726	0.706	0.704	0.668	0.742	0.723	0.723	0.702	0.696	0.667

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

In the high-GA group, GBI has a more profound impact on the overall GI of green bond issuing enterprises (Column 1 of Table 5.6). The Chinese green bond market is established from top to down, aiming to use the power of the bond market to facilitate green transformation (Lee et al., 2023). Policy pressure incentivises local governments to promote the green transition of enterprises, thereby strengthening the impact of GBI on overall GI in the high-GA group. These results align with Wang et al. (2022c). Meanwhile, this chapter finds GBI is more likely to enhance GI quality in the low-GA group than in the high-GA group. Enterprises capable of issuing green bonds tend to demonstrate stronger environmental performance. Supported by superior green technology capabilities, such enterprises are more likely to engage in more advanced GI to maintain competitiveness (Wang et al., 2022c; Wang and Li, 2022). However, if enterprises are under stringent environmental regulations (high-GA), they may incur additional compliance costs in the form of inspections, document filing, and reporting. This can effectively reduce the available funding for more time-consuming and costly quality GI (Tang and Zhou, 2020).

Among peer enterprises, compared to low-GA intensity, the high-GA intensity can still make GBI have a more significant impact on GI, and such results are more obvious for GI_qua. This is consistent with the peer pressure assumption. In the high-GA group, even though strict environmental regulations will bring relatively high compliance costs, peer enterprises are still willing to invest resources in advanced green innovation. It is because this approach not only meets stricter environmental attention or regulatory requirements but also accelerates the green development level of peer enterprises. As a result, they are better prepared to meet the criteria for issuing green bonds in the future (Lins et al., 2017; Xie et al., 2019a). If for peer enterprises are under low GA, although they still innovate, they tend to pay more attention to incremental GI. Without additional funding from GBI and with low government scrutiny, such enterprises may opt for the easier and less risky type of innovation to improve their green performance gradually.

Table 5.7 Heterogeneous analysis of informal supervision (MA)

	Green Bond Issuing Enterprise						Green Bond Peer Enterprise					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High-MA	Low-MA	High-MA	Low-MA	High-MA	Low-MA	High-MA	Low-MA	High-MA	Low-MA	High-MA	Low-MA
Variables	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc
DID	0.399***	0.515	0.395**	0.416	0.354***	0.324						
	(2.66)	(1.08)	(2.47)	(1.04)	(2.79)	(0.95)						
Peer							0.136***	0.041	0.104**	0.024	0.109***	0.042*
							(3.45)	(1.44)	(2.39)	(0.82)	(3.26)	(1.82)
Constant	-1.121*	0.143	-0.861	-0.339	-0.685	0.431	-1.304**	0.097	-1.017*	-0.393	-0.803*	0.391
	(-1.76)	(0.43)	(-1.59)	(-1.07)	(-1.42)	(1.55)	(-2.03)	(0.30)	(-1.80)	(-1.27)	(-1.77)	(1.42)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,102	10,174	10,102	10,174	10,102	10,174	10,006	10,078	10,006	10,078	10,006	10,078
R-squared	0.791	0.712	0.774	0.692	0.739	0.660	0.788	0.711	0.771	0.691	0.736	0.656

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

Next, Table 5.7 demonstrates that GBI has a more profound impact on all types of GI in the high-MA group for both green bond-issuing and peer enterprises. Insufficient supervision can contribute to greenwashing of green bonds. Then, MA, acting as an informal but effective supplement, can put enterprises under increased scrutiny (Zhou and Ding, 2023). Enterprises are more likely comply under high MA, suggesting that funds raised through GBI are more likely to be invested in ways as intended (Chen et al., 2022a; Zhou and Ding, 2023). Consequently, for enterprises with high MA intensity, green bonds tend to play a more significant role in enhancing their GI capabilities. Moreover, when enterprises issue green bonds, the media, acting as an information dissemination and production intermediary, can trigger responsive behaviours among peer competitors. This can inspire more learning and imitation, which can effectively promote GI (Lins et al., 2017; Zhou and Ding, 2023).

5.4.4.2. Heterogeneity by Enterprises' Internal Characteristics

The chapter then investigates how enterprises' internal characteristics may affect their responses to environmental policies. Research shows that the state-owned enterprises (SOEs) may have stronger incentives to utilise green bonds for GI (Zhang et al., 2022a). Furthermore, compared with the heavily polluting enterprises (HPEs), other businesses, especially those with green operations, are more likely to use the funds raised through green bonds for GI, but not the simple replacement of clean production equipment (Xu and Li, 2020). Consequently, the inclusion of enterprise characteristics may help us gain a more comprehensive understanding of the relationship between GBI and GI.

First, regarding the ownership structure, this chapter categorises the sample into SOEs and non-SOEs based on whether enterprises are ultimately state-controlled (Yao et al., 2021). The results are presented in Table 5.8. Second, this chapter classifies enterprises into heavily polluting, green, and other enterprises according to their level of pollution. A HPE is defined according to the 'Guidelines for the Industry Classification of Listed Enterprises' revised by the China Securities Regulatory Commission in 2012 and

Guidelines for Environmental Information Disclosure of Listed Enterprises (Draft for Soliciting Opinions) published by China Environmental Protection Administration in 2010 (Shi et al., 2022). Green enterprises (GEs) are defined as enterprises whose main business is producing environmental-friendly products (Al-Tuwaijri et al., 2004; Wang et al., 2020). Based on the enterprise annual reports and industry classification of the listed enterprises developed by the Tonghuashun Finance and Economic, one of the most influential financial analysis enterprises in China, this chapter manually analyses the main business of every enterprise to determine whether it can be classified as a GE.[60] If the main business of the enterprise is related to environmental protection and green development, it is categorised as a GE. This chapter also compares the selection results of GEs with the ones listed in Hexun, one of the most famous financial and economic platforms, to ensure the accuracy of the classification results.[61] The remaining enterprises are then classified as ‘other enterprises’.

[60] https://www.10jqka.com.cn/
[61] https://www.hexun.com/?from=rongshuxia; Specifically, this chapter uses Python to crawl the main business content of listed enterprises from Tonghuashun Finance and Economic, and the Hexun, then manually judge related information.

Table 5.8 Heterogeneity analysis of the property rights structure

	Green Bond Issuing Enterprise						Green Bond Peer Enterprise					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SOE	Non-SOE	SOE	Non-SOE	SOE	Non-SOE	SOE	Non-SOE	SOE	Non-SOE	SOE	Non-SOE
Variables	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc
DID	0.599***	0.160*	0.423**	0.263**	0.577***	0.018						
	(3.12)	(1.78)	(2.15)	(2.09)	(3.85)	(0.32)						
Peer							0.130***	0.080*	0.104**	0.047	0.091**	0.085**
							(2.81)	(1.76)	(2.55)	(1.00)	(2.35)	(2.56)
Constant	-0.946	-1.422***	-0.766	-1.362***	-0.437	-0.708*	-0.988	-1.478***	-0.805	-1.414***	-0.472	-0.740*
	(-1.36)	(-3.09)	(-1.40)	(-3.80)	(-0.87)	(-1.79)	(-1.47)	(-3.14)	(-1.52)	(-3.76)	(-0.97)	(-1.86)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,884	15,750	9,884	15,750	9,884	15,750	9,774	15,623	9,774	15,623	9,774	15,623
R-squared	0.734	0.682	0.706	0.664	0.671	0.625	0.737	0.674	0.708	0.656	0.674	0.616

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

As shown in Table 5.8, compared with the non-SOEs group, GBI has a more considerable and statistically significant effect on GI in the SOEs group. On the one hand, as issuing a green bond must be approved by regulators, a closer relationship with the authorities makes it easier for the SOEs to raise funding via this channel. On the other hand, to maintain good relationship with the government, SOEs are also under more pressure to exhibit superior performance in GI as a demonstration to the market (Zhang et al., 2022a). Other business may be inspired, especially the state-owned peers, to imitate their strategy, resulting in more widely acceptance of green bonds and sustainable practices throughout the economy (Flammer, 2015; Lins et al., 2017). Furthermore, as SOEs are normally in possession of more advanced and comprehensive technical facilities, this may allow more efficient utilisation of the funds raised via green bonds for GI activities (Zhang et al., 2019). This may explain why GBI generates a more significant influence on GI performance among the SOEs.

Table 5.9a Heterogeneity analysis of the extent of pollution nature by green bond issuing enterprises

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	HPE	GE	Other	HPE	GE	Other	HPE	GE	Other
Variables	GI	GI	GI	GI_qua	GI_qua	GI_qua	GI_inc	GI_inc	GI_inc
DID	0.888	0.459***	-0.074	0.844	0.424***	0.060	0.763*	0.368**	-0.066
	(1.48)	(3.38)	(-1.01)	(1.00)	(4.22)	(0.55)	(1.99)	(2.53)	(-1.58)
Constant	-2.274***	-1.371	-1.028**	-1.672**	-1.250	-1.012***	-1.334***	-0.841	-0.404
	(-3.21)	(-0.80)	(-2.49)	(-2.72)	(-0.91)	(-2.97)	(-3.04)	(-0.60)	(-1.50)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,694	3,136	18,215	4,694	3,136	18,215	4,694	3,136	18,215
R-squared	0.694	0.728	0.688	0.683	0.713	0.663	0.632	0.653	0.632

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

Table 5.9b Heterogeneity analysis of the extent of pollution for green bond peer enterprises

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	HPE	GE	Other	HPE	GE	Other	HPE	GE	Other
Variables	GI	GI	GI	GI_qua	GI_qua	GI_qua	GI_inc	GI_inc	GI_inc
Peer	0.041	0.126*	0.090**	0.041	0.089	0.056	0.014	0.086	0.098***
	(1.06)	(1.90)	(2.32)	(1.15)	(1.55)	(1.29)	(0.48)	(1.63)	(4.18)
Constant	-2.333***	-1.569	-1.090**	-1.729***	-1.328	-1.057***	-1.386***	-1.148	-0.440
	(-3.51)	(-0.92)	(-2.59)	(-3.05)	(-0.97)	(-3.01)	(-3.30)	(-0.80)	(-1.61)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,668	2,985	18,141	4,668	2,985	18,141	4,668	2,985	18,141
R-squared	0.694	0.717	0.687	0.684	0.702	0.663	0.632	0.638	0.632

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

Regarding enterprises of different levels of pollution, it is found that for green bond issuing enterprises, GBI can enhance the GI and GI_qua of green enterprises more effectively, as shown in Table 5.9a. However, the HPEs group shows no such significant positive relationship. Consistent with Du et al. (2022), this may be because these HPEs mainly use green bond financing to purchase new pollution control equipment or foster low-level GI to comply with cleaner production standards. Their capacity of developing more advanced GI is relatively weak. This is further evidenced by the significant positive relationship identified between GBI and GI_inc in the HPEs group. Furthermore, peer enterprises show no significant relationship between GBI and GI in the HPEs group (Table 5.9b). Meanwhile, GBI considerably improves GI performance in the non-HPEs groups. Compared to HPEs, non-HPEs contribute less pollution to the environment and their production operations are more environmentally friendly. Consequently, non-HPEs have a relatively solid technological and production foundation for the development of GI (Xu and Li, 2020). With more superior GI capabilities (Peng et al., 2022), non-HPEs exhibit a more pronounced spillover effect of GBI.

5.4.4.3. Regional Heterogeneities

Regional heterogeneities caused by diversified economic development levels in different regions may also affect the relationship between environmental governance and technology innovation (Frondel et al., 2008; Iraldo et al., 2011). To consider this regional heterogeneity in China, this chapter classifies the country's 30 provincial regions into two groups according to the classification criteria of the National Bureau of Statistics: the economically more advanced eastern region (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan); and relatively less developed other regions, including the middle (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan) and western (Inner Mongolia, Chongqing, Sichuan, Guizhou, Yunnan, Guangxi, Tibet, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang) regions.[62] The results are summarised in Table 5.10.

[62] http://www.stats.gov.cn/tjsj/zxfb/201701/t20170120_1455967.html

Table 5.10 Heterogeneity analysis by regions

	Green Bond Issuing Enterprise						Green Bond Peer Enterprise					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Eastern	Others	Eastern	Others	Eastern	Others	Eastern	Others	Eastern	Others	Eastern	Others
Variables	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc
DID	0.394**	0.712**	0.392***	0.656	0.300**	0.628**						
	(2.44)	(2.42)	(2.94)	(1.63)	(2.08)	(2.33)						
Peer							0.115***	0.082**	0.085**	0.050	0.092***	0.090***
							(3.13)	(2.19)	(2.38)	(0.95)	(3.21)	(2.74)
Constant	-1.225**	-0.837	-1.171***	-0.870*	-0.478	-0.458	-1.368***	-0.780	-1.287***	-0.774	-0.578	-0.444
	(-2.51)	(-1.44)	(-2.92)	(-1.75)	(-1.29)	(-0.97)	(-2.78)	(-1.36)	(-3.14)	(-1.58)	(-1.55)	(-0.96)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,576	7,388	18,576	7,388	18,576	7,388	18,359	7,354	18,359	7,354	18,359	7,354
R-squared	0.707	0.690	0.688	0.656	0.650	0.626	0.703	0.687	0.685	0.652	0.644	0.625

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

GBI enhances the GI outputs of both the issuing and peer enterprises across all regions (Columns 1–2 and 7–8 of Table 5.10). Under the government's strong promotion of green finance (e.g. green bonds) and emissions reduction, enterprises operating in different industries and geographical locations are all endeavouring to enhance GI performance to meet the target of carbon neutrality. A strong learning effect is also observed among the green bond issuing enterprises and their peers in most regions, considering the significant positive relationship between GBI and GI outputs among peer enterprises (Columns 7–12 of Table 5.10). A different picture emerges when the chapter looks at GBI's impact on different types of GI among different regions. GBI significantly affects the GI quality of the bond issuing and peer enterprises only in the Eastern region (Columns 3 and 9 of Table 5.10). Considering the unbalanced economic development in China, significant differences in resource endowment and industrial base exist between the eastern region and other regions The eastern region has a relatively active capital market and more diversified financing channels compared to other regions (Su et al., 2022). Therefore, when green bonds were introduced, enterprises of Eastern regions may have been more likely to be motivated to best utilise this new funding opportunity to build up their own competitive strength for market leadership. GI_qua can be too complicated and costly for enterprises of other regions. Thus, they may not have the needed resources or technologies to pursue such type of GI. Consequently, the relationship between green bond and GI_qua among issuing and peer enterprises is insignificant.

5.4.5. Channel Analysis of R&D

The issuance of green bonds by enterprises can help alleviate financial pressures encountered during the innovation process (Wang et al., 2022c). Consequently, after issuing green bonds, enterprises should be motivated to alter the investment strategies and enhance capital utilisation efficiency.[63] Hence, to examine the underlying

[63] This chapter uses the logarithm of the amount of R&D; the data is collected form CSMAR.

mechanism influencing the relationship between GBI and GI, this chapter investigates the mediating effect of R&D by Combining Eqs. 2 and 3 (Chen et al., 2022b).

$$R\&D_{i,t} = \alpha_0 + \alpha_1 Treat_i \times Post_t + \alpha_2 X_{i,t} + u_p + \nu_t + \gamma_s + \lambda_q + \varepsilon_{i,t} \quad (25)$$

$$LnGI_{i,t} = \gamma_0 + \gamma_1 Treat_i \times Post_t + \gamma_2 R\&D_{i,t} + \gamma_3 X_{i,t} + u_p + \nu_t + \gamma_s + \lambda_q + \varepsilon_{i,t} \quad (26)$$

β_1 in Eq.24 measures the total effect of GBI on GI for the green bond issuing and peer enterprises. α_1 in Eq.25 is the impact of GBI on R&D for the green bond issuing and peer enterprises. γ_1 in Eq.26 represents the direct effects of GBI on GI for the green bond issuing and peer enterprises. γ_2 denotes the effects of R&D on GI for the green bond issuing and peer enterprises. The mediation effect is equal to $\alpha_1 * \gamma_2$, while the total effect is equal to the sum of mediation and direct effects, or $\beta_1 = \alpha_1 * \gamma_2 + \gamma_1$ (Zhao et al., 2022). Other parameters are same as those defined in Section 5.3.3. The results are listed in Table 5.11.

Table 5.11 Channel analysis: R&D

	Green Bond Issuing Enterprise							Green Bond Peer Enterprise						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Variables	R&D	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc	R&D	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc
R&D			0.044***		0.035***		0.019**			0.041***		0.032***		0.017*
			(3.25)		(3.39)		(2.21)			(2.96)		(3.03)		(1.96)
DID	0.271*	0.362***	0.350***	0.377***	0.367***	0.295***	0.290***							
	(1.91)	(3.21)	(3.18)	(3.27)	(3.24)	(2.79)	(2.78)							
Peer								-0.017	0.082**	0.083***	0.052	0.053	0.085***	0.085***
								(-0.55)	(2.61)	(2.66)	(1.33)	(1.35)	(4.65)	(4.67)
Constant	2.091***	-1.295***	-1.387***	-1.303***	-1.376***	-0.490	-0.530	2.152***	-1.356***	-1.445***	-1.345***	-1.414***	-0.544	-0.581*
	(2.92)	(-2.88)	(-3.14)	(-3.53)	(-3.73)	(-1.49)	(-1.64)	(2.97)	(-2.97)	(-3.19)	(-3.56)	(-3.73)	(-1.64)	(-1.77)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,365	19,350	19,350	19,350	19,350	19,350	19,350	19,173	19,158	19,158	19,158	19,158	19,158	19,158
R-squared	0.884	0.713	0.714	0.693	0.694	0.656	0.656	0.883	0.709	0.709	0.689	0.689	0.650	0.651

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

After GBI, enterprises issuing green bonds increase R&D investment, thereby enhancing GI outputs (Columns 1–7). These results suggest that R&D investment mediates the relationship between GBI and enhancing GI performance. The issuance of green bonds can alleviate funding shortages and facilitate the flow of financial resources (such as R&D investment) towards GI, thereby improving enterprises' GI capacity (Irfan et al., 2022; Zhang and Jin, 2021). While GBI does not significantly stimulate R&D investment for peer enterprises, it does enhance their R&D capital utilisation efficiency, thereby improving their GI capabilities (Yan et al., 2022). Thus, in the future, if peer enterprises successfully issue green bonds, the resulting capital inflows may stimulate them to increase their R&D investment further.

5.5. Conclusion and Policy Implications

5.5.1. Conclusion

Based on panel data from Chinese listed enterprises spanning from 2007 to 2019, this chapter investigates the impacts of GBI on GI performance based on the DID model. The chapter further tests the results using several robustness tests, including examining the parallel trend assumption and using the PSM-DID method. Further, the chapter conducts heterogeneity analyses considering the different external supervisory environment, enterprise characteristics, and regional conditions. The results reveal that GBI can significantly and positively impact the GI performance of both green bond issuing enterprises and their peers. However, enterprises issuing green bonds tend to focus more on the advanced quality GI, whereas their peers are more likely to see improvements in incremental GI. Furthermore, bond issuers tend to experience more significant enhancement in GI performance when compared with their peers, highlighting the potential benefits of issuing green bonds. This creates peer pressure, thereby stimulating the GI of the whole industry.

The heterogeneity analysis reveals that external supervision, both formal and informal, is crucial for stimulating the GI performance associated with GBI. It can be found that in the high-GA group, GBI has a more profound impact on the overall green innovation of green bond issuance enterprises (the significance level of DID in Column 1 of Table 5.6 is 5%, which is higher than that of 10% significance level in Column 2). In terms of peer enterprises, compared to low-GA intensity, the high-GA intensity can still make GBI have a more significant impact on GI, and such results are more obvious for GI_qua. In terms of informal supervision (MA), it shows that GBI has a more profound impact on all types of green innovation in the high-MA group, whether for green bond-issuing enterprises (i.e. in Table 5.7, the coefficients of DID in column 1 (0.399) or their peers in column 7 (0.136) are both significant at 1%, whereas they are insignificant in the low-MA group). The relationship between GBI and GI is more pronounced among SOEs, non-heavily polluting enterprises, and in the eastern region of China. Further, the mechanism analysis reveals that GBI actually promotes the GI performance of the bond issuing enterprises and their peers through different channels. For the issuers, with additional funding available, they would increase the R&D investments, leading to more green innovation, whereas for the peer enterprises, their green innovation performance is mainly boosted via enhancement in capital utilisation efficiency. Therefore, to achieve more sustained growth, green bond issuance and peer enterprises are incentivised to continuously enhance their green innovation performance in the future.

5.5.2. Policy Implications

First, to promote GI and emissions reduction effectively, financial mechanisms should be matched with resource allocation criteria to maximise the desired outcomes. Besides indirectly relying on green credit, the direct issuance of green bonds can help facilitate better capital allocation and achieve the government's target of green transformation. Therefore, policymakers should further facilitate enterprises' bond issuing process. In particular, special assistance should be provided to cash-strapped private enterprises and heavy polluters to assist their transformation to a greener and more sustainable development path.

Second, to ensure that the desired outcome of green bond issue is achieved, additional checks and monitoring mechanisms should be put in place. On the one hand, scrutiny on green bond issuers should be strengthened to prevent them from engaging in green behaviour merely for the purpose of policy arbitrage. This can help ensure that funding collect via GBI can be effectively used by high-quality enterprises to enhance their economic and environmental performance. On the other hand, the supervisory and management mechanisms after GBI should be further developed. Besides relying on social forces and media channels to provide some indirect supervision, effective and enforceable legislative measures should be put in place to ensure that the issuing enterprises carry out the promised GI activities.

Finally, the pursuit of high-quality economic development requires long-term commitment and a fundamental transformation of enterprises' operating model. If enterprises are only trying hard to mitigate their own adverse environmental impact, it is far from enough. Some proactive policy initiatives should be put in place to guide/encourage enterprises' development towards a more sustainable path. This can assist the country in achieving green structural transformation over the longer term.

5.5.3. Limitations and Potential Future Work

Due to the data availability, currently it is difficult to obtain other types of green technologies data. Nevertheless, it would be valuable to investigate the effects of GBI on other types of green technologies when data are accessible. Furthermore, future research can broaden the empirical sample to more countries and re-evaluate the conclusions.

Chapter 6: Conclusion and Policy Implications

This thesis examines the relationships between ER, GI, and CO_2 emissions in China. Specifically, this thesis investigates three closely-connected topics: First, how different ERs and GI affect Chinese regional CO_2 emissions (Chapter 3); second, how the MER, GCG, affects GI behaviours of Chinese listed enterprises (Chapter 4); and third, how another important MER, GBI, influences the GI of Chinese listed enterprises (Chapter 5).

These three main chapters build hypotheses around the theme of ER, GI, and CO_2 emissions. Chapter 3 discusses the impact of different ERs and GI on CO_2 emissions from Chinese provincial and macroeconomic perspectives. Chapters 4 and 5 examine the impact of two important MERs, GCG and GBI, respectively, on GI of Chinese listed enterprises from a microeconomic perspective. This chapter summarises the major findings and evaluates them, and then outlines the policy implications, limitations, and future research avenues.

6.1. Conclusion

In the introduction chapter (Chapter 1), the thesis reviews the research background and develop research questions, illustrating the key contributions of the thesis. Then, Chapter 2 reviews the key theoretical foundations and literature (i.e. the PH), and the relationship among ERs, GI, and CO_2 emissions.

Next, based on the panel data of 30 provinces from 2003 to 2019, the first study (Chapter 3) investigates whether ERs moderate the CO_2 emissions reduction effect of GI. To provide a clear understanding of the relationship between the three factors, the thesis employs the panel fixed-effect, spatial Durbin (SDM), and system generalised method of moments (SYS-GMM) models. First, the panel fixed-effect model is applied for the benchmark analysis. By controlling for individual and time fixed effects, it reduces omitted variable bias, enhances estimation accuracy, and leads to the high R-squared values estimated across all models (Hasan et al., 2018). Then, the SDM is adopted to capture the spatial factors and verify the robustness of the empirical findings (Jia et al., 2021). The validation tests confirm the presence of spatial effects; the coefficients of LR-lag and LR-sem are 34.07 and 34.30, respectively, and significant at the 1% level. Third, to mitigate the endogeneity problem and improve parameter estimation efficiency, the SYS-GMM model is used (Zhou and Xu, 2022). The instrumental variables are strictly selected according to the Sargan tests estimation to ensure the effectiveness of tested results (all Sargan-p values exceed 0.1) (Yuan, 2019). Lastly, the DID model is applied to further verify the robustness of the results. The key values of placebo tests confirm that the observed positive moderation effect is indeed caused by the IER.

The empirical results show that ER can positively moderate the impact of Green Knowledge Innovation (GKI) on CO_2 emissions reduction in China, as evidenced by the change in sign of the coefficient of GKI in the benchmark model from 0.130 to -0.428. However, the effect of ER on Green Process Innovation (GPI) and CO_2 emissions reduction is not stable. These results indicate that while ER has an overall moderation effect, the synergistic effect of different regulation tools only performs well and is stable in promoting the emissions reduction effect of more advanced GI. Regarding different regulation tools and GI, CER and IER promote the CO_2 emissions reduction effect of GKI (e.g. in the benchmark results, both coefficients of CER*GKI (-8.887) and IER*GKI (-0.193) are significant at the 5% level). EER exhibits poor ability to positively moderate both GI and CO_2 emissions reduction. These findings remain robust considering spatial factors. ER effectively moderates the relationship between GKI and CO_2 emissions reduction among both local and neighbouring regions, as suggested by the estimated coefficients of ER*GKI (direct effect: -0.320, significant at the 1% level; and indirect effect: -0.504, significant at the 5% level in Table 3.3a). This is consistent with the spillover and positive demonstration effects. GKI remains the most effective type of GI chosen by enterprises for CO_2 emissions reduction as it may benefit them over the long-term period.

Furthermore, this study divides the sample into the eastern region and other regions (the middle and western regions) to investigate the regional heterogeneity. Estimation results show that in the eastern region, overall ER performs well in positively moderating the impact of GKI on CO_2 emissions reduction if the SYS-GMM model is used to mitigate the endogeneity. Among different regulation tools, the positive moderation effect in the eastern region is mainly driven by MER, especially IER, whereas CER and EER have no significant effect (e.g. the coefficients of ER*GKI (-0.104) and IER*GKI (-0.037) are both significant at the 10% level for the eastern region). This result is in line with expectations, as the eastern region is more economically developed and enterprises in the region tend to be driven by investment. This may explain why IER can effectively moderate GKI and CO_2 emissions reduction. In other regions, ERs fail to positively moderate the impact of GI and CO_2 emissions reduction. Overall, the empirical analysis suggests that ER is effective in moderating the emissions reduction effect of GI to some extent, especially for more advanced innovation.

As stated, Chapter 3 mainly investigates the relationship among different ERs, GI, and CO_2 emissions. The findings reveal that an efficient MER is crucial for promoting green economic transformation. Furthermore, the study of ER instruments should delve deeper into the specific behaviours of micro-enterprises to obtain more detailed findings. The GCG can be regarded as a valuable MER designed to mitigate environmental pollution and provide fundings to green activities (Lu et al., 2022). This thesis also empirically investigates whether this policy instrument has achieved the desired outcome or is simply a policy slogan with little practical significance.

Based on panel data of Chinese listed enterprises from 2007 to 2019, Chapter 4 analyses the impact of the GCG on GI performance. The DID model is employed for the benchmark test and then several tests, such as the parallel trend analysis and PSM-DID, are conducted to ensure the robustness of the results. Meanwhile, to consider heterogeneity, factors including types of GI (green quality innovation and green incremental innovation), ownership structure of enterprises (SOEs and non-SOEs), and the degree of external finance dependence are incorporated in the analysis. The findings show that GCG can enhance the GI performance of both HPEs (e.g. the coefficient of DID in column 4 of Table 4.3 (0.123) is significant at the 1% level) and GEs (e.g. the coefficient of DID in column 1 of Table 4.10 (0.104) is significant at the 1% level). Compared with green enterprises, the heavily polluters tend to pay more attention on the GI increment due to limited GI experiences and lack of financial resources (GI_qua: 0.069, significant at the 5% level and GI_inc: 0.124, significant at the 1% in Table 4.5). The investment into incremental GI can be regarded as an easier and more feasible option for them to meet government regulatory requirements while achieving a certain degree of green transformation. Meanwhile, compared to HPEs, with the support of GCG, green enterprises have stronger capability in delivering green quality innovation and this may help them build up long-term competitive advantages. SOEs are better motivated by the GCG to deliver high-quality GI. This is explained by the closer relationship between the SOEs and government. Compared with non-SOEs, their state-owned counterparts tend be favoured by banking credit; however, they are also under more pressure to meet the government's emissions reduction requirements (Wang et al., 2022b). Lastly, enterprises which need more external support are more likely to be affected by the GCG as they are forced to deliver superior performance to meet the borrowing conditions.

Given the close connection among government regulation, GCG, and enterprise innovation, Chapter 4 further investigates the moderation effects of government regulation on the relationship between GCG and enterprise innovation. Both CERs and voluntary environmental regulations (VER) are considered in the regression. The findings reveal that CER_Penalty has no significant moderation effect. However, the incentive-based regulations (CER_Incentive) does have a significant positive moderating effect for HPEs (e.g. the coefficient of DID in column 4 of Table 4.8 (0.031) is significant at the 5% level). VER also has similar effects (e.g. the coefficient of DID in column 7 of Table 4.8 (0.023) is significant at the 1% level). Moreover, both regulatory instruments have a more significant positive moderation effect for the higher quality GI, especially for GEs. A higher intensity of VER signifies the green transition determination of enterprises, motivating them to engage more in high quality GI activities (Huang and Chen, 2015). Lastly, the mechanism analysis shows that the GCG can enhance GI performance by improving the efficiency of green investment use.

Besides green credit, green bonds can be another effective market-based environmental policy instrument. Since its initial offering, green bonds have attracted great attention as they are both an environmental regulatory instrument proposed by the government and a financing source welcomed by enterprises (Lee et al., 2023). Unlike the indirect financing method of bank credit, bond financing is a direct method whereby enterprises do not need to pay excessive intermediary fees, increasing the attractiveness of issuing green bonds (Tang and Zhang, 2020). Furthermore, with clearly defined use of fund, enterprises that issue green bond may have a high social status and been supported by environmentally conscious actors. This can provide enterprises with a more favourable environment for their innovation activities (Tang and Zhang, 2020; Dong et al., 2021). Given the potential positive impact played by GBI in the overall economic structural transformation process, and its growing importance in the Chinese market, Chapter 5 aims to test empirically whether enterprises with green bond issued can deliver better GI performance using panel data on Chinese listed enterprises during the period 2007–2019.

To clarify the relationship between GBI and GI performance, Chapter 5 primarily utilises the DID model and conducts several robustness tests. Further, heterogeneity analyses are conducted to comprehensively study the effects of GBI on GI. The empirical results of benchmark models reveal that GBI can enhance the GI performance of both green bond issuing enterprises and their peers (DID in column 1: 0.434, significant at the 1% level and Peer in column 4: 0.106, significant at the 1% level in Table 5.3). Specifically, enterprises issuing green bonds tend to focus more on the quality of GI (e.g. the coefficients of DID in columns 2 and 3 of Table 5.3 are significant at the 1% and 5% levels, respectively; however, the former, GI_qua (0.424), is larger than the latter, GI_inc (0.342)), whereas the enhancement of GI increment is more prominent among peer enterprises. Furthermore, the GI performance of enterprises issuing green bonds exceeds that of their peers post-GBI, highlighting the potential benefit for peer enterprises to issue green bonds in the future.

The heterogeneity analysis reveals that external supervision, both formal and informal, is crucial for effectively stimulating the GI incentives of GBI. In the high-GA group, GBI has a more profound impact on the overall GI of green bond issuing enterprises (the significance level of DID in Column 1 of Table 5.6 is 5%, which is higher than the 10% level in Column 2). In terms of peer enterprises, compared to low-GA intensity, the high-GA intensity can still make GBI have a more significant impact on GI, and such results are more obvious for GI_qua. Next, GBI has a more profound impact on all types of GI in the high-MA group, whether for green bond-issuing enterprises (i.e. in Table 5.7, the coefficients of DID in column 1 (0.399) or their peers in column 7 (0.136) are both significant at 1%, whereas they are insignificant in the low-MA group). The relationship between GBI and GI is more pronounced among SOEs, non-heavily polluting enterprises, and in the eastern region of China. This relationship generally remains consistent among green bond peer enterprises. Mechanism analysis reveals that GBI effectively promotes the R&D investment of green bond issuing enterprises, thereby enhancing their GI performance. For green bond peer enterprises, GBI primarily boosts GI performance by improving their capital utilisation efficiency. Therefore, to achieve more sustained growth, green bond issuance and peer enterprises are incentivised to continuously enhance their green innovation performance in the future.

6.2. Policy Implications

The Chinese government should effectively use different environmental policy tools in combination to stimulate its synergistic effect. As the penalty-based environmental regulation accentuates the punitive aspect of environmental governance, a moderate regulatory intensity can constrain enterprises' polluting behaviours. However, excessive penalties may result in high governance costs, triggering a negative response from enterprises and undermining the intent of the CER system. The conclusions of this thesis confirm and build upon the PH, demonstrating that flexible MERs can effectively foster GI, and enhance environmental performance more substantially. Thus, MERs should be strengthened to optimise environmental governance outcomes. Efficient MERs can confer greater autonomy to enterprises and leverage their initiative. As environmental protection concepts increasingly permeate public consciousness, the public's desire to participate in environmental governance grows. Due to the much larger body of public, VERs offer a broader scope and greater flexibility. However, public involvement in ER in the Chinese market has just begun, and its potential for enhancing GI and enterprise competitive advantage needs reinforcement. Consequently, future efforts should ensure effective public participation in ER and leverage public environmental opinion to motivate enterprises to actively engage in environmental enhancement.

Greater emphasis should be placed on promoting various MERs, including green credit policy, while also providing policy support for emissions reduction from HPEs. Green credit policy serves as a crucial environmental tool for promoting a green Chinese economy. It does so by allocating funds via the financial market to facilitate emissions reduction. Furthermore, green credit acts as a significant supplement to the traditional CER. As China progresses in its market-oriented reform, the green credit policy should play an increasingly pivotal role in improving environmental quality. HPEs are the primary contributors to pollutant emissions, and marketisation serves as the key method of resource allocation. Therefore, future environmental policies should focus on MER strategies, using market instruments to regulate emissions from significant polluters. In addition, the incentivising role of the green credit policy for enterprise GI should be amplified to achieve more substantial emissions reduction. The policies should provide greater incentives for enterprise GI activities that contribute to improving energy-saving and emissions reduction technologies. Other measures worth considering are granting interest subsidies, besides current preferential interest rates, and establishing a green technology innovation guidance fund for enterprises. This can encourage enterprises to advocate for energy conservation and emissions reduction through technological innovation.

Green bonds, as an important part of the green financial system, significantly bolster GI within enterprises, thereby providing substantial support for the transition towards sustainability. To amplify this supportive role, several strategies can be employed. First, the green bond system's related mechanisms need refinement, with a focus on enhancing relevant incentives, bolstering risk mitigation measures, and amplifying support for GI through green bond financing. With respect to GI, it is crucial to endorse green production and recent breakthroughs as part of green bond usage disclosures. Establishing a two-tier assessment framework for GBI certification, and rewards and penalties for GI can deter greenwashing practices. Second, from the enterprise financing perspectives, enterprises should alter their growth strategies and financing methods, and proactively harness the green financial system for sustainable development. The ratio of green financing, especially via green bond financing, should be increased. Enterprises should also collaborate proactively with environmental protection departments in their environmental assessments, fully leveraging the benefits of green bonds to promote a greener supply chain. Finally, enhancing both internal and external enterprise supervision is critical, as is raising awareness of enterprise environmental governance. Market financial entities should be effectively guided and incentivised to actively fulfil their environmental social responsibilities. From the enterprise governance perspective, optimising the structure, bolstering internal oversight, and ensuring a balance of power can curb self-serving behaviour by management and ensure financial resources are utilised effectively. From regulators' perspective, employing third-party auditing mechanisms strategically and guiding the oversight of market entities can effectively reduce enterprise credit risks, and optimise the information environment.

6.3. Limitations and Potential Future Work

Due to the data availability, currently it is difficult to obtain some green finance and environmental pollution data, for example, the enterprise-level CO_2 emissions in Chinese market. The disclosure of enterprise-level CO_2 emissions is very limited in the Chinese market. As data become accessible, the current research can be extended to understand the impact of policies on enterprises' emissions reduction and innovation behaviours. This can facilitate the drawing of useful experiences to assist the green transformation process among other developing economies.

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Appendix

Appendix 1

Regression results of CER_Incentive1[64]

Variables	(1) GI	(2) GI_qua	(3) GI_inc	(4) GI	(5) GI_qua	(6) GI_inc
DID	0.084**	0.033	0.100***	0.065*	0.061**	0.083***
	(2.71)	(1.34)	(4.40)	(1.90)	(2.67)	(3.24)
CER_Incentive1 × DID	0.045***	0.047***	0.032***	0.067***	0.060***	0.048**
	(4.72)	(9.45)	(7.94)	(3.56)	(6.27)	(2.70)
CER_Incentive1	0.019***	0.013***	0.016***	0.017***	0.013***	0.012***
	(5.86)	(4.81)	(5.46)	(4.27)	(3.76)	(4.35)
Constant	-2.679***	-2.487***	-1.366***	-2.656***	-2.292***	-1.547**
	(-6.71)	(-6.52)	(-4.63)	(-4.56)	(-4.46)	(-2.72)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,169	14,169	14,169	12,893	12,893	12,893
R-squared	0.681	0.655	0.637	0.700	0.674	0.650

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Appendix 2

The comparison of green innovation performance for HPEs and GEs

Variable	Obs.	Mean	Std. Dev.	Min	Max
HPE					
GI	3316	0.544	0.899	0.000	3.829
GI_qua	3316	0.343	0.699	0.000	3.367
GI_inc	3316	0.364	0.699	0.000	3.045
GE					
GI	2026	0.822	1.127	0.000	3.829
GI_qua	2026	0.565	0.913	0.000	3.367
GI_inc	2026	0.548	0.851	0.000	3.045

[64] Columns 1–3 and 4–6 for HPEs and green enterprises, respectively.

Appendix 3

Acronyms

Acronym	Full name
Age	Listing Years
CE	CO_2 emissions
CER	Command-and-control Environmental Regulation
CER_Incentive	Incentive-based Environmental Regulation
CER_Incentive1	Government Subsidy
CER_Penalty	Penalty-based Environmental Regulation
CNRDS	Chinese Research Data Services
CSMAR	China Stock Market and Accounting Research
CSR	Corporate Social Responsibility
DID	Difference-in-Difference
EDU	Education Level
EER	Expenditure-type Environmental Regulation
EFD	External Finance Dependence
EKC	Environmental Kuznets Curve
ER	Environmental Regulation
FDI	Foreign Direct Investment
HPEs	Heavily Polluting Enterprises
Inden	Proportion of Independent Directors
INST	Shareholding Ratio of Institutional Investors
GA	Government Attention
GBI	Green Bond Issuance
GCG	Green Credit Guideline
GEs	Green Enterprises
GHG	Greenhouse Gas
GI	Green Innovation
GI_inc	Green Innovation Increment Performance
GI_inc_ind	Independent Green Innovation Increment Performance
GI_inc_joi	Joint Green innovation Increment Performance
GI_qua	Green Innovation Quality Performance
GI_qua_ind	Independent Green Innovation Quality Performance
GI_qua_joi	Joint Green Innovation Quality Performance
GKI	Green Knowledge Innovation
GPI	Green Process Innovation
GreenInv	Green Investment
GTI	Green Technology Innovation
IER	Investment-type Environmental Regulation
IER2	Alternative Measures of Investment-type Environmental Regulation
INDR	Rate of Industrialization
Leverage	Leverage
LnCE	Logarithm of CO_2 Emissions
LR	Likelihood Ratio

MA	Media Attention
MER	Market-based Environmental Regulation
MLE	Maximum likelihood estimation
PH	Porter Hypothesis
POP	Population
Post	Policy Implementation
PSM-DID	Propensity Score Matching DID
ROA	Profitability
SAR	Spatial Autoregressive Model
SDM	Spatial Durbin Model
SEM	Spatial Error Model
Size	Enterprise Size
SOEs	State-owned Enterprises
SYS-GMM	System Generalised Method of Moments Model
Treat	Treated Group
VER	Voluntary Environmental Regulation

Appendix 4

Re-test Hypothesis 1 of Chapter 4 after including GreenInv

	(1)	(2)	(3)
Variables	GI	GI_qua	GI_inc
DID	0.160***	0.102***	0.173***
	(6.92)	(8.30)	(21.64)
GreenInv	0.010***	0.005***	0.007**
	(4.22)	(3.59)	(2.78)
Constant	-1.039***	-1.154***	-0.294
	(-3.27)	(-6.41)	(-1.25)
Control Variables	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes
Observations	3,045	3,045	3,045
R-squared	0.729	0.719	0.702

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Re-test Hypothesis 2&3 of Chapter 4 after including GreenInv

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.151***	0.105***	0.147***	0.194***	0.150**	0.093***	0.135***	0.060***	0.137***	0.115***	0.015	0.159***
	(7.39)	(12.87)	(9.27)	(3.77)	(3.19)	(3.97)	(17.50)	(4.92)	(22.39)	(11.69)	(1.36)	(23.49)
CER_Penalty × DID	0.087	0.014	0.226***									
	(1.74)	(0.25)	(4.27)									
CER_Penalty	-0.019	-0.088*	0.059*									
	(-0.62)	(-1.89)	(2.03)									
CER_Incentive × DID				0.001	-0.009**	0.029***						
				(0.17)	(-2.74)	(8.05)						
CER_Incentive				0.002	0.003	-0.007						
				(0.41)	(0.83)	(-1.12)						
CER_Incentive1 × DID							0.020	0.039***	0.032***			
							(0.87)	(7.85)	(14.16)			
CER_Incentive1							0.024***	0.017**	0.017*			
							(5.89)	(2.34)	(1.99)			
VER × DID										0.013	0.034***	-0.003
										(1.48)	(4.18)	(-0.81)
VER										0.006	-0.000	0.001
										(0.63)	(-0.08)	(0.15)
GreenInv	0.007*	0.003	0.007**	0.023*	0.015*	0.017	0.013***	0.008***	0.009***	0.007*	0.002	0.007**
	(2.09)	(1.29)	(2.38)	(2.11)	(1.93)	(1.78)	(6.29)	(5.49)	(3.63)	(2.09)	(0.97)	(2.36)
Constant	-1.409**	-1.398***	-0.863***	-1.944	-1.811**	-1.430**	-1.138**	-1.175***	-0.336	-1.479**	-1.591***	-0.796***
	(-2.85)	(-5.59)	(-4.16)	(-1.51)	(-2.36)	(-2.41)	(-2.62)	(-5.19)	(-1.54)	(-3.10)	(-6.19)	(-4.00)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,883	2,883	2,883	1,563	1,563	1,563	2,963	2,963	2,963	2,883	2,883	2,883
R-squared	0.736	0.727	0.714	0.673	0.651	0.668	0.729	0.718	0.701	0.736	0.728	0.713

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Re-test Hypothesis 1&2 of Chapter 5 after including R&D

	Green Bond Issuing Enterprise			Green Bond Peer Enterprise		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.350***	0.367***	0.290***			
	(3.18)	(3.24)	(2.78)			
Peer				0.083***	0.053	0.085***
				(2.66)	(1.35)	(4.67)
R&D	0.044***	0.035***	0.019**	0.041***	0.032***	0.017*
	(3.25)	(3.39)	(2.21)	(2.96)	(3.03)	(1.96)
Constant	-1.387***	-1.376***	-0.530	-1.445***	-1.414***	-0.581*
	(-3.14)	(-3.73)	(-1.64)	(-3.19)	(-3.73)	(-1.77)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,350	19,350	19,350	19,158	19,158	19,158
R-squared	0.714	0.694	0.656	0.709	0.689	0.651

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

Appendix 5

Re-test Hypothesis 1 of Chapter 4 after including Previous GI

Variables	(1) GI	(2) GI_qua	(3) GI_inc
DID	0.080***	0.051**	0.081***
	(3.83)	(2.75)	(6.62)
Previous GI	0.322***	0.344***	0.284***
	(21.64)	(15.15)	(47.45)
Constant	-1.593***	-1.336***	-0.970***
	(-5.57)	(-5.07)	(-5.42)
Control Variables	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes
Observations	13,499	13,499	13,499
R-squared	0.732	0.716	0.685

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Re-test Hypothesis 2&3 of Chapter 4 after including Previous GI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.083***	0.053***	0.078***	0.124*	0.087	-0.000	0.059**	0.031*	0.068***	0.067***	0.032**	-0.000
	(4.41)	(3.46)	(7.06)	(2.14)	(1.37)	(-1.61)	(2.78)	(2.03)	(4.63)	(3.49)	(2.23)	(-0.35)
CER_Penalty × DID	-0.062	0.000	-0.012									
	(-0.34)	(0.01)	(-0.06)									
CER_Penalty	-0.109***	-0.187***	0.013									
	(-3.26)	(-3.16)	(0.61)									
CER_Incentive × DID				0.009	0.005	0.000						
				(0.71)	(1.30)	(1.28)						
CER_Incentive				-0.001	-0.002	0.000						
				(-0.11)	(-0.57)	(0.72)						
CER_Incentive1 × DID							0.017***	0.022***	0.012**			
							(3.19)	(6.95)	(2.20)			
CER_Incentive1							0.013***	0.009***	0.011***			
							(3.30)	(3.80)	(3.37)			
VER × DID										0.011*	0.016***	0.000
										(2.12)	(3.65)	(1.17)
VER										0.003	-0.000	0.000
										(1.33)	(-0.17)	(0.88)
Previous GI	0.295***	0.318***	0.253***	0.184***	0.179***	1.000***	0.312***	0.337***	0.272***	0.293***	0.316***	1.000***
	(18.86)	(13.27)	(40.45)	(33.93)	(13.83)	(1.42e+15)	(19.88)	(13.81)	(44.33)	(18.57)	(13.02)	(2.29e+14)
Constant	-1.512***	-1.283***	-0.868***	-1.831***	-1.575***	-0.000	-1.608***	-1.365***	-0.950***	-1.560***	-1.343***	0.000
	(-5.01)	(-4.48)	(-5.09)	(-3.18)	(-4.78)	(-0.34)	(-5.51)	(-5.13)	(-6.18)	(-5.14)	(-4.69)	(0.42)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,768	12,768	12,768	3,139	3,139	3,139	12,670	12,670	12,670	12,768	12,768	12,768
R-squared	0.739	0.726	0.694	0.735	0.711	1.000	0.729	0.714	0.683	0.739	0.726	1.000

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Re-test Hypothesis 1&2 of Chapter 5 after including Previous GI

	Green Bond Issuing Enterprise			Green Bond Peer Enterprise		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.315**	0.306***	0.261**			
	(2.62)	(3.03)	(2.36)			
Peer				0.080***	0.059**	0.070***
				(3.68)	(2.10)	(4.72)
Previous GI	0.273***	0.291***	0.224***	0.270***	0.288***	0.221***
	(10.73)	(11.31)	(8.26)	(10.86)	(11.39)	(8.24)
Constant	-0.625*	-0.593**	-0.345	-0.711**	-0.660**	-0.405
	(-1.92)	(-2.30)	(-1.27)	(-2.20)	(-2.54)	(-1.51)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,935	22,935	22,935	22,708	22,708	22,708
R-squared	0.740	0.725	0.679	0.737	0.721	0.675

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

Appendix 6

Re-test Hypothesis 1 of Chapter 4 after using $GI_{(t+1)}$

	(1)	(2)	(3)
Variables	$GI_{(t+1)}$	$GI\_qua_{(t+1)}$	$GI\_inc_{(t+1)}$
DID	0.086**	0.051*	0.091***
	(2.61)	(1.87)	(3.99)
Constant	-2.047***	-1.993***	-1.130***
	(-5.49)	(-6.16)	(-4.37)
Control Variables	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes
Observations	13,498	13,498	13,498
R-squared	0.701	0.680	0.658

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Re-test Hypothesis 2&3 of Chapter 4 after using $GI_{(t+1)}$

Variables	(1) $GI_{(t+1)}$	(2) $GI\_qua_{(t+1)}$	(3) $GI\_inc_{(t+1)}$	(4) $GI_{(t+1)}$	(5) $GI\_qua_{(t+1)}$	(6) $GI\_inc_{(t+1)}$	(7) $GI_{(t+1)}$	(8) $GI\_qua_{(t+1)}$	(9) $GI\_inc_{(t+1)}$	(10) $GI_{(t+1)}$	(11) $GI\_qua_{(t+1)}$	(12) $GI\_inc_{(t+1)}$
DID	0.076**	0.046*	0.078***	0.071	0.046	0.052*	0.057*	0.023	0.077***	0.056*	0.024	0.073***
	(2.53)	(1.88)	(3.86)	(1.41)	(1.33)	(1.82)	(1.94)	(1.11)	(3.32)	(1.92)	(1.09)	(3.26)
CER_Penalty × DID	0.475***	0.183**	0.467***									
	(5.62)	(2.19)	(4.31)									
CER_Penalty	-0.119***	-0.181***	0.042***									
	(-3.66)	(-5.40)	(3.57)									
CER_Incentive × DID				0.026***	0.034***	0.008						
				(6.38)	(11.32)	(0.93)						
CER_Incentive				-0.004	-0.005	-0.003**						
				(-1.50)	(-1.48)	(-2.38)						
CER_Incentive1 × DID							0.029***	0.033***	0.013***			
							(5.23)	(9.38)	(3.33)			
CER_Incentive1							0.007*	0.006	0.005			
							(2.01)	(1.30)	(1.46)			
VER × DID										0.022**	0.024***	0.007
										(2.83)	(4.56)	(1.20)
VER										0.001	-0.002	0.004
										(0.32)	(-0.53)	(1.63)
Constant	-1.918***	-1.876***	-1.027***	-2.292***	-2.565***	-1.765***	-2.071***	-2.027***	-1.120***	-1.973***	-1.955***	-1.020***
	(-4.86)	(-5.62)	(-4.57)	(-4.43)	(-7.80)	(-5.19)	(-5.30)	(-6.57)	(-5.07)	(-5.05)	(-5.87)	(-4.52)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,785	12,785	12,785	3,833	3,833	3,833	12,877	12,877	12,877	12,785	12,785	12,785
R-squared	0.714	0.695	0.673	0.722	0.699	0.699	0.700	0.678	0.657	0.714	0.695	0.672

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses.

Re-test Hypothesis 1&2 of Chapter 5 after using $GI_{(t+1)}$

	Green Bond Issuing Enterprise			Green Bond Peer Enterprise		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$GI_{(t+1)}$	$GI\_qua_{(t+1)}$	$GI\_inc_{(t+1)}$	$GI_{(t+1)}$	$GI\_qua_{(t+1)}$	$GI\_inc_{(t+1)}$
DID	0.343**	0.403***	0.238*			
	(2.04)	(2.90)	(1.79)			
Peer				0.105***	0.078**	0.077***
				(4.36)	(2.31)	(4.51)
Constant	-0.820*	-0.944**	-0.339	-0.902**	-0.991***	-0.406
	(-1.98)	(-2.54)	(-1.17)	(-2.22)	(-2.74)	(-1.44)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,948	22,948	22,948	22,721	22,721	22,721
R-squared	0.721	0.701	0.663	0.717	0.698	0.659

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries; robust t statistics are in parentheses.

Appendix 7[65]

Re-test Hypothesis 1 of Chapter 4 after using Negative Binomial Regression

	(1)	(2)	(3)
Variables	GI	GI_qua	GI_inc
DID	-0.001	-0.024	0.153**
	(-0.03)	(-0.34)	(2.28)
Constant	-5.544***	-6.383***	-3.800***
	(-10.70)	(-10.41)	(-6.02)
Control Variables	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	13,604	11,711	10,660
Log likelihood	-15443.992	-10947.479	-9807.4284
Wald chi2	1161.64	1108.63	597.33
Prob > chi2	0.0000	0.0000	0.0000

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Z-statistics are enclosed in parentheses.

65 Based on the requirement of Negative Binomial Regression, the number of green patents is used for all dependent variables, instead of its logarithm version.

Re-test Hypothesis 2&3 of Chapter 4 after using Negative Binomial Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.004	-0.033	0.116	0.158	0.065	0.151	-0.009	-0.089	0.227**	-0.076	-0.140*	0.116
	(0.06)	(-0.43)	(1.54)	(1.28)	(0.42)	(0.98)	(-0.13)	(-0.94)	(2.53)	(-1.11)	(-1.68)	(1.42)
CER_Penalty × DID	-0.080	0.195	-0.064									
	(-0.22)	(0.39)	(-0.16)									
CER_Penalty	-0.231	-0.738**	0.055									
	(-1.09)	(-2.38)	(0.22)									
CER_Incentive × DID				0.044	0.022	0.069						
				(1.20)	(0.51)	(1.59)						
CER_Incentive				0.012	0.013	-0.005						
				(0.67)	(0.65)	(-0.22)						
CER_Incentive1 × DID							0.009	0.027	-0.070**			
							(0.29)	(0.75)	(-2.05)			
CER_Incentive1							0.061***	0.050**	0.075***			
							(3.62)	(2.52)	(3.53)			
VER × DID										0.040***	0.050***	-0.003
										(2.92)	(3.17)	(-0.17)
VER										0.001	-0.005	0.012
										(0.16)	(-0.52)	(1.10)
Constant	-5.653***	-6.808***	-4.470***	-5.658***	-7.757***	-4.598***	-5.933***	-6.982***	-4.580***	-5.702***	-6.969***	-4.321***
	(-9.30)	(-9.49)	(-6.02)	(-4.65)	(-5.16)	(-2.90)	(-9.94)	(-9.85)	(-6.33)	(-9.26)	(-9.61)	(-5.73)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,172	8,073	7,326	2,944	2,488	2,310	9,389	8,292	7,513	9,172	8,073	7,326
Log likelihood	-11172.556	-8046.8824	-7115.8119	-3375.7821	-2360.3046	-2138.0081	-11268.749	-8090.2439	-7185.0907	-11168.733	-8046.3936	-7115.2031
Wald chi2	861.57	856.98	426.19	233.41	208.27	170.15	1009.30	980.77	507.31	879.62	868.77	427.68
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Z-statistics are enclosed in parentheses.

Re-test Hypothesis 1&2 of Chapter 5 after using Negative Binomial Regression

	Green Bond Issuing Enterprise			Green Bond Peer Enterprise		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.575***	0.677***	0.606***			
	(3.94)	(4.41)	(3.74)			
Peer				0.139***	0.149***	0.224***
				(3.18)	(2.98)	(4.22)
Constant	-4.376***	-5.277***	-2.815***	-4.460***	-5.326***	-2.883***
	(-8.97)	(-9.04)	(-4.63)	(-9.04)	(-9.04)	(-4.67)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,107	12,046	11,199	13,894	11,853	10,986
Log likelihood	-16295.593	-11562.95	-10525.059	-15899.785	-11272.269	-10216.466
Wald chi2	1214.31	1237.67	577.24	1155.32	1160.71	548.49
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Z-statistics are enclosed in parentheses.

Appendix 8

The results of PSM for Chapter 4

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.039	0.045	-13.2	97.6
	Matched	0.039	0.039	0.3	
Size	Unmatch	22.375	22.188	14.1	82.1
	Matched	22.375	22.342	2.5	
Leverage	Unmatch	0.431	0.418	6.9	92.4
	Matched	0.431	0.430	0.5	
Age	Unmatch	2.108	2.156	-6.1	80.9
	Matched	2.108	2.099	1.2	
INST	Unmatch	0.465	0.466	-0.6	14.2
	Matched	0.465	0.466	-0.5	
Inden	Unmatch	0.369	0.373	-6.5	50.9
	Matched	0.369	0.367	3.2	
CSR	Unmatch	0.332	0.285	10.4	94.3
	Matched	0.332	0.335	-0.6	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI	Unmatched	0.544	0.391	0.153	0.016	9.28
	ATT	0.544	0.405	0.139	0.024	5.89

The results of PSM (Neighbour) for Chapter 5 – Green Bond Issuing Enterprise - GI

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.036	0.045	-20.4	57.5
	Matched	0.036	0.040	-8.7	
Size	Unmatch	23.372	22.039	99.6	97.3
	Matched	23.372	23.408	-2.7	
Leverage	Unmatch	0.573	0.409	90.7	99.3
	Matched	0.573	0.574	-0.6	
Age	Unmatch	1.935	1.914	2.4	-43.4
	Matched	1.935	1.965	-3.5	
INST	Unmatch	0.592	0.466	52.7	86.5
	Matched	0.592	0.609	-7.1	
Inden	Unmatch	0.374	0.373	2.7	-476.7
	Matched	0.374	0.383	-15.4	
CSR	Unmatch	0.417	0.245	37.1	93.1
	Matched	0.417	0.405	2.6	57.5

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI	Unmatched	1.025	0.354	0.671	0.049	13.76
	ATT	1.025	0.490	0.535	0.103	5.21

The results of PSM (Neighbour) for Chapter 5 - Green Bond Issuing Enterprise – GI_qua

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.036	0.045	-20.4	57.5
	Matched	0.036	0.040	-8.7	
Size	Unmatch	23.372	22.039	99.6	97.3
	Matched	23.372	23.408	-2.7	
Leverage	Unmatch	0.573	0.409	90.7	99.3
	Matched	0.573	0.574	-0.6	
Age	Unmatch	1.935	1.914	2.4	-43.4
	Matched	1.935	1.965	-3.5	
INST	Unmatch	0.592	0.466	52.7	86.5
	Matched	0.592	0.609	-7.1	
Inden	Unmatch	0.374	0.373	2.7	-476.7
	Matched	0.374	0.383	-15.4	
CSR	Unmatch	0.417	0.245	37.1	93.1
	Matched	0.417	0.405	2.6	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI_qua	Unmatched	0.737	0.240	0.497	0.039	12.84
	ATT	0.737	0.345	0.391	0.085	4.6

The results of PSM (Neighbour) for Chapter 5 - Green Bond Issuing Enterprise – GI_inc

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.036	0.045	-20.4	57.5
	Matched	0.036	0.040	-8.7	
Size	Unmatch	23.372	22.039	99.6	97.3
	Matched	23.372	23.408	-2.7	
Leverage	Unmatch	0.573	0.409	90.7	99.3
	Matched	0.573	0.574	-0.6	
Age	Unmatch	1.935	1.914	2.4	-43.4
	Matched	1.935	1.965	-3.5	
INST	Unmatch	0.592	0.466	52.7	86.5
	Matched	0.592	0.609	-7.1	
Inden	Unmatch	0.374	0.373	2.7	-476.7
	Matched	0.374	0.383	-15.4	
CSR	Unmatch	0.417	0.245	37.1	93.1
	Matched	0.417	0.405	2.6	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI_inc	Unmatched	0.712	0.207	0.506	0.034	14.72
	ATT	0.712	0.304	0.408	0.076	5.34

The results of PSM (Kernel) for Chapter 5 - Green Bond Issuing Enterprise – GI

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.036	0.045	-20.4	34.8
	Matched	0.036	0.042	-13.3	
Size	Unmatch	23.372	22.039	99.6	40.7
	Matched	23.372	22.582	59	
Leverage	Unmatch	0.573	0.409	90.7	51.2
	Matched	0.573	0.493	44.3	
Age	Unmatch	1.935	1.914	2.4	-78.1
	Matched	1.935	1.897	4.3	
INST	Unmatch	0.592	0.466	52.7	46.4
	Matched	0.592	0.525	28.2	
Inden	Unmatch	0.374	0.373	2.7	-171.7
	Matched	0.374	0.370	7.2	
CSR	Unmatch	0.417	0.245	37.1	32.4
	Matched	0.417	0.301	25.1	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI	Unmatched	1.025	0.354	0.671	0.049	13.76
	ATT	1.025	0.433	0.592	0.081	7.33

The results of PSM (Kernel) for Chapter 5 - Green Bond Issuing Enterprise – GI_qua

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.036	0.045	-20.4	34.8
	Matched	0.036	0.042	-13.3	
Size	Unmatch	23.372	22.039	99.6	40.7
	Matched	23.372	22.582	59	
Leverage	Unmatch	0.573	0.409	90.7	51.2
	Matched	0.573	0.493	44.3	
Age	Unmatch	1.935	1.914	2.4	-78.1
	Matched	1.935	1.897	4.3	
INST	Unmatch	0.592	0.466	52.7	46.4
	Matched	0.592	0.525	28.2	
Inden	Unmatch	0.374	0.373	2.7	-171.7
	Matched	0.374	0.370	7.2	
CSR	Unmatch	0.417	0.245	37.1	32.4
	Matched	0.417	0.301	25.1	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI_qua	Unmatched	0.737	0.240	0.497	0.039	12.84
	ATT	0.737	0.297	0.439	0.066	6.61

The results of PSM (Kernel) for Chapter 5 - Green Bond Issuing Enterprise – GI_inc

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.036	0.045	-20.4	34.8
	Matched	0.036	0.042	-13.3	
Size	Unmatch	23.372	22.039	99.6	40.7
	Matched	23.372	22.582	59	
Leverage	Unmatch	0.573	0.409	90.7	51.2
	Matched	0.573	0.493	44.3	
Age	Unmatch	1.935	1.914	2.4	-78.1
	Matched	1.935	1.897	4.3	
INST	Unmatch	0.592	0.466	52.7	46.4
	Matched	0.592	0.525	28.2	
Inden	Unmatch	0.374	0.373	2.7	-171.7
	Matched	0.374	0.370	7.2	
CSR	Unmatch	0.417	0.245	37.1	32.4
	Matched	0.417	0.301	25.1	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI_inc	Unmatched	0.712	0.207	0.506	0.034	14.72
	ATT	0.712	0.261	0.452	0.064	7.11

The results of PSM (Neighbour) for Chapter 5 - Green Bond Peer Enterprise – GI

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.041	0.047	-11.6	96.8
	Matched	0.041	0.041	0.4	
Size	Unmatch	22.233	21.943	22.6	85.3
	Matched	22.233	22.191	3.3	
Leverage	Unmatch	0.448	0.390	29.1	99.1
	Matched	0.448	0.448	-0.3	
Age	Unmatch	1.943	1.899	4.8	52.8
	Matched	1.943	1.922	2.3	
INST	Unmatch	0.472	0.464	2.9	58.9
	Matched	0.472	0.468	1.2	
Inden	Unmatch	0.370	0.374	-9.3	86.5
	Matched	0.370	0.369	1.3	
CSR	Unmatch	0.260	0.237	5.2	54.4
	Matched	0.260	0.250	2.4	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI	Unmatched	0.498	0.283	0.216	0.010	21.6
	ATT	0.498	0.326	0.173	0.014	11.99

The results of PSM (Neighbour) for Chapter 5 - Green Bond Peer Enterprise – GI_qua

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.041	0.047	-11.6	96.8
	Matched	0.041	0.041	0.4	
Size	Unmatch	22.233	21.943	22.6	85.3
	Matched	22.233	22.191	3.3	
Leverage	Unmatch	0.448	0.390	29.1	99.1
	Matched	0.448	0.448	-0.3	
Age	Unmatch	1.943	1.899	4.8	52.8
	Matched	1.943	1.922	2.3	
INST	Unmatch	0.472	0.464	2.9	58.9
	Matched	0.472	0.468	1.2	
Inden	Unmatch	0.370	0.374	-9.3	86.5
	Matched	0.370	0.369	1.3	
CSR	Unmatch	0.260	0.237	5.2	54.4
	Matched	0.260	0.250	2.4	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI_qua	Unmatched	0.334	0.193	0.141	0.008	17.81
	ATT	0.334	0.218	0.116	0.011	10.19

The results of PSM (Neighbour) for Chapter 5 - Green Bond Peer Enterprise – GI_inc

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.041	0.047	-11.6	96.8
	Matched	0.041	0.041	0.4	
Size	Unmatch	22.233	21.943	22.6	85.3
	Matched	22.233	22.191	3.3	
Leverage	Unmatch	0.448	0.390	29.1	99.1
	Matched	0.448	0.448	-0.3	
Age	Unmatch	1.943	1.899	4.8	52.8
	Matched	1.943	1.922	2.3	
INST	Unmatch	0.472	0.464	2.9	58.9
	Matched	0.472	0.468	1.2	
Inden	Unmatch	0.370	0.374	-9.3	86.5
	Matched	0.370	0.369	1.3	
CSR	Unmatch	0.260	0.237	5.2	54.4
	Matched	0.260	0.250	2.4	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI_inc	Unmatched	0.311	0.155	0.156	0.007	22.35
	ATT	0.311	0.188	0.123	0.010	12.09

The results of PSM (Kernel) for Chapter 5 - Green Bond Peer Enterprise – GI

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.041	0.047	-11.6	95.9
	Matched	0.041	0.042	-0.5	
Size	Unmatch	22.233	21.943	22.6	79.5
	Matched	22.233	22.174	4.6	
Leverage	Unmatch	0.448	0.390	29.1	89.9
	Matched	0.448	0.442	2.9	
Age	Unmatch	1.943	1.899	4.8	75.9
	Matched	1.943	1.932	1.2	
INST	Unmatch	0.472	0.464	2.9	18.7
	Matched	0.472	0.465	2.4	
Inden	Unmatch	0.370	0.374	-9.3	96
	Matched	0.370	0.370	-0.4	
CSR	Unmatch	0.260	0.237	5.2	63.3
	Matched	0.260	0.252	1.9	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI	Unmatched	0.498	0.283	0.216	0.010	21.6
	ATT	0.498	0.310	0.188	0.011	16.96

The results of PSM (Kernel) for Chapter 5 - Green Bond Peer Enterprise – GI_qua

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.041	0.047	-11.6	95.9
	Matched	0.041	0.042	-0.5	
Size	Unmatch	22.233	21.943	22.6	79.5
	Matched	22.233	22.174	4.6	
Leverage	Unmatch	0.448	0.390	29.1	89.9
	Matched	0.448	0.442	2.9	
Age	Unmatch	1.943	1.899	4.8	75.9
	Matched	1.943	1.932	1.2	
INST	Unmatch	0.472	0.464	2.9	18.7
	Matched	0.472	0.465	2.4	
Inden	Unmatch	0.370	0.374	-9.3	96
	Matched	0.370	0.370	-0.4	
CSR	Unmatch	0.260	0.237	5.2	63.3
	Matched	0.260	0.252	1.9	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI_qua	Unmatched	0.334	0.193	0.141	0.008	17.81
	ATT	0.334	0.212	0.122	0.009	13.81

The results of PSM (Kernel) for Chapter 5 - Green Bond Peer Enterprise – GI_inc

Variables		Mean value		Bias (%)	Bias reduction (%)
		Treated	Control		
ROA	Unmatch	0.041	0.047	-11.6	95.9
	Matched	0.041	0.042	-0.5	
Size	Unmatch	22.233	21.943	22.6	79.5
	Matched	22.233	22.174	4.6	
Leverage	Unmatch	0.448	0.390	29.1	89.9
	Matched	0.448	0.442	2.9	
Age	Unmatch	1.943	1.899	4.8	75.9
	Matched	1.943	1.932	1.2	
INST	Unmatch	0.472	0.464	2.9	18.7
	Matched	0.472	0.465	2.4	
Inden	Unmatch	0.370	0.374	-9.3	96
	Matched	0.370	0.370	-0.4	
CSR	Unmatch	0.260	0.237	5.2	63.3
	Matched	0.260	0.252	1.9	

Treated variable	Sample	Treated	Controls	Difference	Std.Dev.	t-value
GI_inc	Unmatched	0.311	0.155	0.156	0.007	22.35
	ATT	0.311	0.173	0.138	0.008	17.35