Essays on the Economics of Green Innovation and Climate Policy

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Declaration

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it). The copyright of this thesis rests with the author. Quotation from it is permitted, provided that full acknowledgement is made. This thesis may not be reproduced without my prior written consent. I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

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Statement of co-authored work

I confirm that Chapter 1 was jointly co-authored with Jingbo Cui, Chunhua Wang, and Junjie Zhang, and I contributed 40% of this work. Chapter 3 was jointly co-authored with Myra Mohnen and Misato Sato, and I contributed 60% of this work.

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Abstract

This thesis consists of four chapters spanning climate policy and green innovation. The first chapter identifies the impacts of China's regional emission trading scheme pilots on firm carbon emissions and other economic outcomes using a unique dataset of Chinese firm tax records. The results demonstrate evidence that China's ETS reduces carbon emissions despite low carbon prices and infrequent trading. This chapter also identifies the channels through which firms respond to ETS by adjusting energy consumption and sources, employment, capital, and productivity. The second chapter assesses the impacts of ETS on low-carbon innovation of unregulated subsidiary firms affiliated with regulated firms. The findings demonstrate that ETS induces low-carbon innovation of unregulated subsidiaries and suggest policy spillovers of ETS through corporate ownership networks. Such policy spillovers are contingent on technological proximity between parent firms and their subsidiaries, top managers with R&D experience, and parent firms' financial constraints. The third chapter investigates the relationship between firms' green revenues and clean innovation. Using a global firm dataset disaggregating commercial activities based on a new green taxonomy, this chapter finds that firms' green revenues are enhanced by their own clean innovation and clean innovation of other firms close in technological and product market spaces. Such results suggest both private and social economic benefits of clean innovation. The last chapter explores the role of foreign direct investment in green knowledge spillovers to Chinese domestic firms. Through text-mining business description and tracking patents of foreign-invested firms in China, this chapter develops new definitions of green FDI and identifies the impacts of knowledge stocks resulting from green FDI firms on green innovation of domestic firms. The findings show that knowledge stocks of green FDI firms in downstream industries drive domestic firms' green patents and suggest knowledge spillovers from downstream green FDI.

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Introduction

Climate change is a global challenge that needs collective actions to curb increasing carbon emissions around the world. To address climate change, well-designed climate policies and widely-adopted green technologies are both strongly needed as they provide the promising feasibility of reducing emissions without depressing economic growth. Harnessing climate policies and green technologies to fulfil climate targets requires a more comprehensive understanding of the outcomes of climate policies and the benefits of green innovation. Therefore, my research focus is targeted on two themes: The first theme focuses on the direct and indirect impacts of climate policies. I take the emission trading scheme (ETS) in China as the climate policy case as it performs as a flagship climate policy instrument for the world's largest CO_2 emitter to achieve its climate targets. I explore how the ETS reduces emissions in regulated firms while inducing innovation in unregulated firms. The second theme focuses on the economic benefits of green innovation, and how such benefits can be spread to a wider range of firms through technology spillovers, which lead to more revenues from green products and further innovation of green technologies. The two themes are explored in detail in four independent chapters.

The first chapter of this thesis, *The Effectiveness of China's Regional Carbon Market Pilots in Reducing Firm Emissions*, explores the impacts of China's emission trading scheme on emissions and other economic consequences. The emission trading scheme is an important climate policy in China to reduce its ever-increasing greenhouse gas emissions while maintaining rapid economic growth. With low carbon prices and infrequent allowance trading, however, whether China's ETS is an effective approach to climate mitigation has entered the centre of the policy and research debate. This chapter provides a comprehensive assessment of the effects of ETS on firm carbon emissions and economic outcomes by means of a matched difference-in-differences (DID) approach. The empirical analysis is based on a unique panel dataset of firm tax records in the manufacturing and public utility sectors during 2009-2015. This chapter shows unambiguous evidence that the regional ETS pilots are effective in reducing firm emissions, leading to a 16.7 percent reduction in total emissions and a 9.7 percent reduction in emission intensity. Regulated firms achieve emission abatement through conserving energy consumption and switching to low-carbon fuels. The economic consequences of the ETS are mixed. On the one hand, the ETS has a negative impact on employment and capital input; on the other hand, the ETS incentivizes regulated firms to improve productivity. In the aggregate, the ETS does not exhibit statistically significant effects on output and export. This chapter also finds that the ETS displays notable heterogeneity across pilots. Mass-based allowance allocation rules, higher carbon prices, and active allowance trading contribute to more pronounced effects in emission abatement.

The second chapter of this thesis, *Policy Spillover Induces Low-carbon Innovation: Evidence from Corporate Ownership Network in China*, further investigates the policy spillover effects of the emission trading scheme. The emission trading scheme establishes a market price for carbon emissions and induces behavioural changes especially low-carbon innovation, while most policy evaluations focus on the innovation of firms that are directly regulated by the ETS. This chapter attempts to extend the understanding of the ETS policy spillovers through corporate ownership networks. Taking advantage of China's regional ETS pilots as a quasi-experiment, this chapter identifies the causal effects of the ETS on the low-carbon innovation of unregulated subsidiaries that are affiliated with regulated parent firms. By a difference-in-differences (DID) strategy with the propensity score matching, the findings demonstrate that China's regional ETS pilots raise low-carbon innovation of unregulated subsidiaries by 4.92% of patent counts and 7.04% of patent citations. The results suggest the ETS policy spillovers from regulated parent firms to their unregulated subsidiary firms that induce low-carbon innovation in the unregulated subsidiaries. The strength of the policy spillover effects varies by carbon prices, while the effects are similar on invention and utility patents. Such policy spillovers are contingent on technological proximity between parent firms and their subsidiaries, top managers with R&D experience, and financial constraints of parent firms. The results suggest that the effects of the ETS on innovation are underestimated without accounting for the policy spillovers through corporate ownership networks.

The third chapter of this thesis, *Green Revenues, Clean Innovation and Technology Spillover: Evidence from Global Firm Level Data*, focuses on the economic benefits of clean innovation. Innovation of clean technologies is critical to mitigating increasing environmental challenges, while it can generate revenues for the inventing firms and beyond through technology spillovers. However, the extent to which clean technologies are generating private and social economic benefits remains poorly understood to date, due to a lack of suitable data sources. Using a unique dataset disaggregating commercial activities of global publicly listed firms based on a new green taxonomy, this chapter shows the variation of green revenues during 2009-2016. This chapter documents a smooth increase in average green revenues over the years. This increase is mainly driven by the expansion of revenues from green products but not the structure change between green and non-green revenues. This chapter finds that firms' green revenues are enhanced by not only their own clean innovation but clean technology spillovers from other neighbouring firms close in the technological and product market spaces. This chapter also finds that the growing maturity of clean technologies facilitates firms to obtain more green revenues, particularly for firms with more own clean technologies. Firms with larger sizes and higher technology capacities benefit more from their own and others' clean innovation. The new evidence on clean technology spillovers implies considerable social benefits of clean innovation and the need to provide policy support to encourage investments in clean technologies.

The last chapter of this thesis, *Knowledge Spillover from Green FDI: Evidence from Green Innovation in China*, looks back to the starting point of the Chinese green industries' take-off and attempts to explore how green knowledge spills over to Chinese firms via foreign direct investment (FDI). China had rapid development of green industries in the past two decades and foreign direct investment was an important enhancer of bringing cutting-edge green technologies to Chinese domestic firms. However, the contributions of FDI to green knowledge spillovers may not be estimated accurately if one does not differentiate whether an FDI involves environmentally-friendly commercial activities, i.e., green FDI. This chapter develops four new definitions of green FDI by text-mining the business description and tracking patenting activities of foreign-invested firms. I identify the impacts of knowledge stocks resulting from green FDI firms on domestic firms' green innovation using Chinese firm-level data, together with an instrumental variable based on the changes in China's FDI opening-up policy. The results show no impact of green FDI firms' knowledge stocks on domestic firms' green innovation when green FDI firms operate within the same industry as domestic firms. In contrast, I find that a 1% increase in knowledge stocks resulting from green FDI firms in downstream industries contributes to roughly 0.732% increase in green patents of domestic firms. Such knowledge spillover effects of downstream green FDI are more pronounced on domestic high-quality green innovation. I further investigate the factors affecting green FDI knowledge spillovers and find that the location of green FDI firms, technological proximity between industries, and environmental regulation stringency of green FDI origins can influence the strength of the knowledge spillovers from downstream green FDI.

Chapter 1

The Effectiveness of China's Regional Carbon Market Pilots in Reducing Firm Emissions[1]

1.1 Introduction

China has pledged that its carbon emissions will peak by 2030 and that it will achieve carbon neutrality by 2060. To meet these ambitious climate targets while maintaining economic growth, it has implemented an emission trading system (ETS) to achieve cost-effective climate mitigation. China has a long history of experimenting with ETS, originated with the SO_2 ETS in the early 1990s (Karplus et al., 2021). Its experience with carbon markets started in the early 2000s through the Clean Development Mechanism, a voluntary carbon offset scheme created by the Kyoto Protocol (Zhang and Wang, 2011). China's regional carbon ETS pilots, announced in 2011 and launched in 2013, marked its first systematic attempt to use market-based instruments to regulate firm carbon emissions (Zhang et al., 2017). Building on the experience of regional pilots, China brought a national carbon ETS, the largest carbon market in the world, online in 2021. As China is poised to ramp up its effort to fight climate change, whether ETS is an effective approach for climate mitigation has entered the center of debate.

Concerned with the impact of carbon regulations on industrial competitiveness, China has been experimenting with both mass- and rate-based allowance allocation rules in the regional pilots. A mass-based rule sets a cap on total emissions while a rate-based rule regulates emission intensity. The national ETS, which covers only the power sector, has adopted a rate-based rule. A rate-based rule creates less regulatory pressure than a mass-

[1] This paper has been published as a research article in *Proceedings of the National Academy of Sciences*, https://doi.org/10.1073/pnas.2109912118.

based rule (Fischer and Newell, 2008; Boom and Dijkstra, 2009; Pizer and Zhang, 2018; Goulder and Morgenstern, 2018; Goulder et al., 2019). Less regulatory pressure gives rise to low carbon prices and infrequent allowance trading. The average carbon price was \$5.6/t-CO_2e in the regional ETS between 2013 and 2015; the average carbon price was \$7.8/t-CO_2e for the national ETS in the first week of operation. Allowance trading has been sporadic, with most transactions occurring in the narrow windows close to the compliance deadlines. In this context, two questions arise from China's ETS, especially from the regional ETS pilots: First, can a low carbon price create incentives for firms to reduce emissions? Second, is a thin carbon market with few buying or selling allowances still useful for firms to mitigate the cost of compliance?

The empirical evidence from the European Union and the United States shows that ETS is effective in mitigating climate change (Fowlie, 2010; Fowlie et al., 2012; Martin et al., 2014; Jaraite and Di Maria, 2016; Borenstein et al., 2019; Colmer et al., 2020), but the economic consequences are mixed (Linn, 2010; Veith et al., 2009; Commins et al., 2011; Bushnell et al., 2013; Martin et al., 2016; Curtis, 2017; Marin et al., 2018; Joltreau and Sommerfeld, 2019). In particular, a recent study demonstrates that the EU ETS with low carbon prices still works as long as it sends a credible signal to emission entities that the regulation will become more stringent in the future (Bayer and Aklin, 2020). Some literature on the effectiveness of China's ETS has also started to emerge. However, these studies are only focused on certain companies, such as power generators (Cao et al., 2021), large firms (Zhu et al., 2019), or publicly listed companies (Cui et al., 2018). The overall impacts of China's ETS on firms are still largely unknown.

This paper comprehensively evaluates the effects of China's regional ETS pilots on firm emissions and economic outcomes. The pilot ETS provides an excellent setting as a quasi-natural experiment since the pilots cover firms above thresholds in certain sectors in seven jurisdictions (Table 1.A.1). Taking advantage of regulatory variations across sectors, regions, and years, this paper employs a matched difference-in-differences (DID) approach to identify the plausible causal effects of ETS on firm carbon emissions and economic outcomes. The empirical analysis is based on a unique panel dataset of firm tax records from the Chinese National Tax Survey Database (CNTSD). The data have broad coverage of firms in terms of sizes, sectors, regions, and years. With detailed information about firm energy and economic activities, the data enable us to comprehensively assess the ETS effects and identify the channels through which firms respond.

The regional ETS pilots also provide a rich set of variations to study the impacts of carbon market design. First, the two-stage launching of the pilots allows us to distinguish the announcement effect from the trading effect. Second, the variation in carbon market performance across regional pilots allows us to identify the impacts of carbon price and allowance liquidity. Third, the heterogeneity of allowance allocation rules allows us to assess the impact of regulatory stringency (Table 1.A.2). Although our analysis focuses on the regional ETS pilots, it provides important policy implications for the national carbon ETS. After all, the design of the national ETS closely follows regional pilots. Many issues that occurred in the regional pilots are likely to be scaled up to the national level.

1.2 Results

The regression analyses take advantage of the quasi-natural experiment created by China's regional ETS pilots. The estimation of the ETS effects proceeds in two steps. We first construct the comparison group by one-to-one matching. This approach pairs each regulated firm with an unregulated firm in the same sector based on certain observable attributes. We conduct a balancing test to ensure that the unregulated firm can serve as the counterfactual for the regulated firm. With the matched sample, we then employ the DID approach to estimate the effects of ETS on carbon emissions and other firm outcomes of interest.

1.2.1 The regional carbon ETS pilots are effective in reducing firm total emissions and emission intensity after the start of allowance trading

Table 1.1 presents the estimated coefficients and standard errors for the effects of ETS on firm carbon emissions based on the baseline model in Eq (1.1). Columns (1)-(2) report the results for total emissions and columns (3)-(4) show the effects on emission intensity (emissions per unit of output value). The preferred estimation results, contained in columns (2) and (4), control for regional (provincial) and industrial linear trends. We differentiate the ETS effects into two phases: announcement (2011-2012) and allowance trading (2013-2015). The ETS effect in the announcement phase, capturing the anticipation effect, is negative but statistically insignificant in the preferred model. The ETS effect starts to kick in during the trading phase; the preferred model estimates that the ETS reduces total emissions by 16.7% (95% CI: [-26.4%,-6.9%]) and by 9.7% for emission intensity (90% CI: [-18.7%, -0.6%]).

We test the assumption that the regulated firms and the matched comparison firms follow a

Table 1.1: The ETS Effects on Firm Carbon Emissions

Dep Var	Total Emissions		Emission Intensity	
	(1)	(2)	(3)	(4)
Announcement	-0.075*	-0.088	-0.027	-0.017
	(0.038)	(0.072)	(0.028)	(0.084)
Trading	-0.178***	-0.167***	-0.118**	-0.097*
	(0.053)	(0.047)	(0.043)	(0.053)
Observations	2,416	2,416	2,416	2,416
R-squared	0.047	0.198	0.090	0.220
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province Trend	N	Y	N	Y
Industry Trend	N	Y	N	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

similar emission trend by regressing the dynamic effects model in Eq (1.2). The estimated coefficients for the pre-policy indicators are not statistically significant at any conventional level, as shown in Figure 1.1. These estimates cannot reject the null hypothesis that carbon emissions were not statistically different between the regulated and matched comparison firms prior to the initiation of ETS. After trading started, the estimated coefficients for the post-policy indicators display a downward trend. In the Appendix, we conduct a series of robustness checks with regarding to alternative specifications, potential threats from confounding policies, and data treatment (Tables 1.B.3, 1.C.2, 1.D.1, 1.E.2, 1.E.3, 1.E.4, 1.G.1, and 1.G.2). The main conclusion survived all these sensitivity analyses. Furthermore, to examine heterogeneous ETS effects by sectors, we run the baseline regressions for the electricity and manufacturing sectors separately. We find that the ETS effects for the manufacturing sector are similar to the baseline results, while the effects for the power sector are statistically insignificant. This can be partly due to a lack of statistical power since our data only include a small sample size of matched regulated power plants (Table 1.F.1).

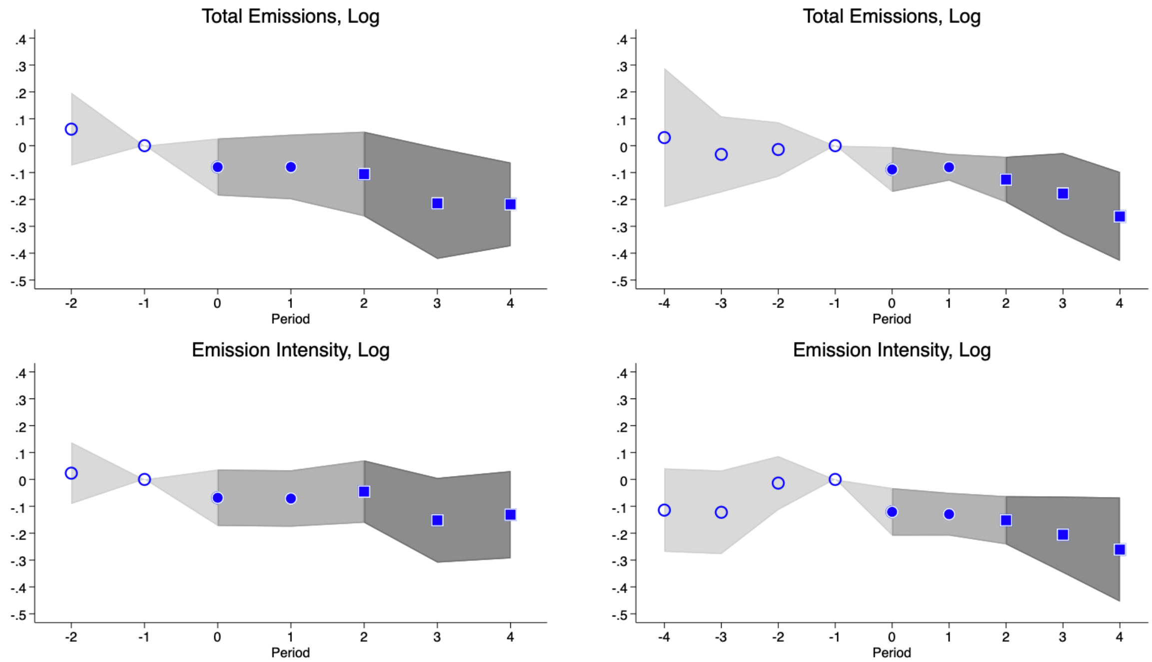


Figure 1.1: Dynamic Effects on Total Emissions and Emission Intensity

Notes: Left panel is based upon the period 2009-2015, and the right panel is for the period 2007-2015. The shaded areas indicate the 95% confidence intervals. The hollow circles represent the point estimates for effects prior to the announcement phase (period -1 and before). The solid circles indicate the effects of the announcement phase (period 0 to 1). The rectangular symbols mark the effects of the trading phase (period 2 and after).

1.2.2 Firms achieve carbon emission reductions through energy conservation and fuel switching

Under carbon regulations, firms can abate emissions through conserving energy, improving energy efficiency, and/or switching to low-carbon fuels (Copeland and Taylor, 2005; Levinson, 2009; Shapiro and Walker, 2018; Colmer et al., 2020). To investigate the channels through which firms achieve emission reductions, we estimate the effects of ETS on firm energy consumption, energy consumption per unit of output value (Energy/Output), carbon emissions per unit of energy consumption (Emission/Energy), and the ratio of natural gas to total energy. Figure 1.2 illustrates the estimated effects of ETS on each component based upon the baseline model in Eq (1.1).

Consistent with the baseline conclusion, the ETS effects mainly occur during the trading phase. Specifically, the ETS reduces firm energy consumption – including coal, gasoline, natural gas, and electricity – by 13% (95% CI: [-23.3%, -2.6%]). Carbon emission abatement is also achieved through fuel switching. Regulated firms reduce emissions per unit of energy consumption by 3.7% (95% CI: [-6.8%,-0.7%]) by switching to low-carbon energy sources. In particular, the ETS increases the share of natural gas by 3.7% (95% CI: [1.1%, 6.4%]). In a nutshell, we find that energy conservation results in the largest portion of emission reductions, while fuel switching also contributes to lower emissions.

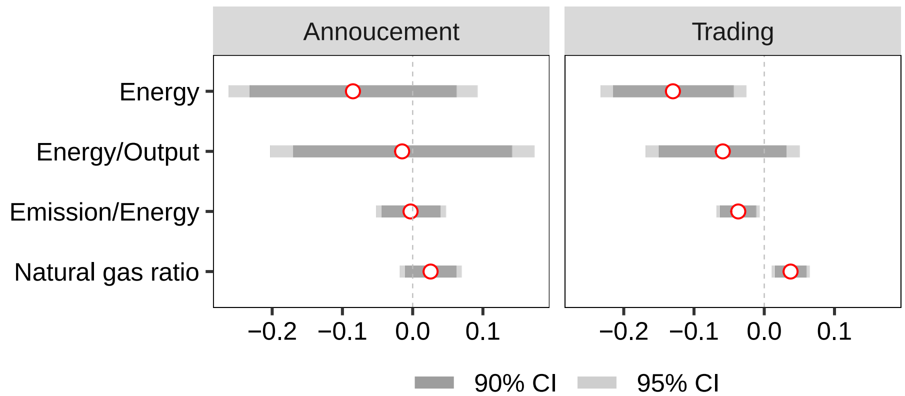


Figure 1.2: The Channels of Carbon Emission Reductions

Notes: The dependent variables except for natural gas ratio are in log form (y-axis). Announcement designates the ETS effects during the announcement period (2011-2012). Trading designates the ETS effects during the trading period (2013-2015). Firm and year fixed effects, as well as province linear trend and industry linear trend, are included.

1.2.3 Firms respond to the ETS by reducing labor and capital inputs, improving productivity while maintaining the same level of output

We examine how firms make economic adjustments in response to the ETS. Specifically, we consider three categories of firm attributes, including output (output value, value-added, and export), input (labor, capital, capital-labor ratio, wage, and investment), and productivity (output-labor ratio, output-capital ratio, and total factor productivity (TFP)). Figure 1.3 illustrates the estimation results for each attribute based upon the baseline model in Eq (1.1).

We find that regulated firms adjust factors of production in response to carbon pricing. The ETS reduces employment by 6.6% (95% CI: [-11.8%,-1.4%]) in the announcement phase and by 11.8% (95% CI: [-23.1%, -0.4%]) in the trading phase. The ETS reduces capital by 15.6% (95% CI: [-30.2%,-1.0%]) in the trading phase, while the effect is statistically insignificant in the announcement phase. Since the relative price of capital and labor is not affected, the ETS has no statistically significant effect on the capital-labor ratio. The ETS effects on wage rate and investment are also statistically insignificant.

While the ETS induces firms to reduce emissions, it also encourages firms to innovate and improve productivity. Our results show that, during the trading phase, the ETS increases

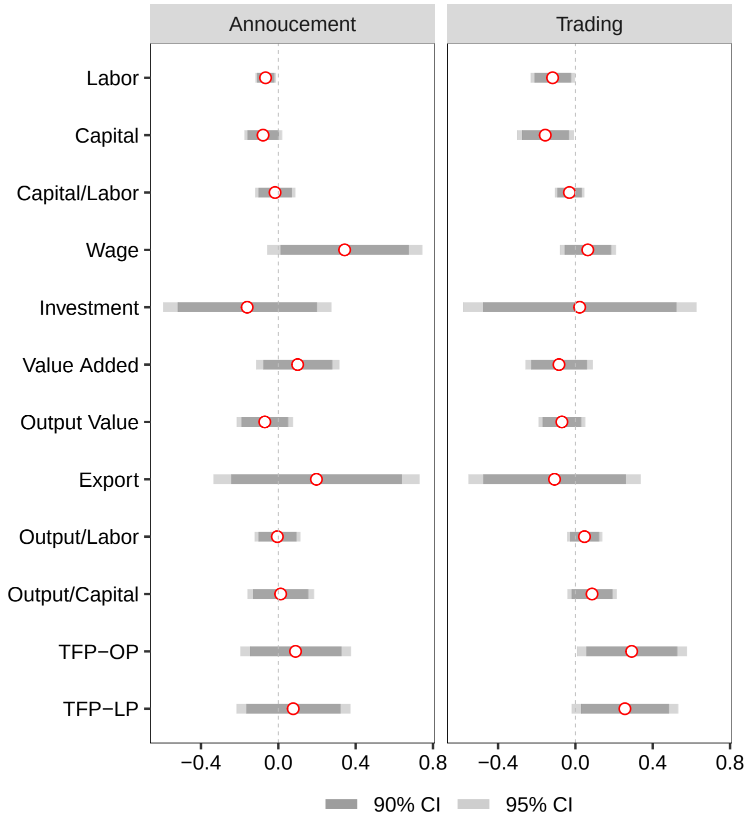


Figure 1.3: The ETS Effects on Firm Economic Attributes

Notes: The dependent variables are in log form (y-axis). Announcement designates the ETS effects during the announcement period (2011-2012). Trading designates the ETS effects during the trading period (2013-2015). Firm and year fixed effects, as well as province linear trend and industry linear trend, are included.

productivity by 29.1% (95% CI: [0.8%, 57.5%]) or 25.6% (90% CI: [2.9%, 48.2%]), following two alternative TFP measures (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). In addition, the ETS has positive effects on output per unit of labor and output per unit of capital, although the estimates are statistically insignificant.

Because the ETS not only increases the cost of production but also boosts firm productivity, the aggregate effects of ETS on firm output can be ambiguous. We find no statistically significant effects of ETS on output values and value-added. This result suggests that emission abatement is probably not being achieved through cutting production. This finding also speaks to the concern that regulating carbon emissions will impose a competitive disadvantage on firms that are exposed to trade. Our empirical result rejects the null hypothesis that the ETS has a negative effect on firm export.

1.2.4 High carbon prices and active allowance trading are more likely to stimulate firms to engage in emission abatement

Heterogeneous carbon market designs lead to variance in market performance. We focus on carbon price and trading activeness. The daily carbon price of the regional ETS pilots ranged from \$1.38 to \$20.88/t CO_2e between 2013 and 2015, with the average carbon price at \$5.6/t CO_2e. The turnover rate of carbon allowance, measured by the ratio of exchanged allowances to total allowances, was 0.018 on average in the same period. Allowance trading is infrequent and mainly occurs before the deadline for compliance.

We interact the trading dummy with carbon price and allowance turnover rate using a variant of the baseline model defined in Eq (1.3). Table 1.2 reports the estimation results. In columns (1) and (3), the estimates show that a 1% increase in carbon price results in a 0.043% decline (95% CI: [-0.065%, -0.020%]) in total emissions and a 0.022% decline (90% CI: [-0.044%, -0.001%]) in emission intensity. In columns (2) and (4), we find that a higher turnover rate also stimulates emission reductions. When the turnover rate increases by 0.01, it can lead to a 3.75% decrease (95% CI: [-5.715%, -1.794%]) in total emissions and a 2.41% decrease (95% CI: [-4.656%, -0.169%]) in emission intensity. The findings highlight the pivotal role of carbon price and trading activeness in incentivizing firm emission reductions.

Table 1.2: Effects of Carbon Price and Allowance Liquidity

Dep Var	Total Emissions		Emission Intensity	
	(1)	(2)	(3)	(4)
Announcement	-0.074	-0.054	-0.006	0.000
	(0.068)	(0.068)	(0.081)	(0.075)
Carbon Price	-0.043***		-0.022*	
	(0.011)		(0.013)	
Turnover Rate		-3.754***		-2.412**
		(0.940)		(1.075)
Observations	2,416	2,416	2,416	2,416
R-squared	0.198	0.194	0.219	0.219
Firm FE, Year FE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y

Notes: The dependent variables and carbon price are in natural logarithms, while turnover rate is shown as a ratio. Announcement equals one for the regulated firms during the announcement period (2011-2012). Carbon price and turnover rate are only available for the regulated firms during the trading period (2013-2015) and are shown as zero otherwise. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

1.2.5 A mass-based allowance allocation rule creates stronger incentives for emission abatement than does a rate-based rule

The regional ETS pilots adopt two types of allowance allocation rules: mass-based and rate-based. Under a mass-based rule, the total allowance for a regulated firm is determined in advance of the compliance period based on its historical emission level or a fixed reference production quantity. In contrast, under a rate-based rule, the total allowance may be adjusted at the end of each compliance period based on a firm's production level during this period. A rate-based rule allows a regulated firm to increase emissions as long as its emission intensity is compliant. Therefore, a rate-based rule implicitly subsidizes production and poses weaker regulatory pressure than a mass-based rule does (Goulder and Morgenstern, 2018).

Table 1.3: Heterogeneous Effects by Allowance Allocation Rules

Dep Var	Total Emissions		Emission Intensity	
	(1)	(2)	(3)	(4)
Announcement	-0.083**	-0.120*	-0.047	-0.068
	(0.039)	(0.063)	(0.033)	(0.073)
Trading	-0.342***	-0.399**	-0.367***	-0.436***
	(0.098)	(0.147)	(0.076)	(0.096)
Trading×Rate	0.212***	0.284*	0.319***	0.414***
	(0.067)	(0.140)	(0.079)	(0.086)
Observations	2,416	2,416	2,416	2,416
R-squared	0.055	0.207	0.102	0.233
Firm FE, Year FE	Y	Y	Y	Y
Province Trend	N	Y	N	Y
Industry Trend	N	Y	N	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

We examine the effect of allowance allocation rules following the regression model in Eq (1.4). The estimation results, presented in Table 1.3, support the argument that the mass-based rule is more effective in incentivizing emission reductions. Specifically, the preferred estimates in columns (2) and (4) show that the mass-based rule reduces firm total emissions by 39.9% (95% CI: [-70.6%, -9.2%]), 43.6% (95% CI: [-63.7%, -23.6%]) for emission intensity. However, under the rate-based rule, the effect of the ETS on total emissions is diminished by 28.4 percentage points (90% CI: [4.2%, 52.5%]) and the effect on emission intensity is weakened by 41.4 percentage points (95% CI: [23.5%, 59.3%]).

1.3 Discussion

This paper demonstrates that China's regional ETS pilots were effective in reducing firm emissions in the early trading phase (2013-2015) despite low carbon prices and allowance liquidity. The magnitude of the effect, a 16.7% reduction in carbon emissions, is on par with that of the EU ETS (8-12%) in the second trading phase (2008-2012) (Wagner et al., 2014; Dechezleprêtre et al., 2018; Colmer et al., 2020). Nevertheless, the regulated firms in China and the EU have responded differently in terms of emission abatement channels. Whereas the EU ETS has reduced consumption of natural gas and petroleum products by manufacturing firms in Germany (Wagner et al., 2014) and France (Colmer et al., 2020), the firms regulated by China's regional ETS have increased natural gas consumption. Because China's energy mix is dominated by coal, switching to natural gas can still reduce carbon emissions.

The cost of regulations is a major concern for many countries, including China, in deciding to take more aggressive climate actions. On the one hand, we find that ETS has a negative impact on employment. By putting a price on carbon, ETS imposes additional costs of production, since energy conservation and fuel switching can be costly. To maintain competitive advantages, regulated firms reduce labor inputs. Our analysis contributes to the heated debate on the impact of carbon regulations on the labor market. Most studies find that ETS has a negative (Abrell et al., 2011; Curtis, 2017) or muted impact (Commins et al., 2011; Wagner et al., 2014; Dechezleprêtre et al., 2018; Colmer et al., 2020) on employment. Our finding also contributes to the literature on how environmental regulations affect employment (Greenstone, 2002; Berman and Bui, 2001; Curtis, 2017; Liu et al., 2021). These results, including those in this paper, suggest that it is important to provide assistance to the workers displaced from carbon-intensive sectors to ensure a just transition.

On the other hand, the measures that firms undertake to reduce emissions may also contribute to higher production efficiency. This hypothesis is supported by our empirical results. We find that ETS stimulates firms to improve productivity. This finding is consistent with the literature documenting how ETS has sparked low-carbon innovation in the EU (Calel and Dechezleprêtre, 2016; Calel, 2020) and in China's regional ETS pilot areas (Cui et al., 2018; Zhu et al., 2019). Productivity growth reduces the cost of compliance with carbon regulations, which alleviates the concern of policymakers regarding the tradeoff between climate mitigation and economic growth.

Firms respond to carbon regulations by reducing labor and capital while improving energy efficiency. This suggests that firms take advantage of low-hanging fruit to reduce energy consumption and carbon emissions. The literature on greenhouse gas abatement cost curves has identified a plethora of technologies that can help achieve this (McKinsey, 2013). In addition, firm management practices are positively associated with energy efficiency and productivity (Bloom et al., 2010; Boyd and Curtis, 2014). For example, firms use sensors and big data to better dispatch cooling systems. This smart technology could free up some air conditioners and reduce capital stocks. It also reduces labor demand since firms need fewer people to manage air conditioners.

This paper sheds important light on the policies regarding carbon markets. First of all, carbon price plays a central role in incentivizing emission reductions. The carbon price in China's regional ETS pilots is relatively low compared with the social cost of carbon or the level in other mature carbon markets. A major cause of low carbon prices is the excess supply of carbon allowances (Zhang et al., 2017). For example, the Guangdong and Shenzhen ETS pilots failed to auction allowances in the primary market, suggesting that carbon allowances were oversupplied. Another concern is that the carbon market is thin and carbon allowances are illiquid. Infrequent trading results from firms' lack of capacity in managing carbon allowances. In addition, most transactions occurred at the end of a compliance period, due to the fact that total allowances are not known until the final output is determined under the rate-based allowance allocation rule. A low carbon price is inadequate to support China's climate ambition. If China could increase its carbon price to the same level as California's cap-and-trade program (\$17/t-CO_2e), it would reduce emissions by 8.83%. If the carbon price could be further increased to the level of the EU ETS (\$32/t-CO_2e), it would reduce emissions by 20.39%. If the carbon price could reach the social cost of carbon (\$50/t-CO_2e) (Nordhaus, 2019), one would expect a 34.31% emission reduction.

Another important policy implication is that allowance allocation rules matter. A mass-based rule creates stronger regulatory pressure than a rate-based rule because the latter implicitly subsidizes production (Pizer and Zhang, 2018; Goulder and Morgenstern, 2018; Goulder et al., 2019). Nevertheless, the national carbon ETS launched in 2021, which covers only the power generation sector, uses a rate-based approach. Given that China has pledged to achieve a carbon emission peak by 2030 and carbon neutrality by 2060, a national ETS without an explicit emission cap is unlikely to achieve China's ambitious climate targets. It is therefore urgent to design a transition from the rate-based system to a mass-based rule.

This paper leaves several areas for future study. First, we are not able to reliably measure firms' entry and exit in the tax survey data. Therefore, this paper only focuses on the intensive margin. Second, our analysis estimates the short-run effects of ETS. Although it is important to trace out the behavioural responses of firms in the long run, such an analysis is implausible since the regional ETS pilots are in the process of being incorporated into the national carbon market. Therefore, this question can only be answered after waiting for the national ETS to operate for several years. Third, this analysis considers only carbon emissions from energy consumption, including direct emissions from burning fossil fuels and indirect emissions from purchased electricity. Due to data limitations, we are not able to include the emissions of other greenhouse gases beyond CO_2, especially those from certain chemical reactions in the manufacturing sectors. Firm-level greenhouse gas emissions are not systematically documented, especially for those firms that are not covered by the ETS. Conducting a more comprehensive analysis in the future should overcome the hurdle of emission data availability.

1.4 Data and Methods

1.4.1 Data

Firm Attributes

The primary firm data are obtained from the Chinese National Tax Survey Database (CNTSD), a large-scale annual survey conducted by China's Ministry of Finance and State Administration of Taxation. This database documents the detailed energy consumption and economic information at the firm level. One notable advantage is its broad coverage of firms. Unlike another widely used Chinese firm-level dataset – the Annual Survey of Industrial Enterprises (ASIE) – that only comprises large firms, the CNTSD covers a much wider range of firms (Liu and Mao, 2019). Another advantage is the detailed firm-level information about energy consumption by source, including coal, oil, natural gas, and electricity. Note that a firm is not the perfect unit of analysis compared with a plant or facility. It is difficult to determine the regulatory status of a multiple-plant firm operating in different jurisdictions. This is a caveat in the Chinese firm data collection system. Nevertheless, more than 95% of firms in the ASIE are single plants (Brandt et al., 2012).

Since ASIE and CNTSD follow similar protocols, dominant single plants should mitigate our concern about misclassification of ETS regulatory status.

ETS Rules and Performances

The ETS rules in the seven regional pilots are compiled from the official websites of local Development and Reform Commissions, which regulate carbon emissions and carbon markets (Table 1.A.1) We compile a list of regulated firms and classify them into a rate- or mass-based system according to the allowance allocation rules (Table 1.A.2). In addition, we obtain the carbon allowance trading data – including price and volume – from the seven carbon exchanges.

Variable Construction

This paper considers both direct emissions from combustion of fossil fuels and indirect emissions from purchased electricity. Emissions are calculated from the CNTSD energy consumption data by source and carbon emission factors (Table 1.C.1) Emission intensity is defined as the ratio of total carbon emissions to gross output value. Firm economic attributes include output value, value-added, export, labor, capital, wage, and investment. Firm total factor productivity (TFP) is measured by means of two standard approaches in the economics literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003).

Summary Statistics

Merging the ETS data with the firm data, the final dataset includes 51,179 unique firms associated with 254,378 firm-year observations during the 2009-2015 period. The procedure of data cleaning and matching is documented in the Appendix. The summary statistics for the variables of interest are reported in the Table 1.B.2.

1.4.2 Empirical Strategy

One-to-one Matching

We use matching to construct a comparison group with firms not regulated by the ETS to serve as the counterfactuals for the treatment group with regulated firms. The estimation of ETS effects can be biased if the treatment and control groups significantly differ in their pre-treatment characteristics (Dehejia and Wahba, 2002). To address this concern, we employ a one-to-one nearest neighbor matching technique. For each regulated firm, we match the closest unregulated firm within the same sector according to the shortest Mahalanobis distance. This distance is calculated based on total carbon emissions, emission intensity, and energy consumption in the two years before the announcement of ETS (i.e., 2009 and 2010). In addition, matching within the sector-year cell can help control for sector-specific, time-variant unobservables that affect both treatment and comparison units. We allow matching with replacement to avoid introducing extra bias in the selection of control units, ensuring that each treated firm is matched with the closest comparison firm.

We carefully assess the credibility of the matching procedure using balancing tests. Specifically, we compare the sample means of covariates between the treatment and matched control groups (Table 1.E.1). We find no significant differences between the two groups in all covariates used in matching and even for those not used. These results suggest that our matching strategy performs well in extracting reasonable comparison firms that are similar to the regulated firms within the same sector prior to the announcement of ETS.

Baseline Model

Using China's regional ETS pilots as a quasi-natural experiment, which regulates carbon emissions for the firms in certain sectors over seven jurisdictions, we employ a difference-in-differences (DID) approach to estimate the ETS effects on firm outcomes. For firm i in sector j from region r at year t, the baseline model specification is given by:

$$Y_{ijrt} = \beta_1 \text{Announcement}_{rt} + \beta_2 \text{Trading}_{it} + \gamma_i + \lambda_t + \eta_{rt} + \delta_{jt} + \varepsilon_{ijrt}. \tag{1.1}$$

In this form, Y_{ijrt} denotes firm carbon emissions (including total emissions and emission intensity, in logarithms) or corporate financial outcomes (input, output, and productivity). The dummy Announcement_{rt} equals one if region r at year t (between 2011 and 2012) has announced its participation in ETS and zero otherwise. The dummy Trading_{it} takes a value of one for regulated firms in the trading phase and zero otherwise. Correspondingly, β_1 captures the announcement effect, and β_2 measures the trading effect.

In addition, we include firm-level fixed effect γ_i to control for unobservable firm attributes that are time-invariant. The time fixed effect indexed by λ_t absorbs year-specific unobservables. We add regional linear trend η_{rt} and industrial linear trend δ_{jt} to control for the region- and industry-specific time-varying unobservables that affect firm outcomes. In the robustness checks, we also use region-by-year and industry-by-year fixed effects. Finally, ε_{ijrt} is an unobserved error term. With the control group constructed by the matching approach, we can consistently estimate the matched-DID model in Eq (1.1) using ordinary least squares.

Dynamic Effects

The validity of the DID model relies on the assumption that the regulated firms do not exhibit a different emission trend from the matched comparison firms. To check this assumption, we conduct the following parallel trends test by running a variant of the DID model while controlling for the lags and leads of the policy year dummies:

$$Y_{ijrt} = \sum_{m=1}^{2} \alpha_{1m}\mathrm{ETS}_{i,s-m} + \sum_{n=0}^{4} \alpha_{2n}\mathrm{ETS}_{i,s+n} + \gamma_i + \lambda_t + \eta_{rt} + \delta_{jt} + \varepsilon_{ijrt}. \tag{1.2}$$

In this form, the dummy variable, denoted by ETS_{it}, integrates the pre-announcement, announcement, and trading effects. $\mathrm{ETS}_{i,s-m}$ is a pre-policy dummy indicating the mth lag of announcing ETS pilots in 2011, while $\mathrm{ETS}_{i,s+n}$ denotes a post-policy indicator for the nth lead, where s is the year of the ETS announcement. The latter measures the announcement effect for $n \in [0, 1]$ and the trading effect for $n \in [2, 4]$. Controlling for lags allows us to examine the pre-ETS effect as a parallel trends test. Controlling for leads helps trace out the treatment effects in the years after the launching of allowance trading.

Carbon Market Performances

The performance of carbon ETS pilots varies across regions due to diverse market designs. Carbon price signals marginal cost of abatement and turnover rate measures the activeness of allowance trading. Utilizing carbon price and turnover rate across pilots and years, we examine how carbon market performance relates to abatement activities. A variant of the baseline model is given by:

$$\begin{aligned} Y_{ijrt} = &\beta_1 \mathrm{Announcement}_{rt} + \beta_2 \mathrm{Trading}_{it} + \\ &\beta_3 \mathrm{Trading}_{it} \times \mathrm{Market}_{rt} + \gamma_i + \lambda_t + \eta_{rt} + \delta_{jt} + \varepsilon_{ijrt}, \end{aligned} \tag{1.3}$$

where Market_{rt} denotes either carbon price or turnover rate at pilot r in year t. The coefficient β_3 captures the effect of carbon market performances.

Allowance Allocation

We classify regulated firms into a rate- or mass-based allowance allocation system. The baseline specification is modified to compare the treatment effects between these two allocation rules by adding another dimension of the variation. A variant of the baseline model is proposed below:

$$\begin{aligned} Y_{ijrt} = &\beta_1 \text{Announcement}_{rt} + \beta_2 \text{Trading}_{it} + \\ &\beta_3 \text{Trading}_{it} \times \text{Rate}_i + \gamma_i + \lambda_t + \eta_{rt} + \delta_{jt} + \varepsilon_{ijrt}, \end{aligned} \tag{1.4}$$

where Rate_i is a binary indicator, equaling one if firm i is in a rate-based allowance allocation system, otherwise zero. The coefficient β_3 captures the difference in treatment effects between rate- and mass-based systems. Some unregulated firms may be used to construct the control groups for both rate- and mass-based treatment groups due to matching with replacement. Nevertheless, in the matched sample, very few unregulated firms appear in both the rate- and mass-based control groups; they are dropped in the analysis.

Robustness Checks

To test the stability of the baseline estimates, we conduct a series of sensitivity analyses. First, we consider alternative data cleaning approaches (Table 1.B.3) Second, to address the concern of missing data on emissions from industrial processes, we run additional regressions without steel, chemical, petrochemical, cement, lime, glass, and other building materials sectors (Table 1.C.2). Third, we isolate the influence of potential confounders at the regional and firm levels (Table 1.D.1). In particular, we account for contemporaneous local air pollution control and energy policies. We also try to control for unobservables with alternative fixed effects. Fourth, we employ alternative empirical strategies such as different matching numbers (Table 1.E.2), different sets of firm-level covariates for matching (Table 1.E.3), alternative matching approaches including propensity score matching, inverse probability of treatment weighting, and coarsened exact matching (Table 1.E.4). Further, we consider four alternative classifications and different model specifications (Table 1.G.1 and 1.G.2). All these results lend strong support to the conclusion that the mass-based allowance rule achieves a more pronounced carbon mitigation impact than the rate-based one does. Overall, our main conclusions survived all these robustness checks.

1.A Policy Background

As the world's largest greenhouse gas (GHG) emitter, China has gradually embodied climate change initiatives in its development planning. In the 2009 Copenhagen Accord, China pledged to reduce its carbon intensity, measured by carbon emissions per unit of GDP, by 40 to 45 percent from the 2005 level by 2020. On October 29, 2011, the National Development and Reform Commission (NDRC) formally approved seven regional carbon emission trading system (ETS) pilots, covering four municipalities (Beijing, Shanghai, Tianjin, and Chongqing), one special economy zone (Shenzhen), and two provinces (Guangdong and Hubei).[2] These pilots began trading carbon allowances in 2013 and 2014.[3] The pilot regions are granted flexibility in designing their own carbon market rules, following general guidelines from the NDRC. While the NDRC sets rules for allowance management, transaction process, and supervision, each pilot is responsible for determining the specific details of their market design, including sectoral coverage, threshold selection, emission targets, allowance allocation, monitoring, reporting and verification (MRV), and compliance (Zhang et al., 2017). Table 1.A.1 provides a summary of ETS policies across pilots. Under the oversight of the NDRC on the planning and development of ETS, each pilot takes advantage of the discretion to adapt the general guidelines to suit the specific local needs.[4]

The pilot ETS has three distinct features. First, it experienced two important phases: announcement (2011 to 2012) and trading (since 2013). During the announcement phase, there existed considerable uncertainty about the coverage and stringency of ETS pilots. Without a list of regulated entities, carbon market prices, and detailed implementation rules, firms in pilot regions may not have had clear expectations regarding their emission reduction paths. Thus, the announcement effect on emission abatement would likely differ dramatically from the trading effect. Therefore, our empirical analysis differentiates the ETS effects between the announcement effect and the trading effect.

Second, the pilot ETS exhibits significant heterogeneity in policy design. The covered sec-

[2]Shenzhen is a sub-provincial city located in Guangdong province but establishes an independent ETS pilot. The firms regulated by the Shenzhen ETS are not covered by the Guangdong ETS.

[3]The first ETS pilot was launched by Shenzhen in June 2013, followed by Shanghai, Beijing, Guangdong, and Tianjin in the same year. The remaining pilots, Hubei and Chongqing, launched ETS in April and June in 2014, respectively. Fujian province opted to launch the eighth carbon market pilot in December 2016, which is beyond our sample period.

[4]For instance, the selection of covered sectors and thresholds aims to strike a balance of encompassing a significant portion of emissions while keeping the number of regulated entities manageable. A broader coverage of entities provides stronger incentives for emission reduction, but it also increases administrative efforts for local governments and compliance costs for covered sectors (Zhang et al., 2014).

Table 1.A.1: Covered Sectors across Regional ETS Pilots

Region	Announcement Year	Launch Year	Covered Sectors	Threshold	Emissions Covered
Beijing	2011	2013	Electricity, heating, cement, petrochemical, and other industries, large public buildings including hospitals, schools and governments	>10kt	40%
Shanghai	2011	2013	Electricity, iron and steel, petrochemical and chemical industries, metallurgy, building materials, paper making, textile, aviation, airports and ports, public and office buildings, railway stations	Industries>20kt; Non-industries>10kt	57%
Shenzhen	2011	2013	Electricity, building, manufacturing, water supply	Industries>5kt; Public buildings>20km^2 Office buildings>10km^2	40%
Guangdong	2011	2013	Electricity, cement, iron and steel, petrochemical industries, public services including hotels, restaurants and businesses	2013: >20kt; Since 2014: industries>10kt; non-industries>5kt	58%
Tianjin	2011	2013	Electricity, heating, iron and steel, chemical and petrochemical industries, oil and gas exploration	>20kt	60%
Hubei	2011	2014	Electricity, heating, metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement, medicine and pharmacy, food and beverage, papermaking	energy consumption>60k tce	33%
Chongqing	2011	2014	Electricity, metallurgy, chemical industries, cement, iron and steel	>20kt	39.5%

Notes: Complied based on Zhang et al. (2017).

tors vary across pilots, ranging from manufacturing to non-manufacturing industries. The threshold of coverage is determined by annual emissions or energy consumption, resulting in various total emission allowances across pilots.[5] While almost all pilots allocate allowances for free,[6] carbon allowances can only be traded within the same pilot, with the result that carbon price and trading activity vary across pilots. Further, each pilot has established its own MRV (measurement, reporting, and verification) system, although the pilots share similar protocols, in which noncompliances is subject to financial and non-financial penalties.[7] The policy variations across sectors and regions enable us to identify different carbon market outcomes.

Third, China's regional ETS used two main allowance allocation rules: mass-based and rate-based. Under the mass-based (cap-and-trade) system (Goulder and Morgenstern, 2018; Goulder et al., 2019), regulators set a total number of allowances – an emission cap – in advance of each compliance period. Each covered facility receives allowances based on its historical emission level (e.g., Phases I & II in the EU ETS) or the product of a pre-established benchmark emission-output ratio and some fixed reference production

[5]Guangdong issues the most carbon allowances (388 Metric tons [Mt]), while Shenzhen has the least (30 Mt). The covered shares of emissions in each pilot range from 33 percent for Hubei to 60 percent for Tianjin.

[6]The exception is that Guangdong and Shenzhen auction a small share of allowances – up to 3 percent.

[7]These include deduction of excessive emissions from the allowance allocation next year, and records of noncompliance in the business credit reporting systems.

quantity (e.g., Phase III in the EU ETS, cap-and-trade in California and Quebec). If a covered facility's emission level exceeds the pre-established number of allowances, it must purchase additional allowances from the carbon market to achieve compliance. In most cases, the allowance allocation is exogenous to a facility's production level during the compliance period.[8]

Some ETS pilots have adopted tradable performance standards, which is a rate-based system (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Goulder et al., 2019). The regulators set an emission intensity ratio – a performance standard or rate – rather than an emission cap for covered firms. The number of allowances depends on output level and a benchmark or historical emission rate. The total number of allowances is not determined until the end of each compliance period when a firm's production level is observed. As an ex-post adjustment, the allowance is thus endogenous within each compliance period.[9] This system can be regarded as an implicit subsidy to firm production since additional output value increases the number of allowances that covered firms receive (Fischer, 2001; Fischer and Newell, 2008). Such flexibility puts less compliance pressure on regulated firms but compromises cost-effectiveness in achieving climate targets (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Goulder et al., 2019). Table 1.A.2 summarizes detailed information about allowance allocation rules across pilots.

[8]There are a few exceptions. If the allowance allocation under the cap-and-trade system is output-based and therefore endogenous, the allowances allocated to a covered firm could be updated based on the production level in the previous compliance period (Goulder et al., 2019). The purpose of such output-based allocation is to mitigate carbon leakage and safeguard the competitiveness of covered facilities by subsidizing additional output with extra allowances (Fowlie et al., 2016; Goulder et al., 2019). In some cap-and-trade systems, the output-based allocation under the cap-and-trade system has been applied to only a small subset of facilities that are in emissions-intensive and trade-exposed sectors.

[9]Under a rate-based system, covered firms receive carbon allowances through a two-step process. At the beginning of a compliance period, each covered firm receives initial allowances based upon its output value in the previous period. At the end of the compliance period, each firm receives additional allowances based on the actual output value in order to bring the total allowances per output value down to the specified benchmark or historical level emissions rate.

Table 1.A.2: Allowance Allocation across Regional ETS Pilots

	Mass-based System				Rate-based System	
Region	Emission-based grandfathering, fixed baseline periods[1]	Emission-based grandfathering, moving baseline periods[2]	Fixed historical production based benchmarking[3]	Moving historical production based benchmarking[4]	Intensity-based grandfathering[5]	Current production based benchmarking[6]
	Exogenous	Endogenous (output-based)	Exogenous	Endogenous (output-based)	Endogenous (output-based)	Endogenous (output-based)
EU ETS	Phases I and II		Phase III	Emission-intensive and trade-exposed industries (Phase III)		
California C&T				Industrial facilities		
Beijing	Cement, petrochemical and other industries, large public buildings including hospitals, schools and governments.				Electricity, heating	
Shanghai	Iron and steel, petrochemical and chemical industries, metallurgy, building materials, paper making, textiles, public and office buildings, railway stations					Electricity, aviation, airports and ports.
Shenzhen					Manufacturing	Electricity, heating, building, water supply.
Guangdong[7]		Electricity (cogeneration genset), cement (cement mining and other grinding process), steel (DR-EAF route), petrochemical industries.				Electricity (pure genset), cement (cement clinker production and cement grinding process), steel (BF-BOF route).
Tianjin	Iron and steel, chemical and petrochemical industries, oil and gas exploration.				Electricity, heating	
Hubei		Metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement (only 2014), medicine and pharmacy, food and beverage, paper making.				Electricity, heating, cement (only 2015).
Chongqing[8]		Electricity, metallurgy, chemical industries, cement, iron and steel (due to self-declaration & ex-post adjustment).				

Notes: (1) Emission-based grandfathering with fixed baseline periods, known as "pure grandfathering", depends on firm's historical emission level in fixed periods to compute the number of allowances. (2) Since the baseline periods of a firm's historical emissions are moving, the number of allowances is updated based on outputs across periods and therefore categorized as "output-based" allocation. (3) Allowance = sectoral benchmark × firms' historical production in fixed baseline periods. (4) Allowance = sectoral benchmark × firms' historical production in moving baseline periods. Hence, the number of allowances is updated based on output values across periods and categorized as "output-based" allocation. (5) Intensity-based grandfathering depends on a firm's historical emission intensity level and firm's current output level to compute the number of allowances. (6) Allowance = sectoral benchmark × firms' current production level. (7) The Guangdong pilot determines allowance allocation methods based on industrial processes and techniques in the electricity, cement, and steel sectors. (8) The Chongqing pilot allocates allowances on the basis of the self-declaration number by covered firms and allows for ex-post adjustment of the allowance number at the end of the compliance period.

1.B Data Cleaning

This section documents the data cleaning process. (1) We remove observations with missing or zero values in output value, sales, emissions, and energy consumption of fuels. Around 20.9% of firms are dropped from the sample for this reason. (2) We drop the regulated firms whose carbon emissions or energy consumption levels during the pre-ETS period are smaller than the coverage thresholds of ETS pilots (as shown in Table 1.A.1). This results in removal of 191 ETS firms, around 0.03% of all firms in our sample, from the sample. (3) Next, we drop observations whose key variables (output value, emission, and emission intensity) have drastic changes across years. In our analysis, any observations with annual change rates above ±500% are excluded. As a result, around 12.5% of firms are excluded during this process. (4) The firms that entered the survey after 2011 are dropped because the matching procedure relies on firm covariates in 2009 and 2010. The firms that exited from the survey before 2012 are also removed from the sample since they do not have the post-treatment observations. Around 50.3% of total firms are removed from the sample. (5) We delete the firms without reported key variables in two consecutive years during our sample period of 2009-2015. Moreover, for a treated firm with missing data in one specific year, we search for a matched firm with the same data missing year during the matching procedure to ensure that the treatment and control units are as similar as possible in the remaining data pattern.[10] This round of cleaning excludes around 6.5% of firms in our sample. (6) We remove observations with outlier values in key variables of interest (either greater than 99% or smaller than 1%). Finally, the cleaned dataset includes 280 regulated firms and 50,899 unregulated firms.

One concern is whether our data cleaning algorithm yields a biased sample. This concern is centered on whether these dropped missing values are affected by ETS-induced entry and exit. To test this, we count the number of dropped firms by region in each data cleaning step. Table 1.B.1 in the Appendix summarizes the results. First, we remove firms without pre-ETS observations (panel b). The number of firms removed in this step accounts for 43.5% of total removals for non-ETS regions and 44.5% for ETS regions. Second, we remove firms without post-ETS observations (panel c). The number of firms removed in this step accounts for 40.9% of total removals for non-ETS regions and 38.9% for ETS regions. Third, we remove firms without both pre- and post-ETS observations.

[10] Keeping firms that are observed for all sample periods, while deemed safer, tends to result in fewer samples appearing in our empirical analysis. This will be particularly true in our case because there exist missing observations in certain variables. Therefore, we choose the threshold for cleaning missing data (no missing observations in two consecutive years) that ensures the representativeness of our samples while not impairing the consecutiveness very much.

Table 1.B.1: Number of Removed Firms due to No Pre- or Post-ETS Observations

	Non-ETS Regions (1)	ETS Regions (2)	Difference (3) = (2) - (1)
a. # of removed firms (row a = b + c + d)	312,311	79,049	
b. # of removed firms due to no pre-ETS data	135,821	35,215	
ratio of removed firms (row b/row a)	43.5%	44.5%	-1%
c. # of removed firms due to no post-ETS data	127,635	30,770	
ratio of removed firms (row c/row a)	40.9%	38.9%	2%
d. # of removed firms due to no pre- & post-ETS data	48,855	13,064	
ratio of removed firms (row d/row a)	15.6%	16.5%	-0.9%

Notes: Row a shows the total number of removed firms that do not have observations before the announcement or after the trading of the ETS. Row b represents the number of firms that enter the survey after the announcement period. Row c stands for the number of firms that exit the survey before trading. Row d records the number of removed firms that enter the survey after the announcement but exit it before trading.

Table 1.B.2: Summary Statistics

Variables	N	Mean	Std	Mean	
				NonETS	ETS
Panel A. Firm-level Carbon Emissions and Energy Consumption					
Emission	2,428	11.06	2.525	11.07	11.06
Emission/Output	2,428	0.222	2.263	0.208	0.236
Energy Consumption	2,428	9.802	2.684	9.785	9.820
Energy/Output	2,428	-1.038	2.434	-1.075	-0.999
Panel B. Firm-level Attributes					
Output Value	2,428	10.84	1.116	10.86	10.82
Sale	2,428	10.91	1.109	10.92	10.91
Labor	2,428	6.505	0.980	6.498	6.512
Wage	2,397	7.989	1.180	7.901	8.080
Wage/Labor	2,397	1.487	0.816	1.403	1.574
Capital	2,295	9.912	1.462	9.864	9.963
Value Added	2,317	9.165	1.302	9.157	9.173
Export	2,428	4.385	4.909	4.237	4.537
Invest	1,833	6.865	1.968	6.847	6.885
Total Factor Productivity	2,185	-0.595	1.479	-0.592	-0.598
Capital/Labor	2,295	3.402	1.624	3.369	3.435
Output/Labor	2,428	4.335	1.134	4.361	4.307
Output/Capital	2,295	0.918	1.044	0.996	0.836
Panel C. Regional Carbon Market Performance					
Carbon Price	2,428	0.739	1.528	0.000	1.500
Turnover Rate	2,428	0.004	0.011	0.000	0.007

Notes: Panels A and B report firm-level carbon emissions and attributes, respectively. Panel C shows regional carbon market performance. Units: Emission - metric tons of CO_2; Energy Consumption - metric tons of standard coal equivalent (TCE), with 1 TCE = 29,307 GJ; Output Value, Sale, Wage, Capital, Value Added, Export, Invest - ten thousands of Yuan; Labor - number of employees; Carbon Price - Yuan (1 Yuan = 0.145 Dollars). All variables are in natural logarithms except Turnover Rate. Turnover Rate is the ratio of trading volume to the total allowance in each carbon market.

The number of firms removed in this step accounts for 15.6% of total removals for non-ETS regions and 16.5% for ETS regions. Across the three steps of data cleaning, we do not observe a dramatic difference in the removal ratios of firms between ETS and non-ETS regions. This suggests that ETS-induced entry and exit may not cause a concern of sample selection.[11]

Table 1.B.2 reports the summary statistics. Column (1) reports the number of observations used in our analysis after matching. The last two columns show the means of each variable by treatment status. All variables except for turnover rate are in logarithms.

Table 1.B.3: Robustness Checks on Alternative Data Cleaning Algorithms

VARIABLES	Growth Rate < ±300%		Growth Rate < ±700%	
	Total Emissions (1)	Emission Intensity (2)	Total Emissions (3)	Emission Intensity (4)
Panel A: Main Effects				
Announcement	-0.012	0.077	-0.147***	-0.101
	(0.090)	(0.081)	(0.052)	(0.084)
Trading	-0.073	0.022	-0.145***	-0.094**
	(0.063)	(0.055)	(0.040)	(0.041)
R-squared	0.255	0.263	0.202	0.209
Panel B: Main Effects by Rate- and Mass-based ETS				
Announcement	-0.038	0.052	-0.182***	-0.150*
	(0.081)	(0.072)	(0.045)	(0.080)
Trading	-0.298	-0.171**	-0.357***	-0.402***
	(0.175)	(0.080)	(0.122)	(0.076)
Trading×Rate	0.274	0.232**	0.256**	0.370***
	(0.166)	(0.098)	(0.114)	(0.080)
R-squared	0.262	0.268	0.206	0.215
Observations	1,942	1,942	2,670	2,670
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Moreover, we test alternative data cleaning algorithms. In our baseline model, we drop

[11] It is a caveat that the data do not allow us to distinguish whether a new record in the tax survey data is from a new market entrant or from an existing one, and the same issue applies to exit. Although we cannot completely rule out the possibility that firms' entry and exit are induced by the ETS, the similar ratios of firms without pre- and post-ETS observations between ETS and non-ETS regions presented in Table 1.B.1 suggest that the missing observations are little likely to be driven by the ETS.

observations with annual growth or shrinkage above ±500% because the drastic changes might include unknown shocks or data entry errors. This threshold is set at the level where we can remove most of the potential bias due to the drastic changes while ensuring sample representativeness. To test the stability of our results, we also employ a stringent threshold of ±300% and a lenient threshold of ±700% in the data cleaning process as robustness checks. Table 1.B.3 shows the corresponding estimated ETS effects on carbon emissions. With a stringent cleaning algorithm, in columns (1) and (2), we observe some modest impacts of the ETS on emission intensity for the mass-based programs during the launching period. Columns (3) and (4) present the results with a lenient cleaning algorithm. We find robust evidence supporting the baseline conclusions.

1.C Carbon Emission Measurement

Total carbon emissions in this paper consider both direct and indirect emissions. The former is from combustion of fossil fuels and the latter comes from consumption of purchased electricity. For each firm, we calculate carbon emissions by multiplying the consumption of each energy type (i.e., coal, oil, natural gas, and electricity) by its carbon emission factor. Energy consumption is measured in metric tons of standard coal equivalent (TCE).[12] Table 1.C.1 summarizes the emission factors for each energy type.

Besides energy-related emissions, those from industrial processes also need to be calculated (e.g., emissions from chemical reactions when producing chemicals, iron, steel, and cement) but require further information on manufacturing techniques and processes. Unfortunately, such information is not available in our dataset. As a robustness check, we drop the firms in the sectors that likely produce significant industrial process emissions, including iron and steel, chemical and petrochemical, cement, lime, glass, and other building materials sectors (IPCC, 2006). Table 1.C.2 presents the results. Overall, the main conclusions still hold.

1.D Potential Confounding Policies

Threats to identification arise from the potential confounding environmental and energy policies that affect firms' carbon mitigation activities. Although provincial and industrial confounding policies are absorbed by the province and industry linear trends in the baseline model, we attempt to remove other confounding factors arising from overlapping policies.

[12] 1 TCE is equivalent to 29,307 GJ

Table 1.C.1: China's CO_2 Emission Factors

Energy	Unit	Emission Factor
Panel A: Emission Factors of Coal, Oil and Natural Gas		
Coal	$kgCO_2/kg$	1.978
Oil	$kgCO_2/kg$	3.065
Natural Gas	$kgCO_2/m^3$	1.809
Panel B: Emission Factors of Electricity		
North China Grid	$kgCO_2/kWh$	0.8843
Northeast China Grid	$kgCO_2/kWh$	0.7769
East China Grid	$kgCO_2/kWh$	0.7035
Central China Grid	$kgCO_2/kWh$	0.5257
Northwest China Grid	$kgCO_2/kWh$	0.6671
China Southern Power Grid	$kgCO_2/kWh$	0.5271

Notes: China has six regional power grids whose carbon emission factors are computed separately. The North China Grid covers Beijing, Tianjin, Hebei, Shandong, Shanxi,and Inner Mongolia. The Northeast China Grid covers Liaoning, Jilin, and Heilongjiang. The East China Grid covers Shanghai, Jiangsu, Zhejiang, Anhui, and Fujian. The Central China Grid covers Henan, Hubei, Hunan, Jiangxi, Chongqing, and Sichuan. The Northwest China Grid Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The China Southern Power Grid covers Guangdong, Guangxi, Yunnan, Guizhou, and Hainan. Source of Panel A: Department of Energy Statistics, National Bureau of Statistics of China and IPCC Guidelines for National Greenhouse Gas Inventories. Source of Panel B: National Center for Climate Change Strategy and International Cooperation, National Development and Reform Comission of China.

Our baseline estimates may be subject to additional potential confounding factors. Table 1.D.1 provides robustness checks.

First, time-variant provincial and industrial regulations may exist as confounders. To address this concern, we supplement the regression model with industry-year and province-year fixed effects. Columns (1) and (2) show the results. In Panel A, both estimates for the trading effects are negative and statistically significant for emissions but not for intensity. The trading effect is more pronounced for carbon emissions but remains muted for carbon intensity. In Panel B, the trading effects are negative and statistically significant at the 1% level, while the rate-based ETS effects remain positive and statistically significant at the 1% level. The inclusion of additional time-variant fixed effects does not change the overall baseline conclusions.

Second, we test the sensitivity against potential confounding environmental policies. In 2011, the Ministry of Ecology and Environment targeted Beijing, Tianjin, and Hebei (BTH), one of the most polluted regions in China, to dramatically heighten air pollution regulations, especially for $PM_{2.5}$. Since CO_2 is co-emitted with many air pollutants, this regional air pollution control policy could also lead to the abatement of carbon emissions. To address this concern, we drop the firms from the BTH region in the robustness

Table 1.C.2: Robustness Checks on Alternative Emission Measurements

VARIABLES	Total Emissions	Emission Intensity
	(1)	(2)
	Panel A: Main Effects	
Announcement	-0.113	-0.031
	(0.068)	(0.072)
Trading	-0.152***	-0.059
	(0.051)	(0.062)
R-squared	0.224	0.261
	Panel B: Main Effects by Rate- and Mass-based ETS	
Announcement	-0.144**	-0.066
	(0.067)	(0.074)
Trading	-0.491**	-0.474***
	(0.192)	(0.126)
Trading×Rate	0.372*	0.455***
	(0.184)	(0.097)
R-squared	0.226	0.219
Observations	1,530	1,530
Firm FE	Y	Y
Year FE	Y	Y
Province Trend	Y	Y
Industry Trend	Y	Y

Notes: We exclude those sectors with significant emissions from industrial process (iron and steel, chemical and petrochemical, cement, lime, glass and other building materials sectors). All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

check. Columns (3) and (4) show the results. The main conclusion still holds. The ETS trading phase plays a substantial role in achieving the target of carbon mitigation. This effect mainly arises from those pilots using the mass-based ETS rule.

Lastly, some contemporaneous energy policies may also confound our estimates. In late 2011, the NDRC launched the Top 10,000 (Top-10k) Firm Energy Conservation Program, covering the top 10,000 energy users, accounting for around 60 percent of nationwide energy consumption in China. This central government-led program requires energy-intensive entities to meet the targets of energy conservation and technology upgrades with higher energy efficiency. Carbon emission activities of ETS firms were likely affected by this policy. In our samples, around 50% of ETS firms are included in this program. To address this concern while avoiding losing a large portion of observations, we add a policy indicator for Top-10k into the model as a robustness check. The last two columns in Table 1.D.1 present the results. The estimates for the Top-10k program are not statistically significant,

Table 1.D.1: Robustness Checks on Confounding Factors

VARIABLES	Additional FE		Without BTH		Top-10k	
	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Main Effects						
Announcement			-0.087	-0.007	-0.088	-0.017
			(0.067)	(0.084)	(0.073)	(0.083)
Trading	-0.190***	-0.069	-0.132**	-0.033	-0.166***	-0.097*
	(0.042)	(0.056)	(0.050)	(0.046)	(0.046)	(0.052)
Top-10k					-0.007	0.026
					(0.059)	(0.045)
R-squared	0.222	0.239	0.197	0.212	0.198	0.220
Panel B: Main Effects by Rate- and Mass-based ETS						
Announcement			-0.118*	-0.063	-0.120*	-0.069
			(0.068)	(0.076)	(0.064)	(0.072)
Trading	-0.474***	-0.408***	-0.333**	-0.378***	-0.400**	-0.439***
	(0.103)	(0.090)	(0.138)	(0.076)	(0.149)	(0.097)
Trading×Rate	0.331***	0.382***	0.230*	0.403***	0.286*	0.417***
	(0.086)	(0.077)	(0.120)	(0.069)	(0.143)	(0.086)
Top-10k					0.016	0.042
					(0.054)	(0.038)
R-squared	0.206	0.233	0.204	0.226	0.207	0.233
Observations	2,402	2,402	2,188	2,188	2,416	2,416
Firm FE	Y	Y	Y	Y	Y	Y
Year FE			Y	Y	Y	Y
Province Trend			Y	Y	Y	Y
Industry Trend			Y	Y	Y	Y
Province-Year FE	Y	Y				
Industry-Year FE	Y	Y				

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. "Without BTH" refers to the removal of observations located in Beijing, Tianjin, and Hebei areas due to the confounding local environmental policy. Top-10k equals one for firms under the Top 10k Energy Conservation Program. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

indicating little impact on carbon mitigation for the firms in our sample. More importantly, the baseline conclusions on the trading effect still hold.

1.E Alternative Matching Approaches

The literature lacks consensus about the inclusion variables and constraints in the matching process. A large number of included covariates and matching restrictions, while deemed safe, are likely to result in fewer matched pairs. Moreover, the performance of Mahalanobis distance-based matching is impaired when there are too many covariates (Rubin, 1979;

Zhao, 2004; Stuart, 2010). Therefore, we choose the variables (total emissions, emission intensity, and energy consumption) that determine a firm's regulatory status in a pilot region to ensure close similarity between the treated and control units while keeping the highest number of matched pairs. Besides, we restrict the matching within the same sector and year to control for the sector-specific time-variant factors that may affect both the treatment and control groups. Table 1.E.1 summarizes matching quality by comparing the sample means of covariates between the treatment and matched control groups. We find no significant differences between the two groups in any of the covariates used or even in those not used in the matching process. These results suggest that our matching strategy performs well in extracting reasonable comparison firms, similar to regulated firms within the same sector prior to the announcement of ETS.

Table 1.E.1: Balancing Test

	Unmatched Sample			Matched Sample		
	280 treated vs 50,899 control firms			198 treated vs 198 control firms		
Variables	Treated	Control	P-value	Treated	Control	P-value
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Covariates Used in Matching						
Emission 2010	11.180	7.194	0.000	11.197	11.204	0.978
Emission/Output 2010	0.330	-1.308	0.000	0.368	0.360	0.973
Energy Consumption 2010	9.906	7.873	0.000	9.914	9.910	0.988
Emission 2009	10.949	7.820	0.000	10.811	10.771	0.888
Emission/Output 2009	0.325	-1.253	0.000	0.302	0.276	0.918
Energy Consumption 2009	9.639	8.132	0.000	9.500	9.457	0.891
Panel B: Covariates Not Used in Matching						
Output Value 2010	10.850	8.502	0.000	10.829	10.844	0.894
Sale 2010	10.923	8.547	0.000	10.901	10.894	0.946
Energy/Output 2010	-0.944	-2.127	0.000	-0.915	-0.934	0.941
Labor 2010	6.552	4.990	0.000	6.551	6.512	0.697
Wage 2010	7.985	7.130	0.000	7.998	7.820	0.091
Capital 2010	9.992	6.978	0.000	10.006	9.885	0.434
ValueAdded 2010	9.199	6.651	0.000	9.182	9.134	0.717
Invest 2010	7.006	4.714	0.000	7.018	6.952	0.785
Output Value 2009	10.624	9.073	0.000	10.509	10.494	0.909
Sale 2009	10.652	9.082	0.000	10.543	10.504	0.764
Energy/Output 2009	-0.985	-1.824	0.000	-1.009	-1.037	0.919
Labor 2009	6.586	5.502	0.000	6.560	6.455	0.366
Wage 2009	7.737	7.037	0.000	7.688	7.527	0.193
Capital 2009	9.894	7.779	0.000	9.809	9.616	0.282
ValueAdded 2009	8.890	7.251	0.000	8.767	8.738	0.854
Invest 2009	7.135	5.267	0.000	7.008	7.058	0.838

Notes: All firm-level attributes used in the matching approach are historical records in 2009 and 2010 during the pre-announcement phase. All attributes are in natural logarithms.

The baseline model adopts a one-to-one nearest neighbor matching estimator. To ensure the stability of the main results, we consider a series of robustness checks, including alternative matching estimators, a rich set of covariates, and other matching approaches. First, we adopt nearest two and nearest five neighbor matching to increase the matched observations. Table 1.E.2 summarizes the estimation results. Columns (1)-(2) report the one-to-two matching results, and columns (3)-(4) report the one-to-five matching results. In all columns, the estimated coefficients for the announcement effect remain statistically insignificant. The estimates for the trading effect are negative and statistically significant at conventional levels. The baseline conclusions are not altered by accounting for different numbers of control units during the matching process.

Table 1.E.2: Robustness Checks on Alternative Matching Numbers

VARIABLES	1:2 Matching (198 treated vs 396 control)		1:5 Matching (198 treated vs 990 control)	
	Total Emissions (1)	Emission Intensity (2)	Total Emissions (3)	Emission Intensity (4)
Announcement	-0.051	0.038	-0.071	-0.004
	(0.066)	(0.067)	(0.049)	(0.032)
Trading	-0.126***	-0.101*	-0.122***	-0.102***
	(0.042)	(0.049)	(0.035)	(0.034)
Observations	3,668	3,668	6,501	6,501
R-squared	0.154	0.185	0.115	0.127
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Second, the baseline uses emissions, emissions per unit of output value, and energy consumption as the key covariates. We consider alternative covariates to select the control firms to match the characteristics of regulated firms prior to the ETS. Specifically, we account for eight additional sets of matching covariates, mixing among emissions, energy consumption, emission intensity, energy intensity, output, and sales. Table 1.E.3 reports the corresponding results. The estimated announcement effects are not statistically significant at any conventional level, while the estimated trading effects are negative and statistically significant. These results provide further corroborating support to the baseline conclusions.

Table 1.E.3: Robustness Checks on Alternative Sets of Covariates in Mahalanobis Matching

VARIABLES	Covariate Set 1 (176 treated vs 176 control)		Covariate Set 2 (169 treated vs 169 control)		Covariate Set 3 (195 treated vs 195 control)		Covariate Set 4 (210 treated vs 210 control)	
	Total Emissions (1)	Emission Intensity (2)	Total Emissions (3)	Emission Intensity (4)	Total Emissions (5)	Emission Intensity (6)	Total Emissions (7)	Emission Intensity (8)
Announcement	0.012	-0.008	-0.121	-0.085	-0.071	-0.024	-0.032	0.030
	(0.070)	(0.093)	(0.081)	(0.093)	(0.081)	(0.094)	(0.048)	(0.070)
Trading	-0.028	-0.107*	-0.182***	-0.185***	-0.153***	-0.110**	-0.132**	-0.099*
	(0.037)	(0.053)	(0.040)	(0.049)	(0.045)	(0.048)	(0.057)	(0.056)
Observations	2,088	2,088	1,983	1,983	2,381	2,381	2,575	2,575
R-squared	0.211	0.236	0.255	0.249	0.202	0.218	0.177	0.217
	Covariate Set 5 (193 treated vs 193 control)		Covariate Set 6 (202 treated vs 202 control)		Covariate Set 7 (180 treated vs 180 control)		Covariate Set 8 (173 treated vs 173 control)	
Announcement	-0.050	0.004	-0.046	0.016	-0.081	-0.091	-0.077	-0.047
	(0.048)	(0.067)	(0.066)	(0.089)	(0.063)	(0.096)	(0.048)	(0.062)
Trading	-0.174***	-0.156***	-0.138**	-0.103*	-0.148***	-0.157**	-0.184***	-0.200***
	(0.046)	(0.040)	(0.053)	(0.057)	(0.044)	(0.056)	(0.043)	(0.060)
Observations	2,336	2,336	2,475	2,475	2,141	2,141	2,050	2,050
R-squared	0.206	0.209	0.195	0.235	0.223	0.250	0.230	0.246
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). A set of covariates used in the matching process vary across columns. Covariate Set 1: emissions, emissions per output, energy consumption, and energy per output. Set 2: emissions, emissions per output, energy consumption, and sale. Set 3: emissions, energy consumption and output. Set 4: emissions, emissions per output, output. Set 5: emissions, energy consumption, sale. Set 6: emissions, energy consumption, energy per output. Set 7: emissions, emissions per output, energy consumption, output. Set 8: emissions, energy consumption, energy per output, sale. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 1.E.4: Robustness Checks on Alternative Matching Methods

VARIABLES	PSM (220 treated vs 220 control)		IPTW (280 treated vs 50,899 control)		CEM (149 treated vs 149 control)	
	Total Emissions (1)	Emission Intensity (2)	Total Emissions (3)	Emission Intensity (4)	Total Emissions (5)	Emission Intensity (6)
Announcement	-0.136**	-0.095*	-0.053	-0.028	-0.036	0.030
	(0.050)	(0.052)	(0.034)	(0.033)	(0.059)	(0.084)
Trading	-0.159**	-0.070**	-0.141***	-0.068*	-0.195**	-0.119**
	(0.059)	(0.034)	(0.033)	(0.035)	(0.066)	(0.056)
Observations	2,715	2,715	254,378	254,378	1,742	1,742
R-squared	0.174	0.210	0.379	0.347	0.205	0.235
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y	Y	Y

Notes: PSM - propensity score matching; IPTW - inverse probability of treatment weighting; CEM - coarsened exact matching. All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Third, we consider three alternative matching approaches, i.e., propensity score matching (PSM), inverse probability of treatment weighting (IPTW), and coarsened exact matching (CEM). Table 1.E.4 presents the corresponding results. PSM is a widely used matching approach, which projects all covariates onto one scalar (i.e., propensity score). PSM can achieve a similar distribution of covariates between treated and control units while containing a higher dimension of information (Austin, 2011). But it also potentially increases model dependence and imbalance on matching variables (King and Nielsen, 2019). A similarly estimated scalar cannot effectively ensure similar values of each covariate used in matching. For robustness, a PSM-DID estimation is conducted. Columns (1) and (2) show the estimates. The results do not alter our baseline conclusions. One potential concern in our baseline is the loss of observations during the matching procedure. To address this, we use the IPTW method to transform the estimated propensity scores to weight firms (Hirano and Imbens, 2001), though this may cause large variance if the weights are extreme (Stuart, 2010). More specifically, each treated firm is weighted by $1/\hat{p}$ and each control firm is weighted by $1/(1-\hat{p})$, where $\hat{p}$ is the propensity score estimated from the matching procedure (Guadalupe et al., 2012). As shown in columns (3) and (4), the results of the inverse probability of treatment weighting are consistent with our baseline results. Another popular approach is the CEM, which can achieve lower levels of imbalance and model dependence (King and Nielsen, 2019). But the proportion of matched units decreases rapidly with the number of strata, which may lead to a potentially larger bias in estimation (Azoulay et al., 2010). Columns (5) and (6) show the corresponding estimates.

The results are consistent with our baseline conclusions. Overall, these results suggest that our findings are robust to different matching approaches.

1.F Heterogeneity: Electricity vs Manufacturing

We split the data by power generation and manufacturing industries and run the baseline regressions separately. Table 1.F.1 in the Appendix presents the results. The estimates for the manufacturing sector are consistent with the baseline results; however, the estimates for the power sector are statistically insignificant for both announcement and trading effects. This suggests that the estimated ETS effects in the baseline model are driven by the manufacturing sector. Please note that this result should be interpreted with caution. Our sample includes only 38 power plants regulated under the ETS, which may not provide adequate statistical power to identify the ETS effects on the electricity sector.

Table 1.F.1: Heterogeneity of ETS Effects by Sectors

VARIABLES	Electricity Sector		Manufacturing Sector	
	Total Emissions (1)	Emission Intensity (2)	Total Emissions (3)	Emission Intensity (4)
Announcement	-0.044	-0.006	-0.047	0.018
	(0.229)	(0.178)	(0.064)	(0.069)
Trading	-0.003	0.014	-0.187***	-0.097*
	(0.172)	(0.192)	(0.037)	(0.055)
Observations	427	427	1,977	1,977
R-squared	0.342	0.329	0.207	0.232
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

1.G Heterogeneity: Allowance Allocation Rules

The classification of ETS pilots into a rate- or mass-based system is not unambiguous. To test the robustness, we provide four sets of alternative classifications for the ETS pilots. Table 1.G.1 presents the estimates.

Table 1.G.1: Robustness Checks on Alternative Classifications for Rate-based Allowance Allocation

VARIABLES	Alt. Classification 1 drop GD&CQ		Alt. Classification 2 exogenous & endogenous		Alt. Classification 3 drop mass-based endogenous		Alt. Classification 4 only grandfathering	
	Total Emissions (1)	Emission Intensity (2)	Total Emissions (3)	Emission Intensity (4)	Total Emissions (5)	Emission Intensity (6)	Total Emissions (7)	Emission Intensity (8)
Announcement	-0.126	-0.073	-0.103	-0.047	-0.221***	-0.136*	-0.090	-0.023
	(0.076)	(0.079)	(0.067)	(0.075)	(0.062)	(0.074)	(0.074)	(0.077)
Trading	-0.546***	-0.571***	-0.538***	-0.542***	-0.634***	-0.676***	-0.400***	-0.426***
	(0.147)	(0.113)	(0.169)	(0.102)	(0.177)	(0.104)	(0.123)	(0.104)
Trading×Rate	0.427***	0.552***			0.516***	0.650***	0.263*	0.410***
	(0.147)	(0.102)			(0.171)	(0.091)	(0.127)	(0.113)
Trading×Endo			0.426**	0.512***				
			(0.160)	(0.097)				
Observations	1,727	1,727	2,416	2,416	2,008	2,008	1,865	1,865
R-squared	0.234	0.273	0.205	0.232	0.227	0.263	0.224	0.251
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. Endo equals one if the regulated firms are categorized into the endogenous rate-based system. Columns (1) and (2) drop all regulated firms in Guangdong (GD) and Chongqing (CQ) ETS pilots and their corresponding control firms. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

First, the Guangdong ETS pilot differentiates allowance allocation methods in the electricity, cement, and steel sectors based on industrial processes.[13] However, we do not have further information to identify the specific industrial processes of each firm in our dataset. Moreover, the Chongqing ETS pilot allocates allowances based on self-declaration by covered firms and allows for ex-post adjustment at the end of the compliance period. This flexible and adjustable emission cap makes the Chongqing ETS pilot not precisely consistent with a mass-based allocation system. To address the ambiguities in the rate-based and mass-based classifications in these two ETS pilots, we drop all regulated firms from the Guangdong and Chongqing ETS pilots and their corresponding control firms. Columns (1) and (2) show the estimation results. Overall, the baseline conclusions hold.

Second, the Guangdong and Hubei ETS pilots update allowances based on moving baseline periods of historical emissions across years. Unlike most mass-based ETS pilots, allocations in these two pilots are affected by firms' output choices in previous compliance periods and hence are endogenous to the firms. To further compare the difference of policy impacts between the output-based (endogenous) and non-output-based (exogenous) allocation methods, we categorize firms as endogenous and exogenous groups.[14] We define Endo_i as a binary indicator, equaling one if a firm is categorized into an endogenous group and zero otherwise. Based upon the allowance allocation model, we replace the variable Rate_i by Endo_i and rerun a variant of this model. Columns (3) and (4) show the policy effects between the endogenous and exogenous groups. The estimates for the interaction term between Trading and Endo are positive and statistically significant at the 1% level. These findings lend further support to the baseline conclusion. Under the rate-based and mass-based classification systems, we remove all mass-based firms under the output-based allocation (endogenous) regime because they are exceptional cases in the mass-based system. Columns (5) and (6) present the corresponding results. The estimates are positive and statistically significant, suggesting the stronger mitigation impacts of the mass-based rule over the alternative rate-based approach.

Third, the rate-based and mass-based allocations include both grandfathering and bench-

[13] Power plants using cogeneration gensets, cement companies engaged in cement mining and other grinding processes, and steelmaking enterprises using a DR-EAR process (direct reduction using electric arc furnace) are granted allowances based on the emission-based grandfathering method (mass-based). Allowances of other firms in the electricity, cement, and steel sectors are allocated via the benchmarking method (rate-based).

[14] The pilots and sectors that use emission-based grandfathering with fixed baseline periods and benchmarking based on fixed historical production are classified as the exogenous method. Other pilots and sectors, which employ emission-based grandfathering with moving baseline periods, benchmarking based on moving historical production, intensity-based grandfathering, and benchmarking based on current production, are categorized as the endogenous method.

marking rules.[15] The difference between grandfathering and benchmarking might blur the comparison of policy impacts between the rate-based and mass-based systems. To deal with this concern, we only compare the mass-based and rate-based systems for grandfathering.[16] Columns (7) and (8) show the results, which are consistent with the baseline conclusions.

Lastly, we have tried different model specifications by splitting samples into the mass-based and rate-based groups. Table 1.G.2 presents the estimates. Accounting for these alternative settings and classifications, we are reassured of the main conclusion that the ETS effects remain negative and statistically significant. More importantly, the rate-based ETS still achieves smaller carbon mitigation targets than the mass-based one.

Table 1.G.2: Alternative Model Specification on Rate-based vs. Mass-based Allocation

VARIABLES	Total Emissions			Emission Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement	0.029	-0.238***	-0.118*	-0.083	-0.069	-0.049
	(0.127)	(0.082)	(0.062)	(0.204)	(0.085)	(0.073)
Trading×Mass	-0.266		-0.389***	-0.428***		-0.326***
	(0.167)		(0.120)	(0.113)		(0.097)
Trading×Rate		-0.115*	-0.117**		-0.018	-0.044
		(0.057)	(0.054)		(0.049)	(0.049)
Observations	674	1,758	2,416	674	1,758	2,416
R-squared	0.447	0.237	0.207	0.398	0.270	0.227
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y	Y	Y
IndustryTrend	Y	Y	Y	Y	Y	Y
Subsamples	Mass-based	Rate-based	Full	Mass-based	Rate-based	Full

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Mass equals one if the regulated firms are categorized into the mass-based group. Rate equals one if the regulated firms are categorized into the rate-based group. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

[15] The grandfathering rule determines allowances according to covered entities' historical levels, while the benchmarking rule allocates allowances based on sector- or technology-specific performance indicators.

[16] No pilots or sectors adopted the mass-based benchmarking method in China's ETS pilots. Hence, we cannot compare the effects between the mass-based and rate-based systems in benchmarking in our analysis.

Chapter 2

Policy Spillover Induces Low-carbon Innovation: Evidence from Corporate Ownership Network in China

2.1 Introduction

In the context of strengthening the global response to climate change, governments around the world are pushing for curbing ever-increasing carbon emissions and maintaining the global temperature increase below 1.5°C (Masson-Delmotte et al., 2018). Emission trading scheme (ETS), as an important market-based climate policy tool, is adopted widely to reduce carbon emissions while inducing behavioural changes for climate mitigation and adaptation, especially for low-carbon technological changes (Jung and Song, 2023).

Recent empirical literature has documented evidence from the United States (Taylor, 2012), European Union (Calel and Dechezleprêtre, 2016; Calel, 2020), and China (Cui et al., 2018; Zhu et al., 2019) that the enforcement of the emission trading policy can induce clean innovation of regulated firms. However, most of the focus is confined to the innovation activities of directly regulated firms, while the role of other unregulated firms in the response to the emission trading policy remains largely ignored. More importantly, such neglect of unregulated firms impedes understanding the spillover effects of emission trading, which ultimately leads to the underestimation of the induced-innovation effects of the policy.

The spillover induced by policies may emerge across wide-ranging channels (Popp et al., 2011; Dechezleprêtre and Glachant, 2014; Chakraborty and Chatterjee, 2017), but such spillover is particularly stronger within the same corporate ownership networks as firms inside share internal capital market (Alfaro and Chen, 2012; Giroud and Mueller, 2015), supply chains (Bena et al., 2022), and knowledge resources (Michailova and Mustaffa, 2012; Argote et al., 2022). Exploiting the launch of China's regional ETS pilots, this paper provides the first empirical evidence on how the ETS policy spills over to unregulated firms through corporate ownership networks, and how such spillovers induce low-carbon innovation in unregulated firms.

Based on a unique dataset linking corporate ownership networks with firms' patenting activities over the period 2010 to 2016 in China, this paper identifies to what extent the policy pressures of China's regional ETS pilots on regulated parent firms induce low-carbon innovation in their unregulated subsidiaries. Specifically, this paper adopts a difference-in-differences (DID) approach with the propensity score matching (PSM) technique, and compares low-carbon innovation between unregulated subsidiaries owned by ETS-regulated parent firms and owned by non-regulated parent firms during the pre- and post-ETS periods. The DID results show unambiguous evidence for the positive impacts of China's regional ETS pilots on unregulated subsidiaries' low-carbon patenting, by raising 4.92% of patent counts and 7.04% of associated citations. These findings suggest the existence of the policy spillovers from regulated parent firms to their unregulated subsidiaries that induce low-carbon innovation in the unregulated subsidiaries. The findings are robust against a rich set of alternative checks on endogenous challenges and empirical strategies. The results further demonstrate that higher carbon prices lead to stronger policy spillovers. The policy spillovers induce both invention and utility low-carbon patents in unregulated subsidiaries. Echoing the literature on factors of intra-organisational spillovers (Barker III and Mueller, 2002; Yang and Steensma, 2014; Forman and Van Zeebroeck, 2019), the results also reveal that closer technological proximity, more top managers with R&D experience, and looser financial constraints enhance the policy spillovers, which indicates more unregulated subsidiaries' engagement in low-carbon innovation when their parent firms are regulated by the ETS.

This paper contributes to the literature on how environmental policies induce firms' innovation. Since the seminal paper by Porter and Van der Linde (1995) documents that firms would adapt their strategies to develop new technologies in response to environmental policies, more following research examines the induced-innovation effects across different policies (Johnstone et al., 2010; Popp, 2010). Despite the prominence of the induced-innovation effects of environmental policies, little is known about how the policies spill over across corporate ownership networks and induce additional innovation in unregulated firms. This paper builds upon the long-lasting focus on how ownership networks facilitate the exploitation of knowledge resources in the corporate management literature (Frost and Zhou, 2005; Phene and Almeida, 2008; Achcaoucaou et al., 2014; Faems et al., 2020), and explains why unregulated subsidiaries perform as knowledge creators when their parent firms face climate policy pressures such as ETS. In addition, previous corporate management discussions on the role of ownership networks in corporate innovation are largely built upon correlation evidence, while this paper provides causality evidence to bring novel empirical support to the literature. With new findings on unregulated subsidiaries' low-carbon patenting induced by the ETS, this paper inspires policy evaluation research to further explore the role of ownership networks in the policy spillovers that induce innovation.

Moreover, this paper makes a contribution to the understanding of the enablers and barriers of the policy spillovers through corporate ownership networks. Although there is an ongoing debate over what proximity between units plays a more crucial role in innovation (Knoben and Oerlemans, 2006; Capaldo and Petruzzelli, 2014; Guan and Yan, 2016; Liang and Liu, 2018), the findings suggest that it is technological proximity rather than geographical proximity can enable the policy spillovers to unregulated subsidiaries and induce low-carbon innovation. While the existing literature recognises how the career experience of top managers influences firms' strategies (Carpenter et al., 2004; Menz, 2012; Qian et al., 2013; Heyden et al., 2017), the findings of this paper add knowledge about how top managers can use their experience to influence the strategies on environmental practices such as low-carbon innovation. The empirical evidence also builds upon the discussion on how constrained financial resources to alter firms' strategies (Kubik et al., 2011; Yang and Steensma, 2014; Amore and Bennedsen, 2016), and reveals that financial constraints of parent firms can influence the engagement of subsidiaries in low-carbon innovation.

Finally, this paper offers policy lessons and managerial implications. Although regional climate policies are usually criticised for potential carbon leakage (Fell and Maniloff, 2018; Bartram et al., 2022), they may also create the policy spillovers that induce additional low-carbon innovation in unregulated units through corporate ownership networks. The awareness of this positive spillover provides a more eclectic view of regional climate policies for policymakers during the policy evaluations. In addition, low-carbon innovation is not an exclusive task only responsible for regulated units in a corporate group. In response to the rising carbon pricing pressures across the globe, corporations could further take advantage of knowledge sources across ownership networks to fulfil the needs for low-carbon technology development.

The remainder of this paper is structured as follows. Section 2.2 introduces the institutional background of China's regional ETS pilots and the rationale of the policy spillovers across corporate ownership networks. Section 2.3 presents data sources, variable construction, and the identification strategy. Section 2.4 shows the empirical results of policy spillovers, the moderating factors, and the robustness checks. Section 2.5 concludes the paper.

2.2 Background

2.2.1 Policy Background of China's Regional ETS Pilots

As the world's largest greenhouse gas emitter, China has gradually become active in global climate mitigation. To control and mitigate carbon emissions cost-effectively, on October 29th of 2011, National Development Reform Committee (NDRC) formally announced the launch of seven regional carbon market pilots, including four municipalities (i.e., Beijing, Shanghai, Tianjin, and Chongqing), one economic-special zone (i.e., Shenzhen), and two provinces (i.e., Guangdong and Hubei). Since June 2013, the seven pilot markets started emission trading.[1] Accounting for around 10% of national CO_2 emissions in the early trading phase, China's regional ETS pilots were the world's second-largest carbon markets and became the flagship policy of the Chinese government to achieve the climate change targets (Zhang et al., 2017). Table 2.A.1 summarises the basic information on each regional ETS pilot. Previous papers document that China's ETS pilots have exerted significant impacts on regulated entities in terms of innovation (Cui et al., 2018; Zhu et al., 2019), emission (Cui et al., 2021), and energy consumption (Cao et al., 2021; Yong et al., 2021). In addition to the direct policy effects, exploring how the policy effects spill over across corporate ownership networks, for example in inducing low-carbon innovation in unregulated firms, can provide both policy and managerial implications. It provides a new perspective for policymakers to evaluate the wider impacts of carbon pricing policies. Meanwhile, focusing on corporate ownership networks sheds light on how firms can use their ownership networks to adjust innovation strategies in response to the rising carbon pricing pressures.

The regional ETS pilots have two distinct features for the empirical strategies. First, each pilot exhibits wide heterogeneity in firm coverage. The seven pilots cover major emitters in the manufacturing and public utility sectors. Under the general guidelines by NDRC, each pilot has discretion in designing its covered entities, carbon trading platforms, allowance allocation, and compliances (Zhang et al., 2014, 2017). The quasi-experimental setting allows this paper to pin down regulated firms and accordingly which unregulated

[1] The first pilot to launch the carbon ETS was Shenzhen in June 2013 and then followed by Shanghai, Beijing, Guangdong, and Tianjin in the same year. The remaining pilots, Hubei and Chongqing, launched the ETS in April and June 2014, respectively. Fujian launched the eighth carbon ETS in December 2016, which is not included in the analysis due to the lack of post-ETS periods in the sample.

subsidiaries are affiliated with the regulated parent firms. It offers an opportunity to tease out the causal relationship between the ETS pilots and the policy spillovers that induce low-carbon innovation in unregulated subsidiary firms.

Second, the ETS pilots present variations in carbon market performances across regions and years. Since the trading in seven ETS pilots is operated separately, it gives rise to the variation in carbon prices and allowance trading turnover rate across pilots. Each covered firm is subject to the carbon pricing stringency and trading activeness within the jurisdiction. Beijing and Shenzhen are two more active markets with carbon prices fluctuating around 50 RMB (or $7 US dollars) per tonne before 2016, while other pilots have carbon prices varying around 20 RMB (or $3 US dollars) per tonne. Such variations in the carbon market performances provide another lens for exploring how corporations form strategic responses to the stringency and activeness of carbon markets.

2.2.2 Policy Spillover Effects on Innovation of Unregulated Subsidiaries

Literature has documented that corporate groups may exploit resources or adjust production throughout their ownership networks in response to local shocks. On the one hand, when positive shocks appear in one region, such as new investment opportunities, plants located in the more profitable region would enjoy more capital and labour support from their headquarters (Giroud and Mueller, 2015). On the other hand, ownership networks provide headquarters with the flexibility to adjust production or investment across affiliated plants and help to build up resilience when one of the plants is exposed to negative local shocks, such as economic downturn shocks (Giroud and Mueller, 2019; Bena et al., 2022), natural disasters (Seetharam, 2018), or environmental regulations (Hanna, 2010; Cui and Moschini, 2020).

Along this line, corporate groups can take advantage of ownership networks to fulfil the strategic purposes of innovation and technology development. Typically, many subsidiaries are initially established as knowledge receivers in the ownership networks and only specialise in existing technologies (Cantwell and Mudambi, 2005). However, they gradually develop their own capabilities and obtain more comparative advantages in innovation by seeking new markets, accumulating capital, and refining existing technologies (Birkinshaw and Hood, 1998; Achcaoucaou et al., 2014). With more subsidiaries becoming valuable sources of new knowledge, parent firms can utilise control rights to exploit and integrate the fragmented knowledge within corporate ownership networks by parent-subsidiary R&D collaborations or R&D outsourcing (Frost and Zhou, 2005; Phene and Almeida, 2008; Faems et al., 2020). China's regional ETS pilots perform as a local shock that exerts regulation pressures on firms within the jurisdictions. Standing in the position of regulated firms, developing low-carbon innovation is not a solo task but a knowledge combination and synergy within corporate ownership networks. Innovation competence in their subsidiaries can be employed by the parent firms to fulfil the needs of new low-carbon technologies. Thus, the policy pressures on regulated parent firms are likely to spill over to their unregulated subsidiaries and induce low-carbon innovation in unregulated subsidiaries.

The strength of the policy spillovers through corporate ownership networks is contingent on the parent firms' capacities and willingness to leverage subsidiaries' knowledge for their needs, which could be influenced by organisational mechanisms (Feinberg and Gupta, 2004). First, it is determined by how "close" the parent and subsidiary firms are. One aspect of the "closeness" is the geographical distance. Due to a lower cost of travel and transport, shorter geographical distance encourages more frequent interactions between partners in organisations (Funk, 2014). This facilitates the collaboration and information exchange that are important to innovation activities (Knoben and Oerlemans, 2006; Capaldo and Petruzzelli, 2014). Another "closeness" is technological proximity. A greater overlap in knowledge spectrums between two entities accelerates the knowledge absorption of each other (Aharonson and Schilling, 2016; Forman and Van Zeebroeck, 2019). Strong absorptive capacities create a solid basis for technology collaboration between entities and facilitate the transfer of knowledge into innovation outcomes more easily (Liang and Liu, 2018). In this regard, a stronger policy spillover effect may derive from a closer pair of parent and subsidiary firms, with respect to geographical and technological closeness.

Second, the exploitation of knowledge within ownership networks is also determined by the expertise of top managers. Top managers play a crucial role in corporate strategies, but they may also be functionally biased during the decision making given their career experience (Carpenter et al., 2004). Top managers with throughput career experience (e.g., production) prioritise efficiency improvement given existing resources (Heyden et al., 2017). In response to policy pressures, managers with production backgrounds are more inclined to optimise efficiency such as energy conservation or waste management (Garza-Reyes, 2015). In contrast, top managers with output career experience (e.g., R&D) focus more on the development of new products and technologies (Barker III and Mueller, 2002; Heyden et al., 2017). Therefore, they may better specialise in exploiting knowledge resources within corporate groups for new low-carbon innovation.

Third, how much parent firms resort to subsidiaries' knowledge depends on the financial resources of parent firms. Innovation is an investment process that incurs higher costs and risks, which adds more financial pressure on firms engaging in innovation (Hall, 2002). Regulated parent firms with limited financial resources would tend to exploit existing knowledge resources from their subsidiaries, rather than explore new knowledge by themselves to fulfil the needs of innovation (Yang and Steensma, 2014). In other words, financially constrained parent firms are more likely to depend on their ownership networks to develop innovation in response to the ETS pressures, which results in a stronger policy spillover to their unregulated subsidiaries.

2.3 Empirical Methodology

2.3.1 Data Sources

The dataset pertains to the Chinese publicly-listed firms in both Shanghai and Shenzhen stock exchanges during the 2010-2016 period.[2] It covers the manufacturing and public utility sectors. This paper assembles the data from three main sources: (1) The list of regulated entities in seven pilot regions is reported by the National Development Reform Committee (NDRC). (2) Corporate ownership networks and economic fundamentals for parent firms are supplied by China Stock Market and Accounting Research Solution (CSMAR). (3) Information on patent applications and citations is provided by China National Intellectual Patent Administration (CNIPA) and Google Patents, respectively.

The CSMAR provides ownership linkage between parent firms and subsidiary firms in publicly listed corporations in Chinese stock markets, including firm names and shareholding ratios of the ownership. This paper also collects fundamental and financial information about conglomerates and parent firms from the CSMAR. Linking to the list of regulated entities in China's ETS pilots, this paper can pin down the ownership linkage between regulated and unregulated firms, which provides the basis for the following construction of the treatment and control groups. However, the CSMAR does not provide complete subsidiary firms' fundamental information, which is needed to capture subsidiary geographical and sectoral variation and measure geographic distances to parents. Therefore, this paper complements location and sector information for subsidiaries by the National Enterprise Credit Information Publicity System of China.[3]

This paper uses patent applications and grant data from CNIPA to measure firms' low-

[2]Shanghai and Shenzhen stock exchanges are the two main stock exchanges covering firms publicly listed in mainland China, around 3,000 listed firms by 2016.

[3]Only a handful of subsidiaries are located outside of mainland China, hence are excluded from the sample. Thus, this paper does not cover carbon pricing pressures from other jurisdictions/countries via corporate ownership networks.

carbon innovation quantity. The CNIPA supplies detailed patent information in China, including application number, application data, grant number, grant date, and International Patent Classification (IPC) code. Moreover, this paper collects citation information associated with patents filed by the sample firms from Google Patents to measure innovation quality.[4]

2.3.2 Variable Construction

The primary dependent variable is low-carbon innovation of unregulated subsidiaries measured by firms' patents. To classify low-carbon patents, this paper matches each patent's IPC code with the IPC Green Inventory code, which is developed by the World Intellectual Property Organization (WIPO)'s IPC Committee of Experts. The IPC Green Inventory classifies environmentally sound technologies based on the list by the United Nations Framework Convention on Climate Change (UNFCCC).[5] This paper defines low-carbon patents as the technologies involved in alternative energy production, energy conservation, and waste management (Cui et al., 2018).[6]

China's patent system differentiates patents into three categories based on their inventiveness and functionality: invention patents, utility model patents, and design patents. The invention patents are defined as new technical solutions with prominent substantive features and notable progress, which are subject to substantive examinations by CNIPA. The utility model patents, or so-called "minor patents" in China, are associated with new technical solutions to the shape and structure of products, which requires only preliminary examinations. This paper takes into account invention patents and utility model patents in the analysis as they are most relevant to low-carbon innovation and their IPC codes are in line with the WIPO.[7]

This paper distinguishes the quantity and quality of low-carbon innovation. Specifically,

[4]Unlike other patent offices, such as European Patent Office (EPO), patent examiners in China are not subject to mandatory requirements for adding citations to patent applications. Hence, there is little citation information documented in CNIPA and patent citation needs to be supplemented from another data source, e.g., Google Patents. This paper retrieves international citations that are received by Chinese patents belonging to the sample firms from Google Patents. Due to the data limitations in this paper, it is not available to measure patent applications and citations based on patent families.

[5]The EPO has developed a category of Cooperative Patent Classification (CPC) codes, labelled as the Y02 class, pertaining to technologies for climate mitigation or adaptation. Although CNIPA does not have adopted the Y02 class yet, this paper has cross-checked the CPC Y02 class and IPC Green Inventory and found these three classes are similar in the scope of low-carbon technologies.

[6]Waste management under the IPC Green Inventory covers a part of climate mitigation related technologies such as carbon capture and storage and reuse of waste materials. Alternatively, I construct a measure of low-carbon innovation that excludes waste management in the robustness checks.

[7]Design patents are only targeted to the external appearance of products and not related to climate mitigation or adaptation functionality. Hence, the analysis excludes design patents.

this paper uses the number of low-carbon patents that are granted to indicate the quantity of firms' innovation (Schankerman and Pakes, 1986; Acs et al., 2002). In addition to the quantity measurement, the quality of innovation is measured based on the number of forward citations received by low-carbon patents (Trajtenberg, 1990; Harhoff et al., 1999; Hall et al., 2005). Although rare in the Chinese patent data, multiple patent applications may correspond to one patent when the patent updates patent claims after its first patent application. To avoid the double-counting of patents, this paper aggregates the patent measures to the patent family level, which identifies whether a group of patent applications derive from the same patent.[8]

This paper considers several mechanism variables that moderate the spillover effects of China's ETS pilots. First, the geographical distance between parent firms and their subsidiary firms is employed to capture the moderating effects of geographic barriers on the policy spillovers through ownership networks. The distance, denoted by $GeogDist$, is computed based on the longitude and latitude of the locations where parent firms and their subsidiary firms lie in. To examine the role of technological barriers, this paper follows the approach proposed by Jaffe (1986) and constructs an index measuring technology proximity between subsidiary firm i and its parent firm m:

$$TechProx_{im} = \frac{F_i F_m'}{\sqrt{(F_i F_i')(F_m F_m')}}, \tag{2.1}$$

where $F_{i/m} = (F_{i/m}^1, F_{i/m}^2, \ldots, F_{i/m}^n, \ldots, F_{i/m}^N)$ is a multidimensional vector and each element $F_{i/m}^n$ indicates the ratio of patents in the technological field n to all patents that are owned by firm i/m. The classification of technological fields relies on IPC 4-digit code and there are 608 fields in the sample (i.e., $N = 608$). The proximity measure varies between 0 and 1, and higher values stand for a more similar distribution of technological fields between subsidiary and parent firms.

Second, this paper looks closer into the professional backgrounds of top management members. Specifically, Num_Prod and $Num\_R\&D$ denote the number of top management members in parent firms who have work experience in production and R&D, respectively. These moderating factors examine how the relevant expertise of decision-makers influences the policy spillovers through corporate ownership networks. As an alternative, this paper also accounts for the average tenure of top management members with production and R&D experience in the robustness checks.

[8] The time dimension of each patent family in the analysis is defined as the period when its first patent application in the patent family is filed. Firms have been able to use the new technology enclosed in the patent in their production and operation when the application is filed.

Last, in the main analysis, the financial constraint of a parent firm is measured by the financial leverage (the ratio of debt to equity), which increases if the parent firm is faced with a higher constraint on its financial resources (Hendricks et al., 2015). In the robustness checks, this paper alternatively uses a financial constraint index proposed by Kaplan and Zingales (1997) to capture if a parent firm lacks financial resources.

After combing the data from multiple sources and removing data with missing values, this paper obtains a final sample of 20,225 subsidiary firms from the original 68,482 subsidiary firms over the period 2010-2016, including 1,012 treated subsidiary firms.[9]

2.3.3 Identification Strategy

To estimate the policy spillovers from regulated parents to unregulated subsidiaries, this paper first extracts regulated parent firms based on the list of regulated entities of China's regional ETS pilots, then finds their unregulated subsidiary firms based on the corporate ownership networks archived by CSMAR. Figure 2.1 illustrates the empirical setting of the treatment and control group. More specifically, the treated firms (marked in shaded blue) are unregulated subsidiaries whose parent firms are regulated by the ETS (in black). The control firms are unregulated subsidiaries whose parent firms are free from the ETS coverage (in grey). The empirical exercise is carried out at the subsidiary level. Any subsidiary firms that are directly regulated by the ETS are removed from the analysis.[10] A comparison in innovation between unregulated subsidiaries with and without regulated parent firms before and after the ETS may shed light on the policy spillovers of China's ETS.

The difference-in-differences (DID) setting is subject to an assumption that a reasonable counterfactual for the treatment group is found. If the treated and control subsidiaries differ substantially in the pre-treatment periods[11], the DID estimate is unlikely to yield an unbiased estimate (Dehejia and Wahba, 2002). This concern further arises when inspecting

[9] Among 20,225 subsidiary firms, 2,277 subsidiary firms are directly regulated by the ETS and will be excluded in the following analysis. The 1,012 treated subsidiary firms take around 10% of total patents and low-carbon patents among all subsidiary firms in the cleaned sample.

[10] There may be a concern about the policy spillovers from regulated subsidiaries to other unregulated subsidiaries within the corporate ownership networks. To deal with this concern, this paper imposes a further restriction on the pool of potential controls and all unregulated subsidiaries in the control group do not have any regulated firms within their corporate ownership network (including their parent firm and other sister subsidiary firms). Moreover, this paper also controls the number of regulated subsidiaries in each corporate group in the robustness checks.

[11] As five ETS pilots (Beijing, Shanghai, Guangdong, Shenzhen, and Tianjin) were launched in 2013 while two ETS pilots (Hubei and Chongqing) were launched in 2014, the treatment period in this paper is set at the launch year of the corresponding ETS pilot where a regulated parent is located (period 0), and pre-treatment and post-treatment periods are set relative to the launch years.

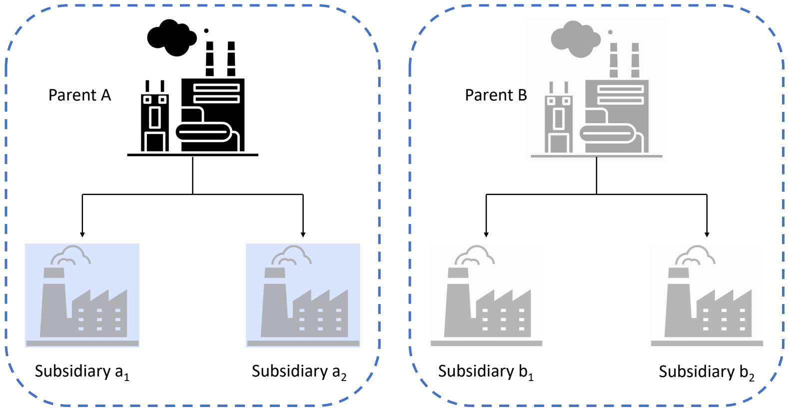


Figure 2.1: Diagram of the Treatment and Control Group Setting

Notes: Dash outline marks corporate ownership networks. ETS firms are in black, while non-ETS firms are in grey. The treated units in blue shade are defined as unregulated subsidiaries owned by a regulated parent firm (i.e., Subsidiary a_1 and a_2). Control units in grey are defined as unregulated subsidiaries owed by an unregulated parent firm (i.e., Subsidiary b_1 and b_2).

the mean statistics in key covariates for the treated and control firms during the pre-ETS periods, as shown in Table 2.1. Columns (1) to (3) show the statistics for 1,012 subsidiaries in the treatment group and 16,936 subsidiaries in the pool of potential controls. The table shows that treated firms significantly differ from control ones in terms of most innovation and economic variables before the ETS.

This paper employs the nearest neighbour propensity score matching (PSM) technique to construct a tenable counterfactual for the treatment group (Dehejia and Wahba, 2002). Although one-to-one nearest neighbour matching can seek out the most similar controls and minimise the difference between the treatment and control group in the pre-treatment periods, it may also sacrifice the precision as decreasing the size of the matched sample (Imbens, 2004). Hence, this paper adopts one-to-two nearest neighbour matching in the main analysis: each treated firm is paired with two control firms that are operating in the same sector as the treat firm and have the closest propensity scores to the treat firm.[12] Using a logistic regression model, the propensity score is estimated based on the pre-treatment innovation outcomes and other predictors of innovation outcomes and the treatment assignment.[13] Specifically, the pre-treatment attributes contain subsidiaries' low-carbon pat-

[12]A simulation research by Austin (2010) finds that matching two untreated units to each treated unit can result in improved precision without a commensurate increase in bias. This paper also performs one-to-one, one-to-three, and inverse probability treatment weighting as the robustness checks.

[13]There is a lack of consensus on which covariates should be included for estimating propensity scores. More covariates and restrictions added in the matching procedure, while deemed stringent and safe, tend to result in fewer matched pairs. As suggested by Austin et al. (2007), this paper chooses the covariates that might strongly affect both the outcomes and the treatment assignment.

Table 2.1: Mean Statistics for Matched and Unmatched Sample

Variable	Unmatched Sample 1012 treated vs 16936 control firms Treated (1)	Control (2)	P-value (3)	Matched Sample 640 treated vs 1020 control firms Treated (4)	Control (5)	P-value (6)
Panel A: 3 periods prior to ETS						
Low carbon patent count	0.009	0.013	0.360	0.009	0.016	0.319
Low carbon patent citation	0.015	0.023	0.309	0.016	0.027	0.351
Total patent stock	0.140	0.108	0.040	0.120	0.165	0.103
Low carbon patent stock	0.009	0.012	0.392	0.009	0.015	0.335
Registered capital	4.598	4.421	0.164	3.938	3.968	0.883
Total patent (Parent)	0.888	0.545	0.000	0.751	0.785	0.645
Low carbon patent (Parent)	0.180	0.094	0.000	0.169	0.154	0.591
Total patent stock (Parent)	0.884	0.545	0.000	0.745	0.785	0.584
Low carbon patent stock (Parent)	0.180	0.094	0.000	0.169	0.154	0.591
Panel B: 2 periods prior to ETS						
Low carbon patent count	0.023	0.021	0.751	0.019	0.023	0.648
Low carbon patent citation	0.036	0.037	0.930	0.029	0.040	0.438
Total patent stock	0.291	0.208	0.000	0.255	0.336	0.047
Low carbon patent stock	0.028	0.027	0.853	0.024	0.029	0.587
Registered capital	6.273	5.911	0.001	5.895	5.892	0.988
Total patent (Parent)	1.530	0.838	0.000	1.462	1.320	0.112
Low carbon patent (Parent)	0.387	0.160	0.000	0.352	0.304	0.250
Total patent stock (Parent)	1.758	0.984	0.000	1.672	1.541	0.179
Low carbon patent stock (Parent)	0.466	0.202	0.000	0.447	0.380	0.146
Panel C: 1 period prior to ETS						
Low carbon patent	0.036	0.030	0.434	0.029	0.034	0.630
Low carbon patent citation	0.054	0.047	0.531	0.043	0.054	0.486
Total patent stock	0.432	0.317	0.000	0.403	0.492	0.074
Low carbon patent stock	0.050	0.044	0.442	0.043	0.049	0.615
Registered capital	7.422	7.167	0.001	7.222	7.256	0.754
Total patent (Parent)	1.804	1.128	0.000	1.662	1.734	0.463
Low carbon patent (Parent)	0.480	0.214	0.000	0.448	0.412	0.441
Total patent stock (Parent)	2.293	1.425	0.000	2.186	2.194	0.940
Low carbon patent stock (Parent)	0.616	0.305	0.000	0.594	0.568	0.628

Notes: All variables are defined in a log fashion. Columns (1) - (3) report the mean statistics for the treated and control subsidiaries for the unmatched sample, while the remaining columns report that for the matched sample.

enting over the three years before the ETS (to capture the growth path of subsidiaries' low-carbon innovation) , subsidiaries' and parents' cumulative number of all patents and low-carbon patents at one year before the ETS (to capture technology stocks of subsidiary and parent firms), and subsidiaries' and parents' capital at one year before the ETS (to capture the sizes of subsidiary and parent firms). All covariates used in the matching are log-transformed. Considering the matching quality, the matching sets a calliper of 0.2 of the standard deviation of the propensity score to remove matched pairs with a larger distance of propensity scores.[14] Replacement is allowed in the matching procedure to ensure

[14] While there is no gold-standard for the maximal acceptable calliper of propensity scores, a simulation study by Austin (2011) suggests that a calliper width equal to 0.2 of the standard deviation of the logit of

that each treated unit matches the closest control units and to avoid extra bias in selecting control units.

To examine the matching quality, a balancing test is performed by comparing the sample means of firm characteristics between the treatment and matched control groups. Columns (4) - (6) of Table 2.1 report the results. Among 1,012 treated subsidiaries, 640 are successfully matched with 1,020 control subsidiaries. For each control unit matching more than one treated unit, a weight is added to the control unit based on how many treated units it matches. Except for few pre-treatment characteristics, there exists no statistically significant difference between the treatment and control groups for the matched sample. These results suggest that the matching procedure performs well in selecting control subsidiaries to mimic historical innovation patterns and economic characteristics of treated subsidiaries before the ETS.[15] The parallel trend prior to the ETS launch is further supported by estimating the dynamic effects using an event study model, which is displayed in Figure 2.2 and discussed in the main results.

Based on the matched sample, Table 2.2 reports the summary statistics for the variables used in the empirical analysis, including measures of low-carbon innovation, indicators of the ETS policy, moderating factors, and firms' financial attributes.

The DID approach is then employed to compare the innovation outcomes between treated subsidiaries with matched control units during the pre- and post-ETS periods. For an unregulated subsidiary firm i in sector j from region r, with a parent firm m in sector s from region p, and at year t, the baseline DID model is specified as:

$$Y_{ijrt} = \beta_0 + \beta_1 ETSParent_i \times Post_t + \beta_2 X_{imt} + \gamma_i + \delta_{jt} + \eta_{rt} + \lambda_{st} + \mu_{pt} + \varepsilon_{ijrt}. \quad (2.2)$$

In this specification, the outcome variable Y_{ijrt} refers to subsidiaries' low-carbon patent family counts and citations (in logarithms). The dummy $ETSParent_i$ is an indicator for the treatment assignment, equaling one if an unregulated subsidiary is affiliated with a parent firm regulated by the ETS pilots, and zero otherwise. The dummy $Post_t$ equals one if the period is after the launch of the ETS pilots, and zero otherwise. X_{imt} is a vector of control variables at both subsidiary and parent firm levels, including subsidiary firms' registered capital, and parent firms' assets, capital, and sales.

To control for unobservable confounding factors that affect low-carbon innovation, The

propensity score could minimise the mean squared error of the estimated treatment effect and eliminate much of the bias in the estimators.

[15] Although there is still a discrepancy of subsidiary firms' total patent stock between the treatment and matched control groups, the discrepancy has been much shrunk due to the matching.

Table 2.2: Summary Statistics for Matched Sample

Variable	N	Mean	S.D.	Min.	Max.
Panel A. Patent Information					
Low-carbon patent count	9810	0.120	0.960	0	26
Low-carbon patent citation	9810	0.300	3.150	0	173
Panel B. Policy Indiactors					
ETSParent	9810	0.390	0.490	0	1
CarbonPriceParent (yuan)	9810	8.830	18.11	0	64.83
TurnoverRateParent	9810	0.0100	0.0200	0	0.140
Panel C. Moderation Factors					
Geographical distance	9792	539.2	677.7	0	3907
Technological proximity	9810	0.110	0.270	0	1
No. of production TM members	9805	1.450	2.100	0	18
Avg tenure of production TM members	9805	3.812	2.247	0.0833	15.25
No. of R&D TM members	9805	2.690	2.640	0	30
Avg tenure of R&D TM members	9805	4.050	2.566	0	14.25
Financial leverage	9695	1.280	1.720	0.0100	65.43
KZ index	9316	0.300	2.160	-9.430	6.870
Panel D. Other Firm Attributes (million yuan)					
Registered capital (subsidiary)	9810	444.7	7223	0.100	250000
Asset (parent)	9801	20415	35331	54.47	271267
Capital (parent)	9801	8934	14619	1.375	131421
Sale (parent)	9805	14123	25522	29.94	222505

Notes: Panel A provides summary statistics of patent information at the subsidiary and parent firm levels. Panel B presents the statistics of policy indicators used in the empirical analysis. Panel C reports moderating factors of the ETS policy spillovers. Panel D displays summary statistics of other firm attributes.

model adds a series of fixed effects at different levels. Subsidiary firm fixed effects, denoted by γ_i, absorb any time-invariant subsidiary-specific characteristics. One may worry about co-existing regional or sectoral policies that affect subsidiaries' innovation. The model includes the subsidiary sector-year and province-year fixed effects, represented by δ_{jt} and η_{rt}, respectively. These two fixed effects help absorb time-variant sectoral and regional shocks that directly affect subsidiaries. Similarly, the parent sector-year fixed effects λ_{st} and province-year fixed effects μ_{pt} are also included to control sectoral and regional time-varying shocks that indirectly affect subsidiaries via their parent firms. Lastly, ε_{ijrt} is an idiosyncratic error term.

Of central interest is the coefficient of the interaction term between $ETSParent_i$ and $Post_t$ dummies. The estimate, denoted by β_1, captures the spillover effect of China's ETS pilots on unregulated subsidiaries' low-carbon innovation. With the matched sample, this paper estimates the coefficients using the ordinary least squares method. Alternative estimation methods including Poisson Pseudo Maximum Likelihood and Iterated Ordinary

Least Squares are conducted in the robustness checks.[16] The standard errors are clustered at the parent firm level to allow for the correlations within corporate groups.

This paper further considers potential mechanisms that moderate the spillover effects of the ETS. Based upon the matched DID model equation (2.2), the ETS policy indicator further interacts with moderating factors. The model specification is:

$$\begin{aligned} Y_{ijrt} = &\beta_0 + \beta_1 ETSParent_i \times Post_t + \beta_2 ETSParent_i \times Post_t \times Mechanism_{imt} + \\ &\beta_3 Mechanism_{imt} + \beta_4 ETSParent_i \times Mechanism_{imt} + \\ &\beta_5 Post_t \times Mechanism_{imt} + \beta_6 X_{imt} + \gamma_i + \delta_{jt} + \eta_{rt} + \theta_m + \lambda_{st} + \mu_{pt} + \varepsilon_{ijrt}. \end{aligned} \tag{2.3}$$

In this form, $Mechanism_{imt}$ represents several moderating variables, specifically geographical distance, technological proximity, top manager backgrounds of production and R&D, and financial constraints. The moderating effects, denoted by β_2, capture how these variables facilitate or impede the policy spillovers from regulated parent firms to unregulated subsidiaries.

2.4 Empirical Results

2.4.1 Baseline Results

Using the DID specification with the PSM technique, this paper first investigates whether the ETS policy pressures spill over from parent firms to their unregulated subsidiaries and induce subsidiaries' low-carbon innovation. Table 2.3 shows the results. In all columns, subsidiary firm fixed effects are included to absorb subsidiary-specific unobservables that may affect the innovation activities. Subsidiary sector-year and province-year fixed effects are also included to control for provincial and sectoral time-variant confounding shocks that affect subsidiaries' low-carbon innovation, such as coexisting environmental, energy, and industrial policies.

Columns (1) and (2) of Table 2.3 report the results on low-carbon innovation quantity. In

[16] Although a Poisson estimator may perform better for count data compared to the ordinary least squares, a very high dimension of fixed effects may lead to serious numerical instability to the Poisson Pseudo Maximum Likelihood estimator and fail to reach the convergence or converge to the incorrect estimates (Silva and Tenreyro, 2011; Bratti et al., 2014; Henn and McDonald, 2014; Correia et al., 2020). A new estimation method, Iterated Ordinary Least Squares, is put forward to overcome the issues with the Poisson models, but it is yet to be widely tested in econometrics literature (Bellégo et al., 2022). The estimation under the case of very high-dimension fixed effects also requires high computing power and finds it difficult to converge. Since the key interest is to estimate the policy spillover effects by controlling both subsidiary and parent firm-level unobservable shocks, this paper mainly uses the ordinary least squares estimator in the analyses.

Table 2.3: The ETS Spillover Effects on Unregulated Subsidiary Firms

Dependent Variable:	Patent Count		Patent Citation	
Low Carbon Patent Family	(1)	(2)	(3)	(4)
ETSParent×Post	0.021*	0.048***	0.030*	0.068***
	(0.012)	(0.016)	(0.017)	(0.024)
Observations	9,799	9,785	9,799	9,785
Firm Attributes	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y
Parent Province-Year FE		Y		Y
Parent Sector-Year FE		Y		Y

Notes: Dependent variables are logarithm one plus low-carbon patent family counts and citations. $ETSParent$ equals one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. $Post$ equals one if the period is after the launch of the ETS, and zero otherwise. All columns contain the firm-level attributes including subsidiaries' registered capital, and parents' assets, capital, and sales. Fixed effects at the subsidiary firm, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels are included. Standard errors in the parenthesis are clustered at the parent firm level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Column (1), the estimated coefficient for the interaction term between $ETSParent$ and $Post$ is positive and statistically significant at the 10% level. The result indicates the ETS policy induces low-carbon innovation of unregulated subsidiaries through regulating their parent firms. However, if the ETS policy can spill over to unregulated subsidiaries through their parent firms, other policy shocks to parent firms would also produce similar spillover effects. Omitting confounding sectoral and regional shocks to parent firms may cause biases in the estimation of the policy spillover effects of the ETS. To further address this concern, the model adds parent firm sector-year and province-year fixed effects in Column (2). The estimated coefficient for the interaction term remains positive. The magnitude of the coefficient becomes larger and the significance becomes stronger, at the 1% level.[17] This result suggests that the ETS policy pressure on parent firms can lead to a 4.92% increase in low-carbon patents in their affiliated unregulated subsidiaries, given other policy shocks to sectors and provinces are controlled.[18]

Columns (3) and (4) show the results for low-carbon innovation quality, measured by the received citations of low-carbon patents. Both columns document positive and statistically significant coefficients for the interaction terms. In the preferred model in Column (4), the estimate of 0.068 indicates that the ETS pressures on parent firms contribute to a 7.04%

[17] The direct effects of the ETS on low-carbon innovation of parent firms are reported in Table 2.A.2. The results document a significantly positive and stronger impact of the ETS on regulated parent firms.

[18] Since the dependent variable is transformed into the logarithm, more rigorously the estimated coefficient should be interpreted as exp(β)-1 as the percentage change. Hence, the coefficient 0.048 indicates a 4.92% increase in low-carbon patent counts.

increase in low-carbon patent citations in unregulated subsidiaries.[19] Overall, the results document supporting evidence that the ETS induces low-carbon innovation in unregulated subsidiaries by the spillover effects through corporate ownership networks.

A more intuitive way to present the spillover effects of the ETS on unregulated subsidiaries' innovation is through a plot of the dynamic effects. Figure 2.2 plots the estimated coefficients for the policy effects in the pre- and post-ETS periods and the 95% confidence intervals of each point estimation. The upper panel shows the dynamic effects on the patent count, while the lower panel displays the results for the patent citation. The coefficient for the year before the launch of ETS is omitted because it is set as the benchmark. All estimated effects are relative to the benchmark year.

There are two features of Figure 2.2 that are worth discussing. First, the coefficients are very similar and statistically insignificant across the pre-ETS periods. This result suggests that there is no significant discrepancy in subsidiaries' low-carbon innovation of treated and control units before the launch of the ETS and lends strong support to the parallel trend assumption, given firm characteristics and other unobservable policy shocks are controlled. Second, the point estimates start to increase significantly in the year when the ETS is launched and the policy spillover effects trend up over the three years after the launch of the ETS. These findings further suggest the policy spillovers to unregulated subsidiaries caused by the ETS.

This paper further investigates the effects of heterogeneous carbon pricing policies and the policy spillovers to different types of innovation. First, the performance of carbon markets varies across pilots and provides an opportunity to explore the spillover effects of heterogeneous policies. Carbon price signals the marginal cost of emission abatement and reflects the regulatory stringency of the carbon pricing policy. Turnover rate captures the activeness of allowance trading in the carbon markets. Using carbon price and turnover rate, this paper examines how different carbon market performances affect the spillover effects of the ETS policy. Panel A in Table 2.4 presents the results for the heterogeneous policies. $ETSParentHetero$ denotes the carbon price and turnover rate of the ETS pilots to which the regulated parent firms are exposed. In Columns (1) and (3), the estimated coefficients for carbon price are positive and statistically significant at the 1% and 5% level, respectively. The findings suggest that a higher carbon price imposed on regulated parent firms leads to stronger policy spillovers to unregulated subsidiaries, where more low-carbon

[19] Due to the log-transformation, more rigorously the estimated coefficient 0.068 should be interpreted as exp(β)-1 percentage change and indicates a 7.04% increase in low-carbon patent counts.

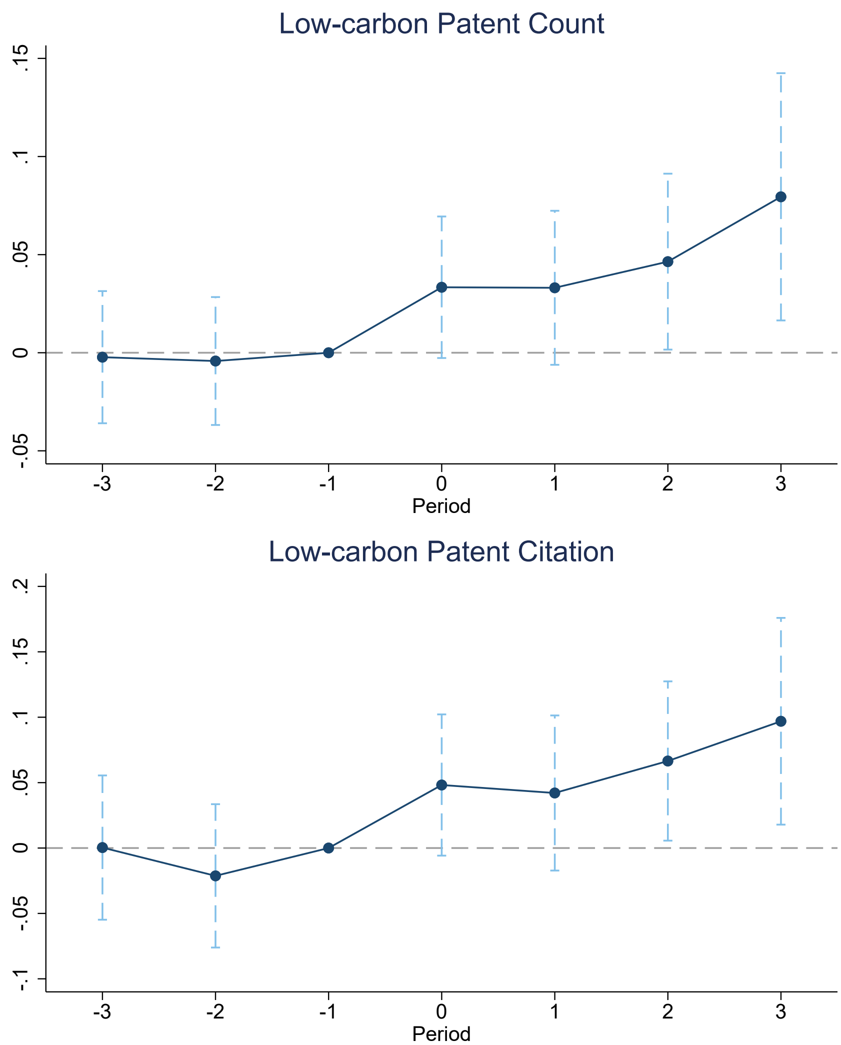


Figure 2.2: Dynamic Effects of the Policy Spillovers

Notes: The upper and lower panel report the dynamic effect results on unregulated subsidiaries' low-carbon patent count and citation, respectively. The dots indicate the point estimates for periods before and after the ETS launch. The intercept indicates the 95% confidence interval. The benchmark is set one year before the ETS launch.

innovation is induced. In contrast, turnover rate in carbon markets has mild impacts on the policy spillovers.

Second, in China's patent system, invention patents usually involve more critical innovativeness and represent a higher quality of innovation compared with utility patents (Wei et al., 2017). Hence, this paper separates invention and utility patents and explores the policy spillover effects on the two types of innovation in unregulated subsidiaries. Panel B in Table 2.4 reports the results for the heterogeneous innovation. The dependent variable of Panel B is low-carbon invention patent in Columns (1) and (3) and utility patent in Columns (2) and (4). The estimated effects on both invention and utility patents are positive and statistically significant. The results indicate that the ETS induces both more innovative and less innovative low-carbon patents in unregulated subsidiaries through the policy spillovers.

Table 2.4: Heterogeneity of Policy and Innovation

Dependent Variable:	**Patent Count**		**Patent Citation**	
Low Carbon Patent Family	(1)	(2)	(3)	(4)
Panel A: Policy Heterogeneity:	Carbon Price	Turnover Rate	Carbon Price	Turnover Rate
ETSParentHetero×Post	0.012***	0.702	0.018**	1.026*
	(0.005)	(0.448)	(0.007)	(0.584)
Observations	9,785	9,785	9,785	9,785
Panel B: Innovation Heterogeneity:	Invention	Utility	Invention	Utility
ETSParent×Post	0.023**	0.035***	0.041**	0.046**
	(0.009)	(0.013)	(0.018)	(0.018)
Observations	9,785	9,785	9,785	9,785
Firm Attributes	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y

Notes: Dependent variables are logarithm one plus low-carbon patent family counts and citations. $ETSParent$ equals one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. $Post$ equals one if the period is after the launch of the ETS, and zero otherwise. Panel A measures the policy heterogeneity by $ETSParentHetero$, which denotes the carbon price and turnover rate of the ETS pilots to which the regulated parent firms are exposed. Panel B captures the innovation heterogeneity by separating low-carbon invention and utility patents in dependent variables. All columns contain the firm-level attributes including subsidiaries' registered capital, and parents' assets, capital, and sales. Fixed effects at the subsidiary firm, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels are included. Standard errors in the parenthesis are clustered at the parent firm level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

2.4.2 Moderating Effects

This paper further explores the roles of geographical and technological proximity, manager background, and financial constraints in the policy spillovers. The additional moderators further interact with the ETS policy indicators based upon the baseline DID model. Table 2.5 reports the results on the quantity and quality of low-carbon innovation.

Table 2.5: The Moderating Effects on the ETS Spillovers to Unregulated Subsidiary Firms

Dependent Variable:	**Patent Count**					**Patent Citation**				
Low Carbon Patent Family	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETSParent×Post	0.060**	0.029**	0.053***	0.017	0.017	0.082**	0.048**	0.079***	0.028	0.018
	(0.027)	(0.014)	(0.017)	(0.019)	(0.018)	(0.038)	(0.022)	(0.025)	(0.027)	(0.026)
ETSParent×Post×GeogDist	-0.003					-0.004				
	(0.004)					(0.006)				
ETSParent×Post×TechProx		0.258***					0.282**			
		(0.094)					(0.109)			
ETSParent×Post×Num_Prod			-0.004					-0.007		
			(0.004)					(0.006)		
ETSParent×Post×Num_R&D				0.010**					0.013*	
				(0.005)					(0.007)	
ETSParent×Post×FinLeverage					0.022**					0.033*
					(0.011)					(0.017)
Observations	9,772	9,785	9,785	9,785	9,665	9,772	9,785	9,785	9,785	9,665
Firm Attributes	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Dependent variables are logarithm one plus low-carbon patent family counts and citations. *ETSParent* equals one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. *Post* equals one if the period is after the launch of the ETS, and zero otherwise. *GeogDist* denotes the geographic distance between subsidiaries and their parent firms. *TechProx* denotes the technology proximity between subsidiaries and their parent firms based on the patent IPC 4-digit. *Num_Prod* and *Num_R&D* denote the number of top management members with production and R&D experience in parent firms, respectively. *FinLeverage* denotes financial leverage of parent firms and increases with financial constraints. For the sake of brevity, it only reports the estimated coefficients for the interaction terms of key interest. All columns contain the firm-level attributes including subsidiaries' registered capital, and parents' assets, capital, and sales. Fixed effects at the subsidiary firm, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels are included. Standard errors in the parenthesis are clustered at the parent firm level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

First, this paper examines the roles of geographical distance and technological proximity between parent firms and their subsidiaries. Columns (1) and (2) of Table 2.5 report the results on the patent count. The results document both positive and statistically significant estimates for the interaction terms of the $ETSParent$ and $Post$ dummy, further confirming the baseline conclusion. Moreover, the estimate for the triple interaction term for $GeogDist$ in Column (1) is not statistically significant at any convention level. It indicates that geographical distance between parent and subsidiary firms is not an obstacle to the policy spillovers through the corporate ownership networks. Standing in sharp contrast, in Column (2), the estimated coefficient for the interaction term of $TechProx$ is positive and statistically significant at the 1% level. This indicates the positive role of technology proximity between parent firms and subsidiaries in the policy spillovers that induce low-carbon innovation in unregulated subsidiaries. The results are consistent with the research on technological proximity and innovation that closer technological proximity can enhance technology exploitation and collaboration (Aharonson and Schilling, 2016; Forman and Van Zeebroeck, 2019). For unregulated subsidiaries sharing a similar technology spectrum with their parent firms, the subsidiaries stand in a better position to utilise their R&D resources and contribute to the needs of low-carbon innovation when the parent firms are exposed to the ETS pressures. When it comes to innovation quality, Columns (6) and (7) report the corresponding results. The estimated coefficient for $GeogDist$ is statistically insignificant, while the coefficient for $TechProx$ is positive and significant at the 5% level. These findings suggest that geographical distance plays a silent role while technology proximity performs a facilitating role in improving subsidiaries' low-carbon innovation quality in response to the policy pressures on their parent firms.

Next, this paper looks at whether professional backgrounds of top management members in parent firms would facilitate the policy spillovers that induce innovation in unregulated subsidiaries. The number of top management members with production and R&D experience is measured by Num_Prod and $Num\_R\&D$, respectively. Columns (3) and (8) present insignificant coefficients for the triple interaction terms of Num_Prod. On the contrary, as shown in Columns (4) and (9), the estimated coefficients for the triple interaction terms of $Num\_R\&D$ are consistently positive and statistically significant. The findings indicate that top managers' R&D experience contributes to the policy spillover effects on unregulated subsidiaries' innovation. The inconsistency in the moderating effects may be explained by the different focus of top managers with production and R&D experience. Under external policy pressures, top managers with output career experience (e.g., R&D) prefer innovation due to their focus on growth through discovering new products and markets (Barker III and Mueller, 2002). In contrast, top managers with throughput career experience (e.g., production) focus more on efficiency improvement given existing resources and therefore, under the ETS pressures, may regard R&D as a discretionary expense rather than a potential opportunity for growth (Heyden et al., 2017). In the robustness check, the average tenure of top management members with production and R&D experience are employed as alternative measures of professional backgrounds of top management members.

Last, this paper investigates how parent firms' financial constraints affect the policy spillover effects. The parent firms' financial constraint is proxied by financial leverage (the ratio of debt to equity). Column (5) reports the results on the low-carbon patent quantity, while Column (10) shows the results on the patent quality. In both columns, the estimates for the triple interaction term are consistently positive and statistically significant. These findings together echo the literature that organisations with deprived financial resources may resort to the exploitation of existing knowledge rather than the exploration of new knowledge (Yang and Steensma, 2014). In the presence of tighter financial constraints, parent firms may respond to the ETS pressures by outsourcing innovation activities to subsidiaries free from any ETS pressures. The tighter the financial constraints, the stronger the policy spillover would be. This paper also uses the KZ index as an alternative measure of the financial constraints, which is tested in the robustness checks.

2.4.3 Robustness Checks

To demonstrate the stability of the results, this paper conducts a rich set of robustness checks regarding endogenous concerns (Table 2.A.3), alternative empirical approaches (Table 2.A.4), and alternative measures of the moderating factors (Table 2.A.5).

Endogenous Concerns. First, an unregulated subsidiary may have affiliated sister subsidiaries that are regulated under the ETS regimes, giving rise to another source of policy spillover within corporate ownership networks. To cope with this concern, this paper accounts for the number of regulated sister subsidiaries as a control variable in the DID regression. Panel A in Table 2.A.3 reports the corresponding results. Both columns still document the positive and significant spillover effects from regulated parent firms to unregulated subsidiary firms.

Second, the baseline matching process selects the cumulative number of all patents and low-carbon patents as two key variables to ensure the similarity in innovation capability between treated subsidiaries and control ones during the pre-ETS periods. One may conjecture that treated subsidiaries may follow a different innovation growth path than control ones. To tackle this issue, this paper adds patent growth rate as a control variable to the DID regression. Panel B in Table 2.A.3 presents the results. In both columns, the estimates are positive and statistically significant at the 1% level, with very similar magnitude.

Third, though a rich set of fixed effects at both the subsidiary and parent firm levels are included, there are still concerns about other contemporary environmental, energy, or subsidy policies that have impacts on low-carbon innovation. One is the air pollution control policy implemented in 2013, which mandated the Beijing, Tianjin, and Hebei (BTH) regions to abate air pollution. To mitigate this concern, this paper excludes samples when subsidiary firms or their parent firms are located in the BTH regions and re-estimates the models. The results in Panel C of Table 2.A.3 do not alter the baseline findings. Another is the "Top 10,000 Enterprises Energy Saving Programme" (ES10k) implemented in 2012, which is an energy policy requiring around 16,000 energy-intensive firms to meet energy efficiency targets. To address this concern, this paper excludes samples when subsidiary firms or their parent firms are regulated by the ES10k programme. Panel D of Table 2.A.3 reports the corresponding results, which are also in line with the baseline findings. In addition, there were subsidy policies supporting low-carbon innovation, including a low-carbon special fund in Shenzhen, and a national subsidy for solar and wind energy technologies. This paper excludes samples when subsidiary firms or their parent firms are located in Shenzhen, displayed in Panel E of Table 2.A.3, and removes solar and wind energy related patents in the dependent variables, displayed in Panel F of Table 2.A.3. The results in both panels remain positive and statistically significant at the 1% level.

Last, one may worry about the measurement errors brought about by including waste management patents in the dependent variables as they contain some patents not closely relevant to climate adaptation or mitigation. To test the robustness of the results, this paper removes waste management patents in the dependent variables, reported in Panel G of Table 2.A.3. The results still document the positive and significant policy spillovers to unregulated subsidiaries.

Alternative Empirical Approaches. The baseline DID model adopts the one-to-two PSM approach to find the most comparable control units while avoiding the overfitting issue. To test the robustness with other matching strategies, this paper considers one-to-one and one-to-three nearest neighbour matching based on the same covariates used in the baseline matching method. The results are reported in Panel A and B of Table 2.A.4 and show that the baseline findings are robust against alternative matching strategies.

Moreover, one potential concern in the baseline model is the loss of observations during the matching procedure. To address this, this paper uses the inverse probability treatment weighting (IPTW) method to transform the estimated propensity scores to weight firms (Hirano and Imbens, 2001), though this may cause a large variance if the weights are extreme (Stuart, 2010). More specifically, each treated firm is weighted by $1/\hat{p}$ and each control firm is weighted by $1/(1-\hat{p})$, where $\hat{p}$ is the propensity score estimated from the matching procedure (Guadalupe et al., 2012). Panel C of Table 2.A.4 shows the results for the IPTW method and still provides supporting evidence for the baseline findings.

One may concern the ETS policy produces lagged effects on low-carbon innovation. To tackle the potential time-lag issues, this paper adds a one-year lag and two-year lag in the robustness checks. Panel D and E of Table 2.A.4 report the results for the one-year lag and two-year lag, respectively. The baseline findings remain unchanged when taking into account the time-lag issues.

Although the very high dimension of fixed effects in the analyses creates many difficulties in the estimation by the Poisson Pseudo Maximum Likelihood and Iterated Ordinary Least Squares, this paper also employs these two alternative methods to estimate the baseline model. The corresponding results are displayed in Panel F and G of Table 2.A.4, respectively. The changes in estimation methods do not qualitatively alter the baseline findings.[20]

Alternative Moderating Factors. This paper further tests the stability of the moderating effects against alternative measures on technological proximity, top managers' professional backgrounds and financial constraints. Table 2.A.5 reports the results of these robustness checks.

The baseline regression adopts the 4-digit IPC class to compute the technological proximity between each subsidiary firm and its parent firm. As a robustness check, this paper considers the 3-digit IPC class. Columns (1) and (5) report the corresponding results. Technological proximity still plays a positive and significant moderating role in the ETS policy spillover.

This paper also uses the average tenure of top managers with production experience and R&D experience. Columns (2) and (6) present the corresponding results and do not show significant moderating effects of production experience. Columns (3) and (7) show the results of the moderating effect of R&D experience. The estimates remain positive and statistically significant. These findings further indicate that R&D experience rather than

[20] The outcome variables are not log-transformed in the estimations by the Poisson Pseudo Maximum Likelihood and Iterated Ordinary Least Squares.

production experience would help the policy spillovers that induce innovation in unregulated subsidiaries.

The financial constraint mechanism is checked by instead using the KZ index (Kaplan and Zingales, 1997). In analogous to the financial leverage, the larger the KZ index, the higher financial constraints the firm confronts. Columns (4) and (8) report the corresponding results. In both columns, the results document the consistently positive and statistically significant estimates for the triple interaction terms. The findings reassure the baseline findings on the moderating role of financial constraints.

2.5 Conclusion

Using data on corporate ownership networks and patent information of Chinese publicly listed companies, this paper identifies whether China's regional ETS pilots induce low-carbon innovation of unregulated subsidiaries when their parent firms are regulated. It further examines the heterogeneity of the policy impacts by carbon market performances and two types of patents. This paper also reveals how such spillover effects through corporate ownership networks are influenced by organisational factors, including geographical and technological proximity between parents and subsidiaries, top managers' career experience, and financial constraints of parent firms.

The main findings of this paper demonstrate that the ETS pilots lead to an increase in low-carbon innovation in unregulated subsidiaries. Compared to unregulated subsidiaries without regulated parent firms, there is a 4.92% increase in low-carbon patent counts and a 7.04% increase in associated citations among those unregulated subsidiaries affiliated with regulated parent firms. This evidence suggests that policy spillovers from regulated parent firms to their subsidiary firms induce low-carbon innovation in the unregulated subsidiaries. Furthermore, the findings show that such policy spillovers are stronger when the ETS pilots have higher carbon prices. The policy spillovers have clear impacts on both invention and utility patents. In addition, the empirical results demonstrate that technological proximity between parent and subsidiary firms is an important enabler for the policy spillovers, while geographical proximity does not play an important role. R&D experience of top managers facilitates the engagement of unregulated subsidiaries in low-carbon innovation, but production experience of top managers does not contribute to the subsidiaries' innovation. Limited financial resources in parent firms also enhance low-carbon innovation activities in their subsidiary firms. To test the stability of the findings, this paper conducts a series of robustness checks on endogenous challenges, empirical strategies, and alternative indicators. The findings survive against these robustness checks.

Existing empirical research indicates that the ETS policy can drive an increase in regulated firms' low-carbon innovation around 10%-30% (Calel and Dechezleprêtre, 2016; Cui et al., 2018; Zhu et al., 2019; Calel, 2020).[21] Although the low-carbon innovation in unregulated subsidiaries induced by the ETS policy spillovers is relatively smaller than the direct policy effects, the evidence clearly contributes to the understanding of how ownership networks become a channel that induces additional innovation and helps to shape a more comprehensive evaluation of climate policies. Particularly, regional climate policies, though more politically feasible than full-scale ones, are usually blamed for the possibility of carbon leakage. However, the evidence on the policy spillovers enhancing additional low-carbon technologies can offer a more eclectic perspective on regional climate policies for policymakers. Without accounting for the policy spillovers through corporate ownership networks, the estimation of how much the ETS policy contributes to innovation would be underestimated.

[21] This paper also examines the direct effects of China's ETS pilots on low-carbon innovation of regulated parent firms, displayed in Table 2.A.2. Although based on the limited samples, The results document around a 30% increase in low-carbon innovation of regulated parents driven by the ETS policy.

2.A Additional Tables

Table 2.A.1: Summary of China's Region ETS Pilots

Region	Announcement Year	Launch Year	Covered Sectors	Threshold	Emission Covered in Region
Beijing	2011	2013	Electricity, heating, cement, petrochemical other industries, large public buildings including hospitals, schools and governments	>10kt	40%
Shanghai	2011	2013	Electricity, iron and steel, petrochemical and chemical industries, metallurgy, building materials, papermaking, textile, aviation, airports and ports, public and office buildings, railway stations	Industries>20kt; Non-industries>10kt	57%
Shenzhen	2011	2013	Electricity, building, manufacturing, water supply	Industries>5kt; Public buildings>20km2 Office buildings>10k m2	40%
Guangdong	2011	2013	Electricity, cement, steel, petrochemical industries, textiles, papermaking, aviation, public services including hotels, restaurants and business	2013: >20kt; Since 2014: industries>10kt; non-industries>5kt	58%
Tianjin	2011	2013	Electricity, hearing, iron and steel, chemical and petrochemical and industries, oil and gas exploration	>20kt	60%
Hubei	2011	2014	Electricity, heating, metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement, medicine and pharmacy, food and beverage, papermaking	energy consumption >60k tce	33%
Chongqing	2011	2014	Electricity, metallurgy, chemical industries, cement, iron and steel	>20kt	39.5%

Sources: Complied based on Zhang et al. (2017).

Table 2.A.2: Direct Effect of ETS on Regulated Parent Firms

Dependent Variable: **Low Carbon Patent Family**	**Patent Count** (1)	**Patent Citation** (2)
ETS×Post	0.297**	0.478**
	(0.144)	(0.198)
Observations	1,180	1,180
CarbonPrice×Post	0.062**	0.108**
	(0.030)	(0.048)
Observations	1,180	1,180
TurnoverRate×Post	9.445**	11.093**
	(4.186)	(4.718)
Observations	1,180	1,180
Firm Attributes	Y	Y
Parent FE	Y	Y
Parent Province-Year FE	Y	Y
Parent Sector-Year FE	Y	Y

Notes: Dependent variables are logarithm one plus low-carbon patent family counts and citations. *ETS* equals one if a parent firm is regulated, and zero otherwise. *Post* equals one if the period is after the launch of the ETS, and zero otherwise. All columns contain the firm-level attributes including parents' assets, capital, and sales. Fixed effects at the parent firm, parent province-year, and parent sector-year levels are included. Standard errors in the parenthesis are clustered at the parent firm level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Table 2.A.3: Robustness Checks on Endogeneity Issues

Dependent Variable: **Low Carbon Patent Family**	**Patent Count** (1)	**Patent Citation** (2)
A. Number of Regulated Sister Subsidiaries as Control	0.044**	0.068**
	(0.018)	(0.027)
B. Patent Growth Rate as Control	0.047***	0.068***
	(0.017)	(0.026)
C. Drop Samples in BTH Regions (Environmental Policy)	0.044**	0.054*
	(0.022)	(0.029)
D. Drop Samples Regulated by ES10k (Energy Policy)	0.048***	0.073***
	(0.017)	(0.027)
E. Drop Samples in Shenzhen (Low-carbon Special Fund)	0.051***	0.068***
	(0.017)	0.024)
F. Drop Solar and Wind Energy Patents (Subsidy Policy)	0.041***	0.059***
	(0.015)	(0.021)
G. Drop Waste Management Patents	0.045***	0.063***
	(0.016)	(0.023)
Firm Attributes	Y	Y
Subsidiary FE	Y	Y
Subsidiary Province-Year FE	Y	Y
Subsidiary Sector-Year FE	Y	Y
Parent Province-Year FE	Y	Y
Parent Sector-Year FE	Y	Y

Notes: Dependent variables are logarithm one plus low-carbon patent family counts and citations. $ETSParent$ equals one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. $Post$ equals one if the period is after the launch of the ETS, and zero otherwise. Panel A includes the number of regulated sister subsidiary firms as an additional control variable. Panel B includes the growth rate of patents as an additional control variable. Panel C excludes samples when subsidiary firms or their parent firms are located in Beijing, Tianjin, and Hebei regions. Panel D excludes samples when subsidiary firms or their parent firms are regulated by China's "Top 10,000 Enterprises Energy Saving Programme". Panel E excludes samples when subsidiary firms or their parent firms are located in Shenzhen. Panel F removes solar and wind energy related patents in the dependent variables. Panel G removes waste management patents in the dependent variables. All columns contain the firm-level attributes including subsidiaries' registered capital, and parents' assets, capital, and sales. Fixed effects at the subsidiary firm, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels are included. Standard errors in the parenthesis are clustered at the parent firm level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Table 2.A.4: Robustness Checks on Alternative Empirical Methods

Dependent Variable: **Low Carbon Patent Family**	**Patent Count** (1)	**Patent Citation** (2)
A. 1:1 Nearest Neighbour Matching	0.046**	0.064**
	(0.019)	(0.027)
B. 1:3 Nearest Neighbour Matching	0.046***	0.064***
	(0.015)	(0.022)
C. Inverse Probability Treatment Weighting	0.012***	0.017***
	(0.004)	(0.005)
D. One-year Lag	0.042***	0.056***
	(0.015)	(0.021)
E. Two-year Lag	0.048**	0.064**
	(0.020)	(0.025)
F. Poisson Pseudo Maximum Likelihood	2.298***	1.927**
	(0.689)	(0.762)
G. Iterated Ordinary Least Squares	4.306***	4.226***
	(0.563)	(0.579)
Firm Attributes	Y	Y
Subsidiary FE	Y	Y
Subsidiary Province-Year FE	Y	Y
Subsidiary Sector-Year FE	Y	Y
Parent Province-Year FE	Y	Y
Parent Sector-Year FE	Y	Y

Notes: Dependent variables are logarithm one plus low-carbon patent family counts and citations in the estimations from Panel A to E. Dependent variables are not log-transformed in the estimations from Panel F to G. $ETSParent$ equals one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. $Post$ equals one if the period is after the launch of the ETS, and zero otherwise. Panel A performs one-to-one nearest neighbour matching. Panel B performs one-to-three nearest neighbour matching. Panel C uses the inverse probability treatment weighting in the regression analyses. Panel D uses one-year lagged independent variables. Panel E uses two-year lagged independent variables. Panel F conducts the estimation by the Poisson Pseudo Maximum Likelihood. Panel G conducts the estimation by the Iterated Ordinary Least Squares. All columns contain the firm-level attributes including subsidiaries' registered capital, and parents' assets, capital, and sales. Fixed effects at the subsidiary firm, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels are included. Standard errors in the parenthesis are clustered at the parent firm level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Table 2.A.5: Robustness Checks on the Moderating Effects

Dependent Variable:	Patent Count				Patent Citation			
Low Carbon Patent Family	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETSParent×Post	0.025*	0.043***	0.021	0.033**	0.044**	0.067***	0.032	0.047**
	(0.013)	(0.016)	(0.017)	(0.014)	(0.021)	(0.025)	(0.026)	(0.020)
ETSParent×Post×TechProx(3-digit)	0.232***				0.254***			
	(0.078)				(0.095)			
ETSParent×Post×AvgTenure_Prod		0.001				0.000		
		(0.003)				(0.004)		
ETSParent×Post×AvgTenure_R&D			0.006**				0.008**	
			(0.003)				(0.004)	
ETSParent×Post×KZ_Index				0.014**				0.020**
				(0.006)				(0.009)
Observations	9,785	9,785	9,785	9,283	9,785	9,785	9,785	9,283
Firm Attributes	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Dependent variables are logarithm one plus low-carbon patent family counts and citations. $ETSParent$ equals one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. $Post$ equals one if the period is after the launch of the ETS, and zero otherwise. $TechProx(3-digit)$ denotes the technology proximity between subsidiaries and their parent firms based on the patent IPC 3-digit. $AvgTenure\_Prod$ and $AvgTenure\_R\&D$ denote the average tenure of top management members with production and R&D experience in parent firms, respectively. KZ_Index is an index by Kaplan and Zingales (1997) and measures the financial constraints of parent firms. For the sake of brevity, it only reports the estimated coefficients for the interaction terms of key interest. All columns contain the firm-level attributes including subsidiaries' registered capital, and parents' assets, capital, and sales. Fixed effects at the subsidiary firm, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels are included. Standard errors in the parenthesis are clustered at the parent firm level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Chapter 3

Green Revenues, Clean Innovation and Technology Spillover: Evidence from Global Firm Level Data

3.1 Introduction

In response to the increasing environmental challenges and regulations, the demand for environmentally friendly goods and services has continuously grown over the last decade and encouraged more firms to alter their business focus to the markets of green products (FTSE Russell, 2022). During the transition to the "green economy", the innovation of clean technologies plays a crucial role as it delivers new solutions to improving environmental performance while boosting firms' competitiveness in green product markets, leading to a "win-win" outcome (Porter and Van der Linde, 1995; Jaffe et al., 2002; Dechezleprêtre and Sato, 2017). However, innovators are not always beneficiaries because the economic benefits of clean innovation largely rely on technology commercialisation, which takes time and does not necessarily happen inside the same firms where new technologies are invented (Teece, 2006; McGahan and Silverman, 2006; Popp, 2017). Commercial practices have shown the separation of innovation and commercialisation, and firms can benefit from others' technologies due to the existence of technology spillovers (Jaffe, 1986; Teece, 1986).[1] The

[1]For example, the leading Israeli biotechnology company Evogene reached a business collaboration with the giant US-based agricultural biotechnology company Monsanto in 2008. Evogene received funding from Monsanto to develop new seeds that produce higher crop yields and become more drought-resistant. Although Evogene held the intellectual property rights and received royalty payments, Monsanto secured exclusive licence rights to commercialise the seeds and grabbed a large share of revenues from the new products based on its well-established business networks (Evogene, 2014; Lianos and Katalevsky, 2017). This business model reveals that the economic benefits of new technologies do not always accrue to innovators but spill over to the owners of commercial advantages that are complementary to the technologies.

focus should not be confined to innovators but extended to other firms sharing similar business markets when one is evaluating clean innovation's benefits.

There are two main research challenges in estimating clean innovation's benefits. First, as summarised by Popp (2019), most existing literature examines the economic impacts of clean innovation based on the aggregated firm-level data, but experiences difficulties in isolating the effects on green economic activities to which clean technologies are practically targeted. Some previous research adopts binary or indirect measures of firms' involvement in green economic activities, though there is still disagreement on how to define and measure green economic activities (Jacobs et al., 2010; Oberndorfer et al., 2013). Considerable measurement errors may also be drawn into the estimation of clean innovation's benefits due to the ambiguity in the measures of green economic activities. Second, many previous studies rely on patenting activities, especially patent citations, to capture the spillover linkages between firms and measure clean technology spillovers when evaluating the economic benefits of clean innovation (Dechezleprêtre et al., 2017; Barbieri et al., 2020a). However, a large share of technology spillovers does not have observable paper trails of citation linkages (Myers and Lanahan, 2022). The spillover linkages based on patenting may also downplay firms that are engaged in green commercial activities while not leading in clean innovation. Relying heavily on patenting activities to construct technology spillover linkages between firms may miss some important spillovers existing in reality.

To better estimate the economic benefits of clean innovation, we resort to a novel dataset from FTSE Russell that provides a detailed breakdown of revenues from green commercial activities across global publicly listed firms. This dataset contains approximately 14,000 publicly listed firms from 2009 to 2016 and covers approximately 98.5% of global market capitalisation. The rich details of firms' revenues from specific green goods and services archived in the data allow us to more accurately measure firms' involvement in green commercial activities. Around 3,400 firms in the data are identified as gaining revenues from green commercial activities. Moreover, the detailed information on firms' revenues from specific green subsectors enables us to construct technology spillover linkages between firms based on the proximity of green commercial activities rather than solely on patent activities or citations. Merged with a global patent dataset from PATSTAT, our data is able to provide a more comprehensive assessment of how much clean innovation contributes to firms' economic benefits, particularly from green commercial activities.

We show that firms' average green revenues are smoothly growing during our sample period, but the growth is fulfilled by expanding green commercial activities but not shifting the structure between green and non-green business. Energy-related business takes around half of the firms' green revenues. Describing the relationship between firms' green revenues and clean innovation, we find that many firms with little clean innovation obtain a large share of green revenues. Further estimation evidence shows that firms' green revenues are enhanced by not only their own clean technologies but also technology spillovers from other neighbouring firms close in the technological space and product market space. The result of technology spillovers across the product market space also suggests that positive technology spillovers dominate the possible negative market-stealing effects between firms in the clean technology field. Such findings reflect the private and social economic benefits of firms' clean innovation. Moreover, we find that an increasing maturity of firms' clean technologies brings firms more green revenues, and this increase in green revenues is enhanced if firms themselves more specialise in clean innovation. In addition, we disaggregate our data into a more granular level and find the significant correlations between clean innovation and green revenues in the fields of alternative energy, energy efficiency, and sustainable transport. Lastly, we find that firms obtain higher green revenues from clean innovation if they have larger sizes or higher technology capacities. Our results survive in a series of robustness checks that address some alternative measures and empirical settings.

This paper relates to extensive literature that investigates the linkage between firms' environmental efforts and economic performance. Porter and Van der Linde (1995) raises the point that innovation activities induced by environmental policies not only help firms recover extra costs caused by regulations but also improve competitiveness in commercial markets. More following papers show that firms' inputs in green products and clean innovation positively relate to profitability and market values (Ambec and Lanoie, 2008; Palmer and Truong, 2017; Kruse et al., 2020). The evidence that firms benefit from their own environmental efforts is further recognised by capital markets and fosters private sector investments in clean assets and technologies (Dechezleprêtre et al., 2021). This paper builds on this strand of literature by providing a new piece of evidence on the relationship between clean innovation and firms' revenues from green products.

This paper also adds to the burgeoning literature that investigates the effect of technology spillovers. Earlier studies including Jaffe (1986) and Teece (1986) observe that innovating firms often do not obtain full economic returns from their own innovation, while other industry participants may gain more benefits from the innovation. These findings motivate more following works to focus on technology spillovers and develop frameworks to separate returns deriving from own and others' innovation efforts (McGahan and Silverman, 2006; Kafouros and Buckley, 2008; Teece, 2018). In addition to the technology spillovers across the technological space (Jaffe, 1986), the closenesses of the product market and geographic location also play important roles in technology spillovers (Bloom et al., 2013; Lychagin et al., 2016). More recent studies differentiate the spillover effects of clean technologies and estimate the economic benefits of clean technology spillovers (Dechezleprêtre et al., 2013; Aghion et al., 2016; Dechezleprêtre et al., 2017; Barbieri et al., 2020a), but the spillover linkages between entities heavily rely on patenting activities in most research. Our study extends the existing approach of measuring clean technology spillovers by using the disaggregated green subsector information to capture the spillover linkages based on the similarity of green commercial activities between firms. By incorporating spillovers across technological, product market, and geographical spaces, we document new evidence of clean technology spillovers to firms' green commercial activities. Following a recent paper on the economic values of clean technologies by Martin and Verhoeven (2022), we also attempt to interpret the social economic benefits of clean innovation based on our estimated clean technology spillovers.

Finally, this paper contributes to the literature on capturing firms' engagement in green commercial activities. Due to the limited disclosure of corporate information, previous studies usually rely on crude and indirect indicators, containing the inclusion in a green stock index (Oberndorfer et al., 2013), the adoption of voluntary green management systems (Jacobs et al., 2010; Eccles et al., 2014), or emission data (Fujii et al., 2013). However, these proxies do not well reflect how much a firm engages in green commercial activities and gains revenues from its green goods and services. The potential measurement errors included in these measures may lead to biased results of estimation. Recent research by Kruse et al. (2020) using the FTSE Russell green revenues data inspires us to capture firms' green revenues based on firms' disclosed information on commercial activities. Built upon their remedy of using the FTSE Russell dataset, our paper constructs an estimated measure of green revenues to more precisely capture firms' revenues from their green commercial activities.

The remainder of this paper is organised as follows. Section 3.2 describes the data used in our study. Section 3.3 presents the construction of key variables and our empirical strategies. Section 3.4 shows empirical results including the relationship between firms' green revenues and clean innovation, clean technology spillovers across different spaces, the role of clean technology maturity, heterogeneity across green sectors and firms' characteristics, and robustness checks. Section 3.5 concludes.

3.2 Data

3.2.1 Green Revenue

One key empirical challenge when estimating the relationship between clean technologies and firms' economic outcomes is the difficulty in capturing green commercial activities to which clean technologies are targeted. Our new data from FTSE Russell allows us to tackle this problem. The FTSE Russell Green Revenues Data Model (FTSE GR) is a global firm-level dataset, designed to measure firms' revenues from green goods and services. The dataset includes approximately 14,000 global publicly listed companies across 48 countries between 2009 and 2016, which covers around 98.5% of total global market capitalisation.

To construct firms' green revenues, a Green Revenue Classification System (GRCS) is developed by the FTSE Russell Industries Advisory Committee and breaks down green commercial activities into 10 green sectors, 64 green subsectors, and 133 green microsectors.[2] Figure 3.1 displays the taxonomy of 10 broad green sectors and 64 green subsectors at a more granular level. Following the defined taxonomy of green sectors, a team of analysts in the FTSE Russell search through corporate disclosures (e.g., annual reports) and map revenues from company-reported business segments and subsegments to the relevant green sectors under GRCS.[3] Finally, subsector-level green revenues are aggregated to obtain firm-level green revenue. Around 3,400 companies are identified as involved in green business activities during the sample period and having non-null green revenue values (named "green firms" henceforth).[4] To avoid confusion of terms, in this paper, "sector" denotes green sectors categorised by the FTSE GR data, "segment" denotes firms' own classification of their disclosed business, and "industry" denotes the standard industrial classification (SIC) that reflects a firm' overall business activities.[5]

[2] FTSE Russell Green Industries Advisory Committee consists of senior and leading experts from the global investment community (including asset managers and technical experts in environmental industries) to ensure the classification system aligns with the EU's environmental objectives and addresses market needs.

[3] The green microsectors, though seem more precise, are much more difficult to be mapped to firms' green business activities due to the limitation of disclosed information. Hence, most green business activities and their revenues are not mapped to green microsectors but only to green subsectors. Due to the lack of data at the green microsector level, our paper constructs green revenue indicators based on values at the green subsector level.

[4] The geographic distribution of firms covered by the FTSE Russell data is shown in Figure 3.A.1.

[5] In the FTSE GR data, the term "sector" is exclusively used for describing the 10 green sectors, 64 green subsectors, and 133 green microsectors in the Green Revenue Classification System (GRCS). Meanwhile, "segment" is exclusively used for firms' disclosed business segments and subsegments. Since firms across regions are subject to different disclosure requirements, the classification of business segments and subsegments is not consistent in the data (e.g., one firm may have "Vehicle" at the segment level but another firm may record "Vehicle" at its subsegment level, depending on specific business and disclosure requirements to which they are subject). Hence, segments and subsegments are not comparable across firms but only reflect relative business layers within each firm. The standard industrial classification (SIC) is also used

Energy Generation (EG)	Energy Management & Efficiency (EM)	Energy Equipment (EQ)	Water Infrastructure & Technology (WI)	Waste & Pollution Control (WP)
Bio Fuels	Buildings & Property (Integrated)	Bio Fuels	Advanced Irrigation Systems & Devices	Cleaner Power
Cogeneration	Controls	Cogeneration	Desalination	Decontamination Services & Devices
Clean Fossil Fuels	Energy Management Logistics & Support	Clean Fossil Fuels	Flood Control	Environmental Testing & Gas Sensing
Geothermal	Industrial Processes	Fuel Cells	Meteorological Solutions	Particles & Emission Reduction Devices
Hydro	IT Processes	Geothermal	Natural Disaster Response	Recycling Equipment
Nuclear	Lighting	Hydro	Water Infrastructure	Recycling Services
Ocean & Tidal	Power Storage	Nuclear	Water Treatment	Waste Management (General)
Solar	Smart & Efficient Grids	Ocean & Tidal	Water Utilities	
Waste to Energy	Sustainable Property Operator	Solar		
Wind		Waste to Energy		
		Wind		

Environmental Resources (ER)	Environmental Support Services (ES)	Food & Agriculture (FA)	Transport Equipment (TE)	Transport Solutions (TS)
Advanced & Light Materials	Environmental Consultancies	Agriculture	Aviation	Railways Operator
Key Raw Minerals & Metals	Finance & Investment	Aquaculture	Railways	Road Vehicles
Recyclable Products & Materials	Smart City Design & Engineering	Land Erosion	Road Vehicle	Video Conferencing
		Logistics	Shipping	
		Food Safety, Efficient Processing & Sustainable Packaging		
		Sustainable Plantations		

Figure 3.1: FTSE Russell Green Revenue Classification System

Notes: The FTSE Russell Green Revenues Data Model develops a new green taxonomy - Green Revenue Classification System (GRCS), containing 10 green sectors and 64 subsectors. It is worth noting that the names of the sectors and subsectors listed above are created according to the green taxonomy and only capture the green activities in these sectors and subsectors. For example, "Transport Equipment" under the GRCS does not cover all business activities related to any transportation equipment but only the activities related to green transportation. More details on the green taxonomy of FTSE Russell Green Revenues at https://www.ftserussell.com/data/sustainability-and-esg-data/green-revenues-data-model.

One caveat of using the green revenue data from the FTSE GR is the ambiguity of the green revenue values. Some firms' business subsegments have been mapped to specific green subsectors, but the exact revenue values from these business subsegments are not fully disclosed. In the raw dataset, zero revenue values are assigned to the green business without full disclosures, and accordingly the FTSE Russell reports the minimum value of firm-level green revenues. As the distribution of the minimum green revenues is highly skewed towards zero, simply using the minimum values may threaten the following analyses due to measurement error.

in our empirical analyses. Therefore, we distinguish "sector", "segment", and "industry", and these three terms are not interchangeable in this paper.

Segment	Segment Revenue Share	Subsegment	Subsegment Revenue Share
Vehicle	60%	Hybrid power vehicle	10%
		Fuel emission control	N.A.
		Non-green vehicle	70%
		Spare parts & accessories	N.A.
Energy storage	10%	Solar battery	100%
Building Heating, ventilation, and air conditioning (HVAC)	30%	Geothermal products	10%
		Non-green building HVAC	90%
Minimum value of green revenue share	60%(vehicle) × 10%(hybrid power vehicle) + 10%(energy storage) × 100%(solar battery) + 30%(HVAC) × 10%(geothermal products) = 19%		
Unreported revenue share	60%(vehicle) × [1 - 70%(non-green vehicle) - 10%(hybrid power vehicle)] = 12%		
Imputed green revenue share of fuel emission control	With 20% industry(SIC) average green revenue share: 12% (unreported revenue share) × 20%(industry average green revenue share) = 2.4%		
Total green revenue share after imputation	19% (minimum green revenue share) + 2.4% (imputed green revenue) = 21.4%		

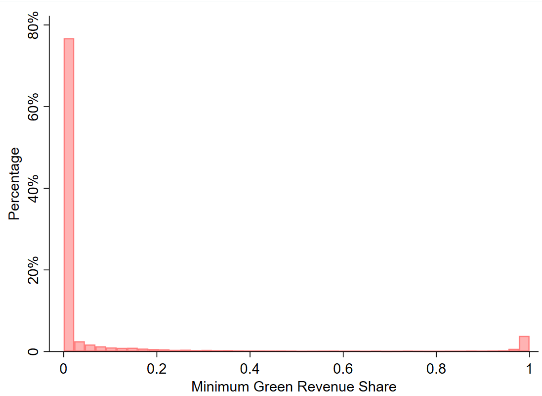
Figure 3.2: Example of Undisclosed Green Revenue Imputation

Notes: The business subsegments without full revenue disclosure are recorded as zero in the dataset, which is labelled as "N.A." in this example. Subsegments in green shade indicate green business. Our imputation process assumes that the unknown revenue has a similar green revenue share to the industry average level.

To tackle this issue, we follow the approach by Kruse et al. (2020) to impute the undisclosed share of green revenues, accompanied by an example of the imputation process for a clearer interpretation (shown in Figure 3.2). Firstly, we utilise the disclosed information of business segments and subsegments to pin down minimum and unreported revenue share. For the particular firm in the example, the three business segments "Vehicle", "Energy Storage", and "Building HVAC" generate 60%, 10%, and 30% of the firm's total revenues, respectively. Four subsegments are identified as green business, but the revenue share from "Fuel emission control" subsegment is not disclosed.[6] A non-green business subsegment "Spare parts & accessories" is not disclosed, too. The minimum green revenue share is 19% [=60%×10%+10%×100%+30%×10%)] as zero revenue is assigned to "Fuel emission control" subsegment. The unreported revenue share is 12% [=60%×(1-70%-10%)], including both unreported revenues from the both green and non-green business. The 19% green revenue share is obviously an underestimation. In order to develop a more precise estimation of green revenues, we need to impute the revenue share of the undisclosed "Fuel emission control" subsegment. Secondly, we employ the yearly average of green revenue share in the industry (2-digit US SIC primary code) where the firm operates to impute the green revenue share of undisclosed business subsegments. In this particular example,

[6] Revenue values at the business segment level are fully-reported in all firms while some subsegments do not disclose their values.

if we observe green business accounts for 20% of firms' total revenues on average in the industry, the imputed revenue share from the undisclosed green business subsegment "Fuel emission control" is 2.4% [=12%×20%]. Accordingly, the final estimated firm-level green revenue share [21.4%] is obtained by adding the imputed green revenue share [2.4%] to the minimum green revenue share [19%]. The imputation builds upon the assumption that the business with unreported revenue is likely to have a similar share of green business to the industry average level. Although this assumption does not perfectly reflect the real share of green business among the unreported revenues, it offers a proximate share closer to the real green revenue share than simply assigned zero value.



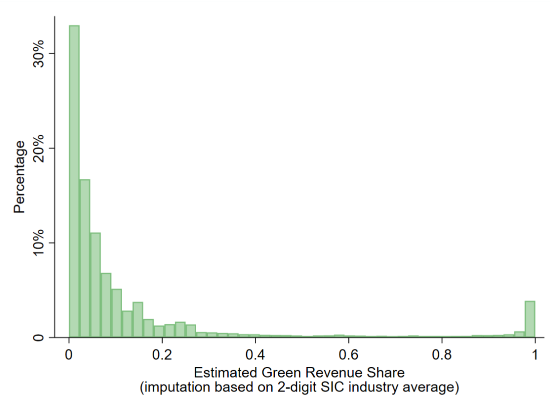


Figure 3.3: Distribution of Minimum and Estimated Green Revenue Share

Notes: The left panel shows the distribution of the original minimum green revenue share provided by the FTSE Russell Green Revenue dataset, where nearly 80% observations with green revenue level between 0 and 0.022 (the first bar in the figure) and 70% observations do not disclose any specific green revenue values (recorded as zero in the dataset). The right panel shows the distribution of estimated green revenue after the imputation process, where around 30% observations have green revenue between 0 and 0.022 and less than 10% observations have zero green revenues.

Figure 3.3 compares the distribution of the original minimum green revenue share provided by the FTSE GR and the estimated green revenue share by our imputation strategy. The observations with nearly-zero green revenues drop from more than 70% to around 30% of the sample after the imputation, which relieves the concern of highly skewed distribution of green revenues and measurement errors.

Figure 3.4 shows an overview of the trend and composition of green revenue among global publicly listed firms. The top half of the figure is the average green revenue value from 2009 to 2016, decomposed by 10 FTSE GR green sectors.[7] The average green revenue has been a growing overall during the sample period, while increased more from 2009 to 2013 and

[7]Figure 3.4 excludes firms that are not identified as engaged in green business as they do not have any green revenues.

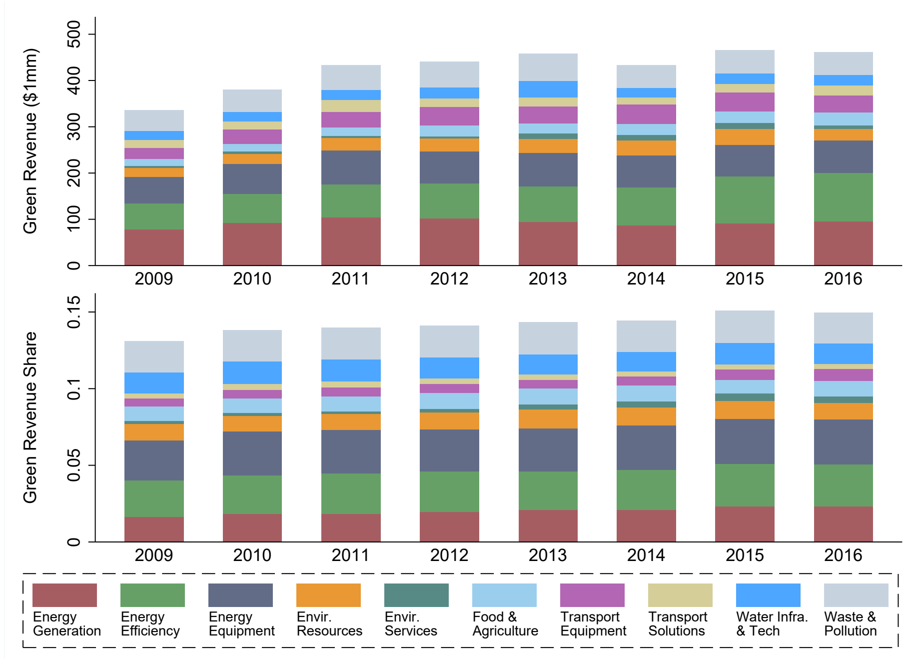


Figure 3.4: Trend and Composition of Green Revenue and Green Revenue Share

Notes: The two graphs show the average green revenue value and green revenue share of global publicly listed firms in our sample from 2009 to 2016. The graphs exclude firms that are not identified as engaged in green business as they do not have any green revenues.

held steady thereafter. The bottom half displays the average green revenue share in each firm. Although the absolute value of green revenue increases, the share of green revenue remains stable over the years. The trends imply that the development of green business is fulfilled by expanding green business but not fundamentally altering the structure between green and non-green business. Among the 10 main green sectors, energy-related business (energy generation, energy equipment, and energy efficiency) take the lion's share, with around 50% of green revenues.

3.2.2 Clean Innovation

Our variables of clean innovation are constructed by patents drawn from the EPO Worldwide Patent Statistical Database (PATSTAT). The PATSTAT is the largest global patent database, covering all of the world's major patent offices such as the United State Patents and Trademark Office (USPTO), European Patent Office (EPO), Japan Patent Office (JPO), and China National Intellectual Property Administration (CNIPA). Detailed bibliographic information of each patent is archived in the database, including applicants, inventors, date of application and publication, granted by which patent office, technology classes, citations, and patent families.[8] We identify patents pertaining to clean technologies by using the Y02 category in the Cooperative Patent Classification (CPC) system, which provides a tagging scheme that contains patents with potential contributions to climate change adaptation and mitigation (Veefkind et al., 2012; Haščič and Migotto, 2015; Angelucci et al., 2018). To ensure the relevance between technologies in the Y02 category and green business in the FTSE GR data, we manually link each Y02 category to related FTSE GR green subsectors for a more precise check of corresponding green revenues from clean technologies. In our analyses, we focus on successfully granted patents but use their patent application filing dates because the patent granting justifies the innovativeness of a patent and it is reasonable to expect a firm can incorporate the attached technology into its business after the application filing dates. Each patent is mapped to companies in the FTSE GR dataset based on the Orbis Intellectual Property database, which provides the linkage of companies to the patents which they possess at a global level.

3.3 Empirical Methodology

3.3.1 Variable Construction

Our main outcome variable is firms' green revenue. We estimate firms' green revenue share based on the minimum green revenue share reported by the FTSE GR and the imputed unreported green revenue share following the imputation process in Section 3.2.1. Firms' green revenue is calculated by firms' total revenue and the estimated green revenue share after the imputation.

Our baseline measure of clean innovation is the cumulative stocks of clean patent applications. Specifically, we retrieve patent documents starting from 1970 and calculate patent stocks using a perpetual inventory method with a 15% depreciation rate (Hall et al., 2005). A firm's clean patent stock $CleanTech$ in year t is $CleanTech_t = CleanPat_t + (1-\delta)CleanTech_{t-1}$, where $CleanPat_t$ is the new clean patent applications filed by this firm in yeat t, and δ denotes depreciation rate. In addition to using the count of clean patent applications as the quantity measure, we also construct clean patent stocks using patent citations, international patent families and triadic patent families to capture the quality of clean innovation. Specifically, a firm's clean patent stock based on patent citations is constructed by accumulating the number of forward citations received by the firm's clean patents. International patent families are defined as patent families that cover a set of ap-

[8] Technology classes of patents in the PATSTAT are categorised by International Patent Classification (IPC) and Cooperative Patent Classification system (CPC).

plications filed in more than one country. A firm's clean patent stock based on international patent families is calculated by accumulating the stocks of the firm's clean international patent families. Similarly, triadic patent families are defined as a set of patent applications within one patent family submitted to the USPTO, EPO, and JPO three patent offices. A firm's clean patent stock based on triadic patent families is computed based on accumulating stocks of the firm's clean triadic patent families.[9] The 15% depreciation rate is also taken into account during the calculations of the quality measures based on patent stocks.

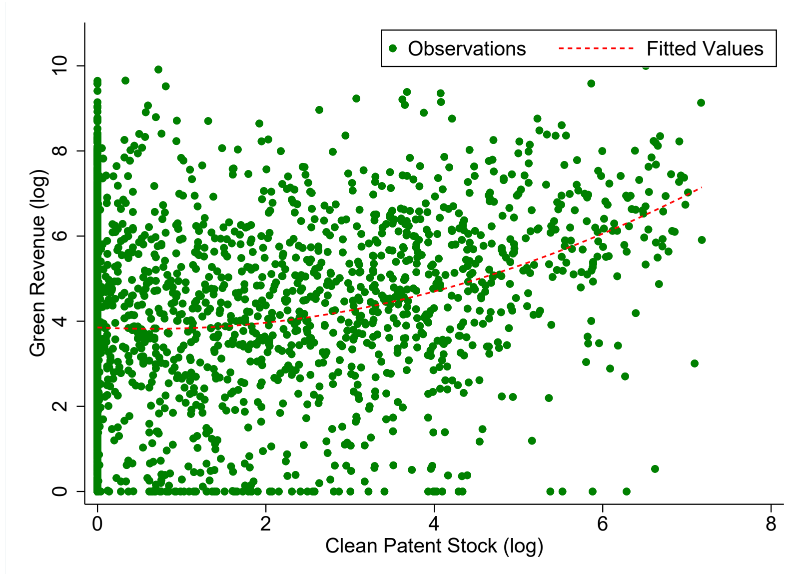


Figure 3.5: Scatter Plot of Green Revenue and Clean Innovation

Notes: This scatter plot shows cross-sectional observations in 2016 and their fitted values. The Y-axis represents firms' green revenue values. The X-axis stands for firms' clean patent stocks.

To have a glimpse of the relation between green revenues and clean innovation, we draw a scatter graph based on cross-section data in 2016, as shown in Figure 3.5. It is not surprising that firms' green revenues generally increase with their own clean innovation, while firms with higher clean innovation do not always obtain higher green revenues.[10] This graph further justifies the existence of clean technology spillovers.

For a firm receiving clean technology spillovers from others, the spillovers are determined by: (1) how much clean technologies are available, which can be measured by the clean technology pools of other firms; (2) how close the receiver firm is to other firms with clean

[9] A firm's clean international patent families represent the number of international patent families that include clean patents owned by the firm, while a firm's clean triadic patent families represent the number of triadic patent families that include clean patents owned by the firm.

[10] Some firms with little clean innovation grab a large share of green revenues (dots in the upper left), while some others leading in clean innovation do not retain a decent share of green revenues (dots in the lower right).

technology pools, which can be captured by some "proximity" measures between firms. Specifically, clean technology pools of other firms accessed by a receiver firm (i.e., focal firm) i at year t are defined as:

$$CleanSpill_{it} = \sum_{j \neq i} w_{ijt} \cdot CleanTech_{jt} \tag{3.1}$$

where $CleanTech_{jt}$ is the cumulative stock of clean patents that other firms j possess up to year t. w_{ijt} is a weight reflecting the "proximity" between firms i and j.[11] The "proximity" indicators capture the possible spillover linkage between firms. In this paper, we investigate the "proximity" measures in the technological, product market, and geographical spaces. The clean technology pools of other firms weighted by the "proximity" in different spaces capture clean technology spillovers over different channels.

Proximity in Technological Space

We construct our measure of "proximity" in technological space, i.e., technological proximity, built upon the approach first used by Jaffe (1986). More specifically, for a focal firm i and one of its peers j, the technological proximity between them is:

$$w_{ijt}^{TechSpace} = CL_{ijt} \cdot TechProx_{ijt}^{Jaffe} = CL_{ijt} \cdot \frac{T_{it}T'_{jt}}{\sqrt{T_{it}T'_{it}}\sqrt{T_{jt}T'_{jt}}} \tag{3.2}$$

where T_{it} is firm i's patent portfolio vector up to year t, defined as $T_{it} = (T_{i1,t}, T_{i2,t}, ..., T_{iK,t})$, in which $T_{ik,t}$ is the share of patents of firm i in technology class k up to year t.[12] The proximity index $TechProx_{ijt}^{Jaffe}$ ranges between 0 and 1, showing the similarity of a pair of firms' patent distributions across technology classes, and is symmetric to firm ordering. One distinction compared to Jaffe's conventional index is the additional term representing historical citation linkage between firm i and j: CL_{ijt} is a dummy that indicates if firm i has cited patents possessed by firm j up to year t.[13] It is stronger to justify the likelihood of clean technological spillover from firm j to firm i if the historical citation linkage exists.[14] Bloom et al. (2013) (BSV) develops an alternative Mahalanobis-distance index of technological proximity that takes into account the relatedness between different

[11] This approach is built upon the assumption that the technology spillover from firm j to firm i is proportional to the "proximity" between this pair of firms.

[12] Technology classes in our variable depend on International Patent Classification (IPC) 4-digit code, 647 technology classes in total in our sample.

[13] Similar to the technological proximity index, we take into account the citation linkage happening prior to the observation year t.

[14] For example, for a pair of firms that have not had any linkage with respect to technologies, even if having the same distribution of technology classes, it would be difficult to argue that one firm learns and benefits from the other firm's technologies.

technology classes. This alternative measure does not dramatically affect the magnitude of the technology spillovers across the technological space. We also use the technological proximity built upon the BSV's approach in our robustness checks.

Proximity in Product Market Space

In many previous studies, technology spillovers across the product market space is simply divided into intra-industry and inter-industry spillovers, i.e., spillovers from the same or different industries (Bernstein and Nadiri, 1989; McGahan and Silverman, 2006; Kafouros and Buckley, 2008; Liu, 2008). However, it is closer to business practices that firms, especially large and global publicly listed ones in our sample, provide goods and services in multiple industries. The conventional dichotomous indicators of technology spillovers cannot well reflect firms' proximity in the product market space when multiple products are taken into account. Therefore, we are inspired by Bloom et al. (2013)'s idea and extend the "proximity" measure used in the technological space to the product market space. Since our interest lies in revenues from green goods and services, a proximity indicator specifically capturing green products is more aligned with our focus. Based on detailed revenue data broken down into the green subsector level by the FTSE GR dataset, we advance the literature by constructing the proximity of green product markets across global firms to measure the "proximity" in the product market space. More specifically, the product market proximity between a focal firm i and one of its paired firms j is computed by:

$$w_{ijt}^{ProdMktSpace} = ProdMktProx_{ijt} = \frac{S_{it}S'_{jt}}{\sqrt{S_{it}S'_{it}}\sqrt{S_{jt}S'_{jt}}} \tag{3.3}$$

Analogous to the vector T_{it} in Eq (3.2), $S_{it} = (S_{i1,t}, S_{i2,t}, ..., S_{iG,t})$ where $S_{ig,t}$ is the share of revenues of firm i in green subsector g up to year t.[15] S_{it} indicates the distribution of firm i's business across green product markets. A higher $ProdMktProx_{ijt}$ suggests a stronger overlap of green products between a pair of firms, which may generate another spillover that has not been well captured by the channel of technological proximity. In addition, unlike technological proximity or patent citation linkage, this indicator of the "proximity" between firms is not confined to firms with patenting activities but all firms with green commercial activities. Technology spillovers like the Evogene and Monsanto case may not be well captured by the spillover indicators based on the technological proximity or patent citation as that spillover does not necessarily lead to new innovation in the receiver. In

[15] $G = 64$ as firms' business is categorised into 64 green subsectors in the FTSE GR dataset.

contrast, the spillover indicator based on the overlap of green products between firms can better cover the technology spillovers that lead to technology commercialisation.

Proximity in Geographical Space

Previous studies often focus on the location of firms' headquarters and measure the geographical proximity by a binary variable indicating if a pair of firms located in the same region or a Euclidean distance between the location of headquarters (Keller, 2002; Orlando, 2004; Aldieri and Cincera, 2009). However, where firms' innovation activities emerge is not always consistent with where headquarters locate. In reality, innovation activities are more likely to be scattered in research labs located in different regions rather than clustered in headquarters, especially for large and global firms in our sample. A proxy variable reflecting the geographical distribution of innovation activities is helpful to better estimate the spillover effect due to geographical closeness between firms (Lychagin et al., 2016). Although we do not have detailed information on the geographic locations of research labs owned by each firm, we instead use the locations of firms' priority patents to capture where innovation activities emerge.[16] More specifically, the geographic proximity between a pair of firms i and j is calculated as:

$$w_{ijt}^{GeogSpace} = GeogProx_{ijt} = \frac{L_{it}L'_{jt}}{\sqrt{L_{it}L'_{it}}\sqrt{L_{jt}L'_{jt}}} \tag{3.4}$$

where the vector $L_{it} = (L_{i1,t}, L_{i2,t}, ..., L_{iC,t})$, in which $L_{ic,t}$ is the share of patents of firm i in country c up to year t.[17]

Clean Technology Maturity

The recent decline in new clean innovation raises concern if the green economy is able to keep a sustainable momentum in expansion and development (Probst et al., 2021). From the perspective of the technology life cycle, however, the observed decrease may suggest the increasing maturity of clean technologies and a higher degree of knowledge codification (Barbieri et al., 2020b). As technologies move towards maturity, though it is more challenging to achieve breakthroughs, they enhance the reliability, applicability and cost-effectiveness of technology adoption in business (Capaldo et al., 2017). The lower risk and higher value of commercial applications encourage firms to put more focus on business

[16] We use priority patent, i.e., the first patent in every patent family, to define the location of innovation activity. The further patent applications following the first patent in a patent family do not create new technologies but only aim at expanding the property rights of patents to more regions.

[17] $C = 77$, which means there are 77 countries observed in patent applications of our sample firms.

involving clean technologies. Building on these premises, we study how clean technology maturity plays a role in the revenues from corresponding green goods and services.

There is no widely-recognised consensus on how to measure technology maturity. One approach is to use the average age of technology classes that a firm engages in. More specifically, a firm-level clean technology maturity can be constructed as:

$$CleanTechMat_{it} = \sum_{g=1}^{G} GR\_Ratio_{igt} \cdot (\frac{1}{P} \sum_{p=1}^{P} TechAge_{ipt}) \tag{3.5}$$

A straightforward measure of $TechAge_{ipt}$ is the age of patent p owned by firm i up to year t,[18] and P represents the number of firm i's clean patents categorised into the technology classes which are linked to green subsector g.[19] GR_Ratio_{igt} denotes the ratio of green revenue from green subsector g to total revenue in firm i at year t. This index represents the average age of clean patents weighted by the ratio of green revenue in each green subsector.

The information enclosed in backward citations offers another idea to quantify technology maturity (Sørensen and Stuart, 2000; Lanjouw and Schankerman, 2004; Alnuaimi and George, 2016; Capaldo et al., 2017). Prior arts that a patent cites describe the composition of knowledge that this focal patent draws on (Popp, 2005). Patents in technological fields that are more mature are typically built upon prior arts with longer years elapsed. Hence, another measure of $TechAge_{ipt}$ is the age of patent p cited by firm i until year t, and now P represents the number of patents cited by firm i's clean patents. This maturity measure indicates the average age of prior arts that are cited by clean technologies, weighted by the ratio of green revenue in each green subsector.

Summary Statistics

After combining the data sources of green revenues from FTSE Russell and patents from PATSTAT, we obtain a panel sample of approximately 14,000 firms spanning the periods from 2009 to 2016. Among these firms, around 3,400 firms are identified as green firms that involve in green business activities and have non-null green revenue values during 2009-2016. Table 3.1 presents the basic descriptive statistics of all sample firms and green firms. The firms in our sample are relatively large and the green firms are much larger than

[18] Some old patents, which were invented before the creation of the clean technology class Y02, have been assigned to the corresponding Y02 categories in PATSTAT. Consequently, those old patents are also taken into account during the calculation of the technology age.

[19] Patents in each clean technology class, defined by CPC codes, are manually linked to green subsectors under the FTSE Green Revenue Classification System (GRCS).

other non-green firms. In terms of innovation activities, green firms emerge to be much more active among the full sample of firms (both in total patenting and clean patenting activities). Additionally, we compare the mean and important quartiles of key variables between green and non-green firms, as shown in Figure 3.6. It further highlights that green firms play a much bigger role in both aspects of markets and technologies compared to other non-green firms.

Since green revenue information is available only for green firms, our analyses mainly focus on the 3,400 green firms. However, all other non-green firms are still taken into account when constructing the measures of spillovers across firms and other industry- or country-level indicators.

Table 3.1: Summary Statistics

Variables	All Sample Firms					Green Firms				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Panel A: Firm Revenue and Innovation Indicators										
Total Revenue ($million)	99868	3439.270	13877.859	0.001	485873.000	23641	6159.857	20575.153	0.001	484489.000
Green Revenue ($million)	99868	101.657	780.896	0.000	69347.938	23641	429.435	1560.552	0.000	69347.938
Green Revenue Share	99868	0.034	0.135	0.000	1.000	23641	0.143	0.248	0.000	1.000
Total Patent Stock	99868	191.006	1817.162	0.000	84109.594	23641	595.852	3484.876	0.000	84109.594
Total Patent Citation Stock	99868	1347.914	16078.088	0.000	1053903.600	23641	4069.185	30762.437	0.000	1053903.600
Total Intl. Patent Family Stock	99868	126.306	1330.372	0.000	69045.703	23641	396.270	2533.814	0.000	69045.703
Total Triadic Patent Stock	99868	51.617	574.084	0.000	32172.787	23641	153.562	1009.540	0.000	26483.842
Clean Patent Stock	99868	16.996	229.034	0.000	16797.014	23641	62.342	458.053	0.000	16797.014
Clean Patent Citation Stock	99868	119.706	1666.066	0.000	121040.990	23641	419.314	3247.658	0.000	121040.990
Clean Intl. Patent Family Stock	99868	12.521	177.253	0.000	12778.706	23641	45.694	352.113	0.000	12778.706
Clean Triadic Patent Stock	99868	6.051	92.996	0.000	6640.184	23641	21.514	180.840	0.000	6640.184
Panel B: Spillover and Maturity Indicators										
Spill_TechSpace(Jaffe)	99868	2790.327	7669.344	0.000	79506.078	23641	6696.314	11923.744	0.000	79506.078
Spill_TechSpace(BSV)	99868	2165.920	5685.711	0.000	58772.676	23641	5065.481	8673.051	0.000	58772.676
Spill_ProdSpace	99868	3748.545	10460.613	0.000	88721.188	23641	15783.419	16430.997	0.000	88721.188
Spill_GeogSpace	99868	18415.357	32606.241	0.000	144539.310	23641	31885.647	40343.176	0.000	144539.310
CleanTechMat(PatAge)	-	-	-	-	-	23641	5.229	3.153	0.000	22.393
CleanTechMat(BkwAge)	-	-	-	-	-	23641	11.734	5.641	0.000	37.522

Notes: The left half of the table reports summary statistics of all sample firms, while the right half reports values of green firms. Panel A shows the indicators of revenue and innovation. Panel B shows the measures of clean technology spillovers and clean technology maturity. $Jaffe$ denotes that the technology spillover is built upon the technological proximity based on Jaffe (1986)'s method, and BSV denotes the spillover is built upon the technological proximity based on Bloom et al. (2013)'s method. $PatAge$ indicates the clean technology maturity is calculated based on average patent age, and $BkwAge$ indicates the clean technology maturity is calculated based on average backward prior art patent age. Since the indicators of clean technology maturity are weighted by the ratio of firms' green revenue from the green subsector to firms' total revenue, the indicators are only applicable to "Green Firms".

3.3.2 Empirical Strategy

We start by examining the simple relationship between firms' green revenue and their own clean technology stocks. For firm i in industry j from country c at year t, the correlation can be estimated by the following model:

$$Y_{itjc} = \beta_0 + \beta_1 CleanTech_{i,t-1} + X_{i,t-1} + \gamma_i + \delta_{jt} + \lambda_{ct} + \varepsilon_{ijct} \tag{3.6}$$

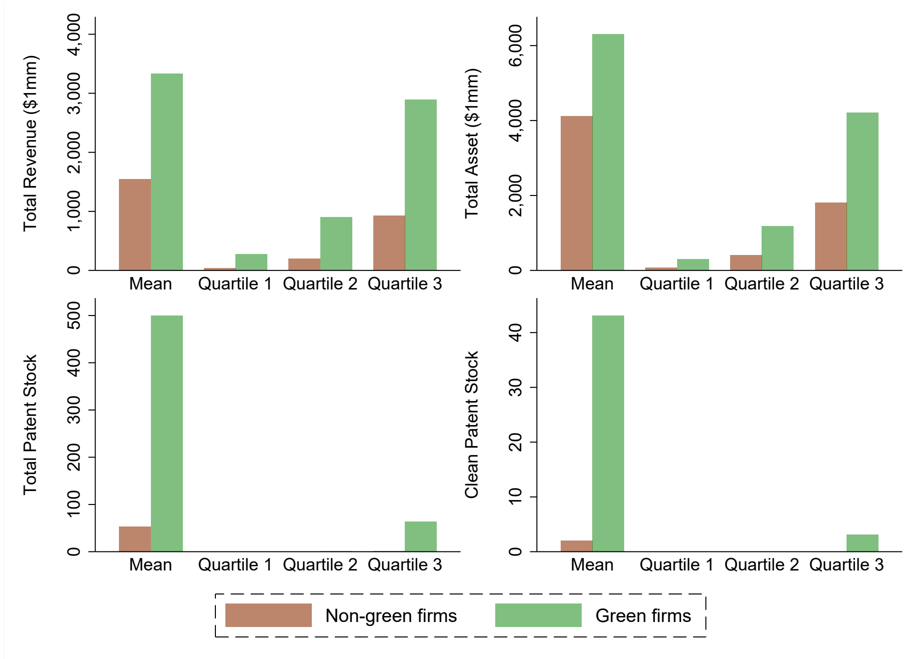


Figure 3.6: Comparison between Green and Non-Greene Firms

Notes: This figure compares the values of mean, lower quartile, median, and upper quartile between green firms (i.e., firms identified as involved in the green business) and other non-green firms, with respect to total revenues, total assets, total patent stock, and clean patent stock.

where Y_{ijct} is the outcome variables of our interests, including green revenue value and green revenue share. $CleanTech_{i,t-1}$ denotes the cumulative stock of clean patents. We lag the key independent variable by one year as clean technologies may take time to be commercialised and produce revenues. $X_{i,t-1}$ is a series of firm-level control variables including market capitalisation, the number of employees, the assets-to-sales ratio, operating profit margin (operating income divided by revenue), and current ratio (current assets divided by current liabilities).[20] We use firms' market capitalisation and the number of employees as proxies for firm size. The assets-to-sales ratio captures capital intensity for firms' business. The operating profit margin measures firms' profitability, and the current ratio reflects the liquidity and financial resources. All variables except green revenue share are transformed into logarithms. We also control firm-specific fixed effects γ_i, industry-year fixed effects δ_{jt}, and country-year fixed effects λ_{ct} to absorb firm-specific and time-variant industry and country unobservable factors. ε_{ijct} is an idiosyncratic error term. The standard errors are clustered at the industry (SIC 2-digit) level.

However, firms not only benefit from their own clean technologies but also from the clean technologies of other firms. The above regression Eq (3.6) cannot capture the spillover

[20]The information of control variables derives from the FTSE Russell dataset.

effects of other firms' clean technologies. Hence, the clean technology pools of other firms should be also added to the regression model:

$$Y_{it} = \beta_0 + \beta_1 CleanTech_{i,t-1} + \beta_2 CleanSpill_{i,t-1} + X_{i,t-1} + \gamma_i + \delta_{jt} + \lambda_{ct} + \varepsilon_{ijct} \quad (3.7)$$

where $CleanSpill_{i,t-1}$ represents clean technology pools of other firms close to firm i. As firm i's closeness to other firms can be measured in the technological, product market, and geographical spaces, $CleanSpill_{i,t-1}$ includes three separate indicators to capture clean technology spillovers to firm i from other firms via different channels.

3.4 Empirical Results

3.4.1 Baseline Results

Table 3.2 summarises the relationship between firms' own technologies and their revenues. Technology is measured from the perspectives of both quantity and quality: patent count in Panel A, and patent citation in Panel B. Columns (1) and (2) show the role of technologies (measured by total patent stock $AllTech$) in firms' total revenues. We observe that firms with more technologies obtain higher revenues in general, and the results are consistent for the sample of all firms and green firms (firms identified as involved in the green business) in the FTSE Russell dataset. Due to the availability of green revenue information, we further look into the role played by clean technologies only for green firms in the following analyses. We find that, in Column (3), firms' own clean technologies can help them gain more revenue from green goods and services. This increase in revenues from green business does not alter the structure between green and non-green businesses, which is shown by the insignificant effect on green revenue share in Column (4). The similar results in Panel A and B indicate that both the quantity and quality of clean technologies contribute to firms' green revenue.

Since firms' green revenues may also benefit from other firms' clean technologies, we next estimate the clean technology spillovers by Eq (3.7). Table 3.3 contains the results taking into account clean technology spillovers across different spaces. The measures of clean technologies in this table are based on clean patent counts. In Column (1), the specification includes both firms' own clean technologies and clean technology pools of other firms weighted by technological proximity. The coefficients show that firms' green revenues are not only positively associated with their own clean technologies but also with clean tech-

Table 3.2: Correlation between Innovation on Revenue

Dependent Variable:	Total Revenue		Green Revenue	Green Revenue Share
	(1)	(2)	(3)	(4)
Panel A: Innovation Measured by Patent Count				
AllTech_{t-1}	0.077***	0.058***		
	(0.012)	(0.020)		
CleanTech_{t-1}			0.078***	-0.003
			(0.025)	(0.003)
Panel B: Innovation Measured by Patent Citation				
AllTech_{t-1}	0.057***	0.041**		
	(0.010)	(0.019)		
CleanTech_{t-1}			0.066***	0.000
			(0.019)	(0.002)
Observations	85,300	19,996	19,996	19,996
Covered Firms	All	Green	Green	Green
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y

Notes: The dependent variables are total revenue in Columns (1) and (2), green revenue in Columns (3), and green revenue share in Columns (4). Innovation indicators in Panel A are constructed based on patent count, and in Panel B are based on patent citation. *AllTech* and *CleanTech* denote total and clean patent stock, measured by the cumulative stock of total and clean patents with a 15% yearly depreciation rate, respectively. All variables except green revenue share are measured in logarithms. Column (1) cover all sample firms, and Columns (2)-(4) only cover green firms (i.e., firms identified by FTSE Russell as involved in the green business). All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

nologies of other neighbouring firms close in the technological space. This result suggests the existence of spillovers across the technological space.

The product market space is also accountable for clean technology spillovers, as shown in Column (2). The estimated coefficient on $Spill\_ProdSpace_{t-1}$ is positive and statistically significant at the 1% level. This result indicates that firms also benefit from the clean technology spillovers from other neighbouring firms close in the product market space. It is worth noting that some previous studies on generic technology spillovers find a firm's benefit is negatively affected by technologies of other firms close in product markets, which implies a market-stealing effect (Bloom et al., 2013). Our different result suggests that, in the product market space, a positive technology spillover effect dominates a possible negative market-stealing effect in clean technologies.

We also examine whether geographical closeness also contributes to the technology spillovers. As the result displayed in Column (3), the estimated coefficient on $Spill\_GeogSpace_{t-1}$ is statistically insignificant and suggests that a firm's green revenues do not benefit from

Table 3.3: Estimation of Clean Technology Spillovers

Dependent Variable:	Green Revenue			
Measure: Patent Count	(1)	(2)	(3)	(4)
CleanTech_{t-1}	0.058**	0.085***	0.077***	0.067***
	(0.027)	(0.022)	(0.024)	(0.024)
$\text{Spill\_TechSpace}_{t-1}$	0.033***			0.035**
	(0.012)			(0.015)
$\text{Spill\_ProdSpace}_{t-1}$		0.093***		0.093***
		(0.010)		(0.010)
$\text{Spill\_GeogSpace}_{t-1}$			0.005	-0.011
			(0.009)	(0.013)
Observations	19,996	19,996	19,996	19,996
Covered Firms	Green	Green	Green	Green
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y

Notes: The dependent variable is green revenue in all columns. Innovation indicators are constructed based on patent count. *CleanTech* represents clean patent stock, measured by the cumulative stock of clean patents with a 15% yearly depreciation rate. *Spill_TechSpace*, *Spill_ProdSpace*, and *Spill_GeogSpace* denote clean technology pools of other firms weighted by technological proximity, product market proximity, and geographical proximity, respectively. All variables are measured in logarithms. All results focus on green firms. All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

clean technologies of other firms close in the geographical space. The muted effect of technology spillovers in the geographical space does not surprise us because global public firms in our sample have been strongly capable to access technology resources across different regions, and physical distance is a relatively unimportant obstacle for them.

Column (4) includes technology spillovers across all three spaces. Conditional on all clean technology spillovers, it further supports the evidence that a firm's green revenues are increased by clean technologies of other firms close in the technological space and product market space. The results when clean technologies are measured based on patent citations are presented in Table 3.B.1, which shows similar results as Table 3.3. In sum, the positive and statistically significant effects of firms' own clean innovation and others' technology spillovers imply the considerable private and social economic benefits of clean innovation.

3.4.2 Clean Technology Maturity

Clean technologies moving towards maturity may facilitate the commercialisation of these technologies and therefore generate more corresponding revenues. To examine the role of clean technology maturity, we add the maturity indicators constructed by Eq (3.5) to our regression.

Table 3.4 contains the results for clean technology maturity. Columns (1) and (3) have the technology maturity indicator based on firms' average patent age, and Columns (2) and (4) have the maturity indicator based on firms' average prior art (backward cited patent) age. In Columns (1) and (2), the estimated coefficients on clean technology maturity suggest that firms' green revenues are positively associated with the maturity of firms' clean technologies. Moreover, the results on the interaction terms of clean technology maturity with firms' own clean technologies and technology spillovers suggest that firms benefit more from technology maturity if these firms have more own clean technologies. Columns (3) and (4) measuring clean technologies by patent citation numbers also display a positive relationship between technology maturity and green revenue. The interaction terms between firms' own clean technologies and their technology maturity further support that if firms themselves more specialise in clean innovation, they benefit more from technology maturity. The consistent results in technology maturity indicate that observed growth in revenues from green goods and services is partly explained by the increasing maturity of clean technologies. Such growth in green revenues by firms' own technology maturity can be enhanced if firms own more clean technologies. The findings imply that the economic benefits of clean technologies also depend on the commercialisation of mature technologies.

3.4.3 Heterogeneity of Green Sector

Due to the variance in technical features and business models, certain green goods or services may benefit from clean technologies stronger than others. Hence, we explore the heterogeneity of the role played by clean technologies in different green sectors. To separate the effects across green sectors, we disaggregate the firm-year panel into a more granular firm-subsector-year level. We focus on three main green business fields: alternative energy (energy generation & energy equipment sectors in FTSE GR), energy efficiency (energy management and efficiency sector in FTSE GR), and sustainable transport (transport equipment sector in FTSE GR). The results are presented in Table 3.5, where the coefficients of technology quantity measures are shown in Panel A and quality measures in Panel B. We observe that a firm's green revenue is positively associated with its own clean technologies in all three fields. However, clean technologies of other firms only contribute to green revenues when firms are close in the product market space, and the spillovers via the technology space do not appear to be positively significant. These findings suggest that firms primarily benefit from others' technologies when they have a substantial overlap

Table 3.4: Clean Technology Maturity and Green Revenue

Dependent Variable:	Green Revenue			
Innovation Measured by:	Patent Count		Patent Citation	
Technology Maturity Measured by:	PatAge	BkwAge	PatAge	BkwAge
	(1)	(2)	(4)	(5)
CleanTech_{t-1}	-0.010	-0.029	0.011	-0.003
	(0.030)	(0.043)	(0.013)	(0.027)
$\text{Spill\_TechSpace}_{t-1}$	0.045**	0.045	0.037**	0.035
	(0.020)	(0.027)	(0.015)	(0.021)
$\text{Spill\_ProdSpace}_{t-1}$	0.052***	0.050***	0.044***	0.041***
	(0.007)	(0.007)	(0.006)	(0.006)
$\text{CleanTechMat}_{t-1}$	1.027***	0.744***	0.966***	0.753***
	(0.227)	(0.225)	(0.273)	(0.274)
$\text{CleanTech}_{t-1}\times\text{CleanTechMat}_{t-1}$	0.040**	0.045**	0.037***	0.035***
	(0.015)	(0.018)	(0.013)	(0.013)
$\text{Spill\_TechSpace}_{t-1}\times\text{CleanTechMat}_{t-1}$	-0.012	-0.007	-0.011*	-0.006
	(0.008)	(0.009)	(0.006)	(0.007)
$\text{Spill\_ProdSpace}_{t-1}\times\text{CleanTechMat}_{t-1}$	0.014	0.009	0.017	0.006
	(0.021)	(0.023)	(0.022)	(0.024)
Observations	19,996	19,996	19,996	19,996
Covered Firms	Green	Green	Green	Green
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y

Notes: The dependent variable is green revenue in all columns. Innovation indicators in Columns (1) and (2) are based on patent count, and in Columns (3) and (4) are based on patent citation. *CleanTech* represents clean patent stock, measured by the cumulative stock of clean patents with a 15% yearly depreciation rate. *Spill_TechSpace* and *Spill_ProdSpace* denote clean technology pools of other firms weighted by technological proximity and product market proximity, respectively. *CleanTechMat* is clean technology maturity, based on average patent age (*PatAge*) and backward prior art patent age (*BkwAge*), respectively. All variables are measured in logarithms. All results focus on green firms. All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

in green product markets within the broad fields of alternative energy, energy efficiency, and sustainable transport.[21]

3.4.4 Heterogeneity of Firm Characteristic

How much firms' green revenues can benefit from their own clean technologies and others' clean technologies may vary with firms' characteristics. Hence, we construct a series of sub-

[21] It is a caveat that the results of spillovers via the technology space in these three broad green business fields differ from the main findings of this paper. One possible explanation for this discrepancy is that the classification of green business fields in this heterogeneity analysis remains relatively broad and is potentially difficult to capture the inherent heterogeneity in more granular green business fields. For instance, the alternative energy field comprises approximately 10 distinct green subsectors in the data, each with its own market structure and innovation mode that could introduce additional heterogeneity that affects technology spillovers. Consequently, caution should be exercised in interpreting the current results of the heterogeneity analysis.

Table 3.5: Heterogeneity across Green Sectors

Dependent Variable:	Green Revenue		
	Alternative Energy (1)	Energy Efficiency (2)	Sustainable Transport (3)
Panel A: Innovation Measured by Patent Count			
CleanTech_{t-1}	0.214***	0.139***	0.526***
	(0.026)	(0.024)	(0.096)
$\text{Spill\_TechSpace}_{t-1}$	-0.008	-0.047**	-0.004
	(0.005)	(0.023)	(0.006)
$\text{Spill\_ProdSpace}_{t-1}$	0.051***	0.019***	0.078***
	(0.007)	(0.004)	(0.023)
Panel B: Innovation Measured by Patent Citation			
CleanTech_{t-1}	0.131***	0.086***	0.323***
	(0.013)	(0.013)	(0.071)
$\text{Spill\_TechSpace}_{t-1}$	-0.001	-0.027	0.003
	(0.003)	(0.017)	(0.005)
$\text{Spill\_ProdSpace}_{t-1}$	0.039***	0.015***	0.055***
	(0.005)	(0.004)	(0.017)
Observations	426,027	182,583	81,148
Firm Attributes	Y	Y	Y
Firm FE	Y	Y	Y
Industry-Year FE	Y	Y	Y
Country-Year FE	Y	Y	Y

Notes: The sample is disaggregated to the firm-subsector-year level (64 green subsectors). The dependent variable is green revenue in all columns. Innovation indicators in Panel A are based on patent count, and in Panel B are based on patent citation. *CleanTech* represents clean patent stock, measured by the cumulative stock of clean patents with a 15% yearly depreciation rate. *Spill_TechSpace* and *Spill_ProdSpace* denote clean technology pools of other firms weighted by technological proximity and product market proximity, respectively. Columns (1) to (3) show the results for alternative energy (energy generation and energy equipment sectors in FTSE GR), energy efficiency (energy management and efficiency sector in FTSE GR), and sustainable transport (transport equipment in FTSE GR), respectively. All variables are measured in logarithms. All results focus on green firms. All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

samples to examine the role of firm size and technology capacity in the relationship between green revenues and clean technologies. Table 3.6 presents the corresponding results.

We first divide firms into two groups based on their firm sizes: one group with market capitalisation higher than the median, and the other group with market capitalisation lower than the median. The corresponding results are shown in Columns (1) and (2). Comparing the estimated coefficients in the two columns, we find that large firms' green revenues can benefit more from their own clean patents, and technology spillovers from other firms close in the technological and product market spaces. In contrast, small firms do not benefit as much as large firms from their own or others' clean technologies.

We then separate firms by their technology capacities: one group with total patent stocks higher than the median, and the other group with total patent stocks lower than the

Table 3.6: Heterogeneity by Firms' Characteristics

Dependent Variable:	Green Revenue			
	Firm Size		Tech Capacity	
	Low	High	Low	High
Measure: Patent Count	(1)	(2)	(3)	(4)
CleanTech_{t-1}	0.027	0.073*	-0.094	0.056**
	(0.028)	(0.038)	(0.205)	(0.022)
$\text{Spill\_TechSpace}_{t-1}$	-0.006	0.032**	0.020	0.025
	(0.014)	(0.015)	(0.038)	(0.016)
$\text{Spill\_ProdSpace}_{t-1}$	0.079***	0.112***	0.083***	0.105***
	(0.012)	(0.012)	(0.019)	(0.008)
Observations	7,857	8,844	7,821	8,896
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y

Notes: The dependent variable is green revenue in all columns. Innovation indicators are based on patent count. *CleanTech* represents clean patent stock, measured by the cumulative stock of clean patents with a 15% yearly depreciation rate. *Spill_TechSpace* and *Spill_ProdSpace* denote clean technology pools of other firms weighted by technological proximity and product market proximity, respectively. Columns (1) and (2) divide the sample into two groups based on if firms' market capitalisation is higher or lower than the median. Columns (3) and (4) divide the sample into two groups based on if firms' total patent stock is higher or lower than the median. All variables are measured in logarithms. All results focus on green firms. All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

median. Columns (3) and (4) report the results. The coefficients in the two columns show that firms with higher technology capacities can benefit more from their own clean technologies, and the technology spillovers from other firms close in the product market space. The results in Table 3.6 echo the opinion that firms' complementary assets play an important role in how much firms can benefit from innovation (Teece, 1986; Pisano, 2006)

3.4.5 Robustness Checks

First, Bloom et al. (2013) (BSV) develops an alternative measure of technological proximity that takes into account the relatedness between different technology classes.[22] To examine whether our results are sensitive to different measures of technological proximity, we build upon BSV's method to construct the proximity in the technological space as:

$$w_{ijt}^{TechSpace} = CL_{ijt} \cdot TechProx_{ijt}^{BSV} = CL_{ijt} \cdot \frac{T_{it}\Omega T'_{jt}}{\sqrt{T_{it}T'_{it}}\sqrt{T_{jt}T'_{jt}}} \tag{3.8}$$

[22]One limitation of the technology spillover indicator based on the technological proximity by Jaffe (1986) is that it assumes the spillover only occurs within the same technology class, and rules out the possibility of spillover between different classes.

The relatedness between each pair of technology classes is captured by the additional $K \times K$ matrix Ω, where each element $\Omega_{uv} = \eta_u \eta_v'$ $(u, v = [1, K])$, in which $\eta_k = [T_{k1}, T_{k2}, ..., T_{kN}]$ represents the share of patents of technology class k across total N firms.[23] We re-estimate our models by using the BSV's technological proximity. The results for this robustness check are kept in Table 3.B.2, which provides very similar estimated coefficients to using our baseline Jaffe (1986)'s technological proximity.

Second, we employ alternative indicators of innovation to test the sensitivity of our results. Following prior research (Dernis and Khan, 2004; Palangkaraya et al., 2011; Probst et al., 2021), we use international patent families and triadic patent families to capture the value of clean patents instead. In other words, all variables of clean technologies are constructed by the stocks of international patent families and triadic patent families, respectively. The results for the two innovation indicators are presented separately in Columns (1) to (3) and (4) to (6) of Table 3.B.3. The magnitude and significance of the effects remain fairly stable compared to our previous results.

Third, some existing literature reinforces the idea that the effect of market competition may co-exist with technology spillovers (Qu et al., 2013; Banal-Estañol et al., 2022; Tseng, 2022). Hence, we rerun our regression models by adding an industry-country level Herfindahl-Hirschman Index to capture market concentration. The results for this robustness check are kept in Columns (1) and (2) in Table 3.B.4. None of these results changes our main conclusion.

Last, since clean innovation may take a longer time to produce green revenues, we estimate the regression models with a two-year lag of innovation variables. The results are reported in Columns (3) and (4) in Table 3.B.4. Although a further shrink of the sample size may undermine the solidity of our results, the coefficients of our interests still remain similar to our baseline results.

Overall, this series of robustness checks further supports our conclusion that firms' green revenues benefit from their own clean innovation and clean technology spillovers from other firms close in the technological and product market spaces.

[23] The proximity index by Jaffe (1986) is a particular case of the technology relatedness matrix when $\Omega = I$, where different technology classes are orthogonal rather than related to each other. The intuition behind the BSV's technology class relatedness matrix is that technology spillovers may exist between classes if firms specialise in these classes simultaneously.

3.5 Conclusion

In this paper, we investigate the role that clean innovation plays with respect to firms' revenues from green products. Measuring green revenues based on detailed information on commercial activities of global publicly listed firms, we show that firms' green revenues are overall trending up during our sample period, but the increasing green revenues do not alter the relative share between green and non-green business. Examining the relationship between firms' green revenues and clean innovation, we find that firms' green revenues are strongly and positively correlated with their own clean innovation. With further exploring clean technology spillovers across different spaces, the results show that firms' green revenues are enhanced by clean technologies of other firms close in the technological and product market spaces. The result of the spillovers across the product market space suggests a dominant position of the positive externalities from technology spillovers compared to the negative externalities from market-stealing effects. We also find evidence that firms with more mature clean technologies are able to derive higher green revenues. In addition, firms with larger sizes and higher technology capacities obtain more economic benefits from clean innovation. Our results are robust to alternative measures of innovation and spillovers and alternative settings of model specifications.

Our conclusion supports the implication that firms not only benefit from their own but also from others' clean innovation. The positive externality brought by clean technology spillovers is important to enhance the development and diffusion of clean technologies. The new evidence on the effects of firms' own innovation and technology spillovers across firms implies private benefits for innovators and social benefits beyond innovators from clean innovation. Therefore, strong policy support to clean innovation is needed to spread the economic benefits of clean technologies and achieve the green transition.

3.A Additional Figures

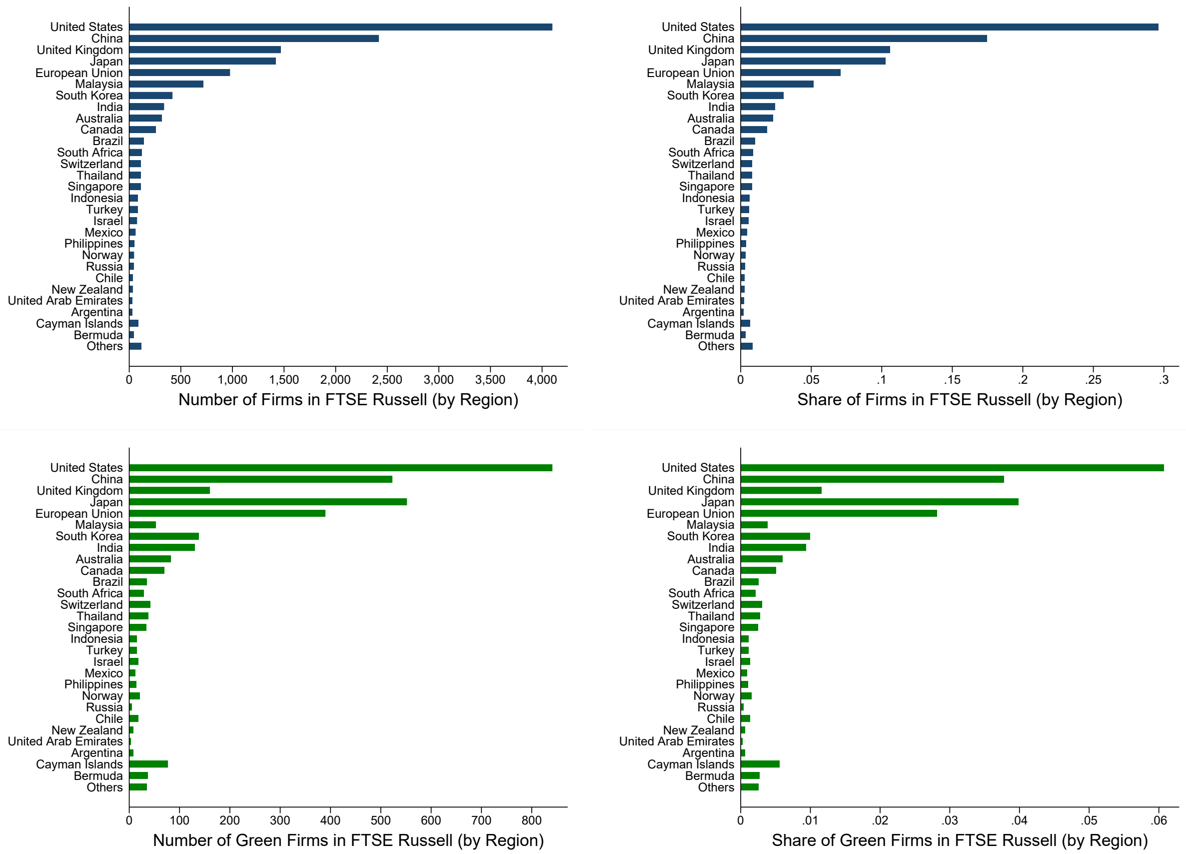


Figure 3.A.1: Geographic Distribution of Firms in FTSE Russell Dataset

Notes: The upper left panel presents the number of firms in each region. The upper right panel displays the proportion of firms in each region relative to the total number of firms in the FTSE Russell dataset. The lower left panel shows the number of firms identified as green firms in each region. The lower right panel exhibits the proportion of firms identified as green firms in each region relative to the total number of firms in the FTSE Russell dataset. It is worth noting that firms located in Cayman Islands and Bermuda are usually not for operating business in these two regions but only for the sake of tax avoidance due to their zero corporate tax rate.

3.B Additional Tables

Table 3.B.1: Estimation of Clean Technology Spillovers (measured by patent citation)

Dependent Variable:	Green Revenue			
Measure: Patent Citation	(1)	(2)	(3)	(4)
CleanTech_{t-1}	0.054**	0.062***	0.064***	0.051***
	(0.021)	(0.016)	(0.019)	(0.018)
$\text{Spill\_TechSpace}_{t-1}$	0.025***			0.026**
	(0.009)			(0.011)
$\text{Spill\_ProdSpace}_{t-1}$		0.077***		0.077***
		(0.008)		(0.008)
$\text{Spill\_GeogSpace}_{t-1}$			0.006	-0.007
			(0.008)	(0.011)
Observations	19,996	19,996	19,996	19,996
Covered Firms	Green	Green	Green	Green
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y

Notes: The dependent variable is green revenue in all columns. Innovation indicators are constructed based on patent citation. *CleanTech* represents clean patent stock, measured by the cumulative stock of clean patents with a 15% yearly depreciation rate. *Spill_TechSpace*, *Spill_ProdSpace*, and *Spill_GeogSpace* denote clean technology pools of other firms weighted by technological proximity, product market proximity, and geographical proximity, respectively. All variables are measured in logarithms. All results focus on green firms. All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 3.B.2: Robustness Checks for Alternative Spillover Measures (BSV)

Dependent Variable:	Green Revenue			
	Patent Count		Patent Citation	
	(1)	(2)	(3)	(4)
CleanTech_{t-1}	0.058**	0.066***	0.053**	0.051***
	(0.027)	(0.024)	(0.021)	(0.018)
$\text{Spill\_TechSpace(BSV)}_{t-1}$	0.035***	0.037**	0.026***	0.026**
	(0.012)	(0.016)	(0.009)	(0.011)
$\text{Spill\_ProdSpace}_{t-1}$		0.093***		0.077***
		(0.010)		(0.008)
Observations	19,996	19,996	19,996	19,996
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y

Notes: The dependent variable is green revenue in all columns. Innovation indicators in Columns (1) and (2) are based on patent count, and in Columns (3) and (4) are based on patent citation. *CleanTech* represents clean patent stock, measured by the cumulative stock of clean patents with a 15% yearly depreciation rate. *Spill_TechSpace* and *Spill_ProdSpace* denote clean technology pools of other firms weighted by technological proximity (BSV method) and product market proximity, respectively. All variables are measured in logarithms. All results focus on green firms. All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 3.B.3: Robustness Checks on Alternative Innovation Measures

Dependent Variable:	Green Revenue					
	International Patent Family			Triadic Patent Family		
	(1)	(2)	(3)	(4)	(5)	(6)
CleanTech_{t-1}	0.070***	0.087***	0.076***	0.071**	0.086***	0.079***
	(0.023)	(0.020)	(0.021)	(0.029)	(0.025)	(0.026)
$\text{Spill\_TechSpace}_{t-1}$	0.037***		0.040**	0.042***		0.042**
	(0.013)		(0.016)	(0.015)		(0.018)
$\text{Spill\_ProdSpace}_{t-1}$		0.096***	0.095***		0.104***	0.103***
		(0.010)	(0.010)		(0.011)	(0.011)
Observations	19,996	19,996	19,996	19,996	19,996	19,996
Firm Attributes	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y

Notes: The dependent variable is green revenue in all columns. Innovation indicators in Columns (1)-(3) are based on international patent family, and in Columns (4)-(6) are based on triadic patent family. *CleanTech* represents clean patent stock, measured by the cumulative stock of clean patents with a 15% yearly depreciation rate. *Spill_TechSpace* and *Spill_ProdSpace* denote clean technology pools of other firms weighted by technological proximity and product market proximity, respectively. All variables are measured in logarithms. All results focus on green firms. All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 3.B.4: Robustness Checks on Additional Control and Lag

Dependent Variable:	Green Revenue			
	Additional Control (HHI)		Alternative Lag (t-2)	
	Patent Count (1)	Patent Citation (2)	Patent Count (3)	Patent Citation (4)
CleanTech_{t-1}	0.067***	0.051***	0.055*	0.050**
	(0.024)	(0.018)	(0.028)	(0.020)
$\text{Spill\_TechSpace}_{t-1}$	0.028***	0.022***	0.041**	0.030**
	(0.010)	(0.008)	(0.016)	(0.012)
$\text{Spill\_ProdSpace}_{t-1}$	0.093***	0.077***	0.050***	0.042***
	(0.010)	(0.008)	(0.006)	(0.005)
$\text{HHI(Ind-Cnt)}_{t-1}$	1.391	1.457		
	(1.065)	(1.070)		
Observations	19,996	19,996	16,713	16,713
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y

Notes: The dependent variable is green revenue in all columns. Innovation indicators in Columns (1) and (3) are based patent count, and in Columns (2) and (4) are based on patent citation. *CleanTech* represents clean patent stock, measured by the cumulative stock of clean patents with a 15% yearly depreciation rate. *Spill_TechSpace* and *Spill_ProdSpace* denote clean technology pools of other firms weighted by technological proximity and product market proximity, respectively. HHI stands for Herfindahl-Hirschman Index, which is computed at the industry-country level. Columns (3) and (4) lag independent variables by two years. All variables except HHI are measured in logarithms. All results focus on green firms. All models incorporate firm control variables, firm fixed effects, industry-by-year fixed effects (SIC 2-digit) and country-by-year fixed effects. Standard errors in the parentheses are clustered at the industry (SIC 2-digit) level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Chapter 4

Knowledge Spillover from Green FDI: Evidence from Green Innovation in China

4.1 Introduction

China has undergone explosive growth in green industries such as solar and wind energy beginning in the early 2000s (Linster and Yang, 2018). The boom came as a surprise to many observers because most green industries in China only emerged in the late 1990s but rapidly rose to one of the world's largest markets within two decades.[1] The rapid expansion of China's green industries followed closely behind a large scale of opening up to foreign direct investment (FDI) after China joined the World Trade Organisation (WTO) in 2001 (Davies, 2013). The larger inflows of foreign investment facilitated Chinese domestic manufacturers to engage in multinationals' supply chains (Ueno, 2009). Along with industrial policies such as public procurement and local content requirement, foreign multinationals deepened the engagement of Chinese domestic firms in production and technology, which enhanced technology transfer to Chinese firms (Lema et al., 2011; Urban et al., 2012). Chinese domestic firms managed to gradually build up production capacities and develop indigenous innovation during the engagement with foreign multinationals (Fu and Zhang, 2011; Lema and Lema, 2012). Although many Chinese domestic manufacturers currently achieve their advantage even dominance in China's green industries, foreign direct investment still contributed to shaping China's green industries in the early phase and helping Chinese firms catch up with cutting-edge foreign green technologies.

[1] For example, the cumulative installed wind capacity in China was around 0.3 Gigawatts (GW) in 2000 but reached 44.7 GW and surpassed the United States as the globally largest wind energy market in 2010 (Ru et al., 2012). The cumulative installed photovoltaic (PV) capacity was around 0.7 GW in 2000 but rose to 180 GW in 2014 (Zhang and Gallagher, 2016).

However, there are two main challenges in identifying the contributions of FDI to green knowledge spillovers in the host countries. First, most existing literature on FDI and the environment regards FDI as generic and does not differentiate whether an FDI project involves clean and pro-environment investment. However, generic FDI includes much foreign investment that is irrelevant to environmentally-friendly commercial activities or even negatively contributes to environmental performance. Consequently, the analyses based on generic FDI contain considerable ambiguities in quantifying how much FDI can contribute to green knowledge spillovers in the host countries. Such ambiguities also partially explain why many previous studies on FDI and the environment obtain mixed results (Cole et al., 2017). Second, the relationship between domestic green innovation and knowledge spillovers from FDI is usually endogenous. The correlation results cannot quantify well the contributions to green knowledge spillovers by FDI as potential problems associated with omitted variables and reverse causality may bias the estimated magnitude of knowledge spillovers (Lu et al., 2017). To resolve current research challenges, I put forward new approaches of how to define "green FDI" (i.e., FDI involving environmentally-friendly commercial activities) based on the detailed information on FDI, and employ Chinese FDI opening-up policy as an exogenous shock to causally identify the knowledge spillovers effects of green FDI.

In this paper, I use a new Chinese firm-level dataset that combines detailed information on firms' innovation and received foreign investment during the period 2000-2013. The rich details of foreign direct investment allow me to more accurately identify foreign-invested firms (FDI firms) with environmentally-friendly commercial activities. Specifically, I develop four approaches to defining if foreign-invested firms involve environmentally-friendly commercial activities (green FDI firms) by text-mining the investment business description and tracking patenting activities in foreign-invested firms and foreign investors. Built upon the newly defined green FDI, I construct how much domestic firms are exposed to the knowledge stocks resulting from green FDI firms, and estimate the impact of knowledge stocks resulting from green FDI firms on the green innovation of domestic firms to capture the knowledge spillovers from green FDI. I separate knowledge stocks resulting from green FDI firms into three types based on the industrial linkage between domestic firms and green FDI firms: knowledge stocks resulting from green FDI firms in the same industry (horizontal industry), green FDI firms in downstream industries, and green FDI firms in upstream industries, to further distinguish the knowledge spillovers from different channels. To overcome the endogeneity in identification, I utilise the changes in the *Catalogue for the Guidance of Foreign Investment Industries*, capturing the openness of specific industries to

FDI in China, as an exogenous shock to construct instrumental variables for the knowledge stocks resulting from green FDI firms. The validity of the instrumental variables is further consolidated by controlling possible non-random selections of FDI openness and other causality paths through which the FDI policy changes affect domestic green innovation.

I find that there is a big discrepancy in green technologies between newly defined green FDI and other FDI, and such discrepancy cannot be explained well by other generic factors such as firm sizes or generic technologies. The result implies that considerable noise may be brought in when estimating the contributions of FDI to green knowledge spillovers if one only focuses on generic FDI but not exclusively on green FDI. Based on the new green FDI definitions, there is no evidence that green innovation of domestic firms benefits from knowledge stocks of green FDI firms within the same industry. In contrast, the results show that a 1% increase in the knowledge stocks of green FDI firms in downstream industries contributes to around 0.732% increase in green patents of domestic firms, which indicates the knowledge spillovers from downstream green FDI. The positive impacts of downstream green FDI firms' knowledge imply that domestic firms benefit from knowledge stocks of green FDI firms by becoming suppliers to green FDI firms. Moreover, the knowledge spillovers from downstream green FDI mainly boost most innovative patents (i.e., invention patents). Further evidence on patent citations also supports the positive spillover effects on the quality of green innovation. Breaking down technological fields, the positive knowledge spillover effects of green FDI appear to be more pronounced for domestic innovation in alternative energy and sustainable transportation. In addition, I further examine the possible mechanisms for the knowledge spillover effects of downstream green FDI. The findings suggest that green FDI firms located in the same regions as domestic firms appear to generate more pronounced knowledge spillovers than green FDI firms located in different regions. The closer technological proximity between industries facilitates knowledge spillovers from downstream green FDI firms to domestic firms. I also find higher stringency of environmental regulations in green FDI origin countries enhances knowledge spillovers in the host countries. Most results survive under a bunch of robustness checks.

This paper contributes to the literature on how to define and measure green FDI. There is so far little discussion on the definitions of green FDI, though a few policy discussions raise some rough guidelines of the definitions, such as FDI related to environmentally-friendly sectors, mitigation of climate damage, or research and production of clean goods and services (Golub et al., 2011; UNCTAD, 2016; Johnson, 2017). However, these guidelines do not provide concrete approaches to green FDI definitions. Several previous empirical studies made pioneering efforts to distinguish green FDI. For example, Glachant and Dechezleprêtre (2017) and Dussaux et al. (2017) define low-carbon FDI based on whether foreign investing firms own at least one low-carbon patent. Castellani et al. (2022) defines green-tech FDI as the cross-border investment occurring in sectors that are most specialised in green technologies. A major constraint with these definitions is that they only use indirect proxies but do not directly capture the characteristics of FDI projects. Considerable measurement errors of green FDI may be included due to the ambiguities of the green FDI measures.[2] I develop four new definitions of green FDI built upon the previous efforts. The new definitions focus on the characteristics of FDI projects, including FDI firms' business description with keywords related to environmentally-friendly activities, FDI firms' green patenting activities, prior arts of FDI firms' patents, and FDI firms' investor patenting activities. The newly defined green FDI more accurately captures the FDI that is likely to involve green knowledge spillovers.

This paper also relates to the extensive literature on FDI and domestic production, innovation and environmental performance in the host countries. Earlier studies such as Aitken and Harrison (1999) raise the point that domestic firms may enjoy a positive spillover effect but also suffer from a negative competition effect brought by FDI. The mixed effects of FDI stimulate a strand of following research exploring the relationship between FDI and domestic firms' output (Liang, 2017), productivity (Javorcik, 2004), R&D (Sun et al., 2021), export (Bajgar and Javorcik, 2020), and product upgrade (Javorcik et al., 2018; Bai et al., 2020). Moreover, not consistent with the conventional pollution haven hypothesis, more empirical research on FDI and the environment finds that FDI can contribute to the domestic environmental performance by improving corporate social responsibility (Kellenberg, 2009; Poelhekke and Van der Ploeg, 2015) and energy efficiency (Brucal et al., 2019). This paper extends to examining the impacts of FDI knowledge spillovers on domestic green innovation performance and attempts to differentiate the channels of knowledge spillovers.

Finally, this paper adds to a strand of burgeoning literature that identifies the impacts of FDI spillovers. Many earlier studies on FDI produce correlation evidence, but this raises concerns about the reliability of the results and drives more focus on proper identification strategies that provide causality evidence. Several new identification strategies are put forward including merge and acquisition (M&A) (Guadalupe et al., 2012), export orientation (Crescenzi et al., 2015), joint venture partner (Jiang et al., 2018), geographic distance (Lin

[2] For example, an FDI project in China invested by Siemens, which owns a variety of clean energy related patents around the world, may be a manufacturing factory producing household appliances irrelevant to clean energy. Moreover, although the household appliance sector overall involves a decent level of green specialisation (e.g., energy-saving appliances), a specific FDI project in this sector does not necessarily specialise in energy-saving appliances.

et al., 2021), and FDI regulations (Lu et al., 2017; Chen et al., 2022). However, most of the current identification strategies are targeted at generic FDI or a few individual FDI cases. Built upon the identification strategy put forward by Lu et al. (2017), I utilise the changes in FDI opening-up policy in China and develop an instrumental variable specifically for green FDI. I further discuss the potential concerns in the validity of this instrumental variable and the corresponding methods to relieve the concerns.

The rest of this paper is organised as follows. Section 4.2 describes the data and the key measures used in this study. Section 4.3 presents the identification strategy and discusses the potential challenges to the identification. Section 4.4 reports the main empirical results, robustness checks, results for innovation heterogeneity, and discussions on mechanisms of green FDI knowledge spillovers. Section 4.5 concludes.

4.2 Data and Measures

4.2.1 China's Industrial Firms

The main firm-level panel data is from the Annual Survey of Industrial Enterprises (ASIE), conducted by the National Bureau of Statistics of China. This survey covers all state-owned enterprises and non-state-owned enterprises in China with annual sales above 5 million Yuan (around US$ 620000), involving mining, manufacturing and public utility sectors. Abundant firm-level fundamental, operation and financial information are included, such as identification number, 4-digit industry code, location code, output, sales, asset, employment, wage, export, and ownership. The dataset used in this paper spans the period 2000-2013.

There are some caveats to using this data. First, the industry classification during the sample period was modified from the version GB/T 4754-1994 (adopted during 1994-2001) to GB/T 4754-2002 (adopted during 2002-2010) and finally to GB/T 4754-2011 (adopted during 2011-2016). To address this issue, I link the three classifications and develop a consistent classification system throughout my entire sample period.[3] Second, some firms re-appear in the data after several years of missing. To avoid the possible impacts of the inconsistency of the data collection, I drop firms with missing observations for three consecutive years. Third, I drop observations where firms' identification number, location code and industry code are missing as the missing information affects the merge of datasets and construction of variables.

[3] Brandt et al. (2012) have constructed a concordance table that well links GB/T 4754-1994 to GB/T 4754-2002. I follow their process and extend the linkage to the version GB/T 4754-2011.

4.2.2 Green Innovation

Firms' innovation is measured by patenting activities in this study. I retrieve Chinese patent data from the China National Intellectual Property Administration (CNIPA), which has full coverage of all patent applications and publications filed in China since 1985. The CNIPA provides detailed bibliographic information on each patent, including applicants, application and publishing number, application and publishing date, and the International Patent Classification (IPC) code. In addition, I complement the information on patent priority, patent claim, patent citation, and Cooperative Patent Classification (CPC) code by the EPO Worldwide Patent Statistical Database (PATSTAT), which is the largest global patent database covering all of the world's major patent offices.

There are two widely-used definitions of green patents: (1) The IPC Green Inventory, developed by the World Intellectual Property Organization (WIPO)'s IPC Committee of Experts. The IPC Green Inventory covers a list of IPC codes that are closely relevant to environmentally sound technologies. (2) The Y02 category in the Cooperative Patent Classification (CPC) system, which tags technologies with contributions to climate change adaptation and mitigation (Haščič and Migotto, 2015). To have more comprehensive coverage of green technologies, I identify patents pertaining to green technologies by combining the two definitions, where a patent is green if either its IPC lies in the IPC Green Inventory or its CPC belongs to the Y02 category.

In the raw Chinese patent data, one patent innovation may correspond to multiple patent applications when they cover several different patent claims. To avoid double-counting of patents, I aggregate patent applications to the patent family level (DOCDB family code by PATSTAT), which identifies a group of patent applications that derive from the same patent innovation.[4]

4.2.3 Green Foreign Direct Investment

Although the dataset from ASIE includes information on firms' ownership, it only provides the share of ownership by state, foreign, and other domestic private entities. The lack of details on FDI creates a large barrier to differentiating the specific features of FDI and identifying green FDI accordingly. Therefore, I further retrieve the details of foreign-invested firms archived by The Ministry of Commerce of China, which fully covers FDI establishment and modification in China during 1980-2016 and records fundamental information

[4]The time dimension of each patent family is the patent priority year, which is the year when the earliest application in the patent family is filed.

such as names of firms receiving foreign direct investment, type of FDI, investors, investment amount, the origin of country, and text description of business scope. These details of FDI records allow me to identify green FDI more accurately.

Although there is currently no consensus on the green FDI definition, a green FDI is generally deemed to involve environmentally-friendly commercial activities, including production, operation or technology transfer in the mitigation of pollution and climate change (Golub et al., 2011; UNCTAD, 2016; Johnson, 2017). Accordingly, I developed four new approaches to defining which foreign-invested firm is green FDI.

Text description of foreign-invested firms' business. First, I take advantage of the text description of each foreign-invested firm's business scope and define a foreign-invested firm as a green FDI firm if its business scope includes keywords related to environmental governance, clean production, clean energy, or green technology.[5] The text of business scope disclosed by FDI displays the business focus of each FDI firm and helps to detect whether a foreign-invested firm involves in environmentally-friendly commercial activities.

Green patents in foreign-invested firms. Second, I employ the patenting activities of foreign-invested firms and identify a foreign-invested firm as a green FDI firm if it files green patents in China. To relieve the concern that green patents derive from a firm's pre-existing knowledge rather than new knowledge brought in by FDI, only green patents that are filed after foreign investment enters the firm are counted. The existence of new green patenting activities after foreign investment enters helps to capture whether a foreign-invested firm acquires new green knowledge from foreign investment.

Prior arts of green patents in foreign-invested firms. One may question that green patents in foreign-invested firms may be mainly driven by domestic knowledge outside the foreign-invested firms and do not convincingly demonstrate green technology transfers via foreign investment. To respond to this concern, I further trace the prior arts of green patents in each foreign-invested firm and define a foreign-invested firm as a green FDI firm if its green patents cite prior arts invented outside China. The prior arts of FDI firms' green patents indicate where the knowledge enclosed in the green patents originates from and helps to further demonstrate that the new green knowledge of foreign-invested firms derives from foreign investment.

Green patents of foreign investors. In the fourth approach, I focus on patenting activities of foreign investors and define a foreign-invested firm as a green FDI firm if

[5] To obtain a more precise result of keyword searching, I break down environmentally-friendly commercial activities into more than 200 keywords, which are shown in Table 4.A.1.

the firm's foreign investors have filed green patents in China. If foreign investors intend to utilise their existing technologies in China, they may file new applications of these technologies to the Chinese patent office to better protect the intellectual property rights of these technologies in China. This approach may capture stronger evidence of green technology transfers to China, though some technology transfers may be omitted as foreign investors probably resort to other ways rather than new patent applications to protect their existing technologies.

Figure 4.1 compares the performance of identifying green FDI by different approaches. The value in the left panel of the figure displays the ratio of foreign-invested firms defined as green FDI firms to all foreign-invested firms in China.[6] The value in the right panel is the average stock of green patents (depreciation rate 15%) owned by green FDI firms. The first definition (based on the text description of foreign-invested firms' business scope) achieves the largest coverage of green FDI firms (about 13% of all foreign-invested firms), while these green FDI firms have relatively lower green patent stocks compared to other green FDI definitions. The second definition (based on green patents in foreign-invested firms) extracts a slightly lower number of green FDI firms (about 12% of all foreign-invested firms) because it excludes the FDI firms operating in green commercial activities but not filing green patents. The third definition (based on prior arts of green patents in foreign-invested firms) narrows down to the FDI firms with stronger evidence of cross-border green technology transfers. Only focusing on green FDI firms that have green patents originating from foreign knowledge extracts the foreign-invested firms with higher specialisation in green innovation, though at the expense of a lower coverage of firms identified as green FDI. The fourth definition (based on green patents of foreign investors in China) does not perform well in identifying green FDI with respect to the coverage of FDI firms and the level of green patent stocks. One possible reason for the poor performance of the fourth definition is that foreign investors' green knowledge is not necessarily transferred via publicly filing and using patents in the host countries but in less conspicuous or codifiable channels such as trade secrets, technical specialists, or management experience.

In addition, I also compare the performances when using combinations of different green FDI definitions. The overlap of green FDI identified by the first and second definitions extracts a smaller pool of foreign-invested firms but ensures the identified green FDI firms have a higher level of specialisation in green technologies. The combinations of the first and third or fourth definitions similarly lead to a lower firm coverage while a higher green

[6] Figure 4.1 is drawn based on cross-section data in 2007, but the performances are very similar in other years during the sample period.

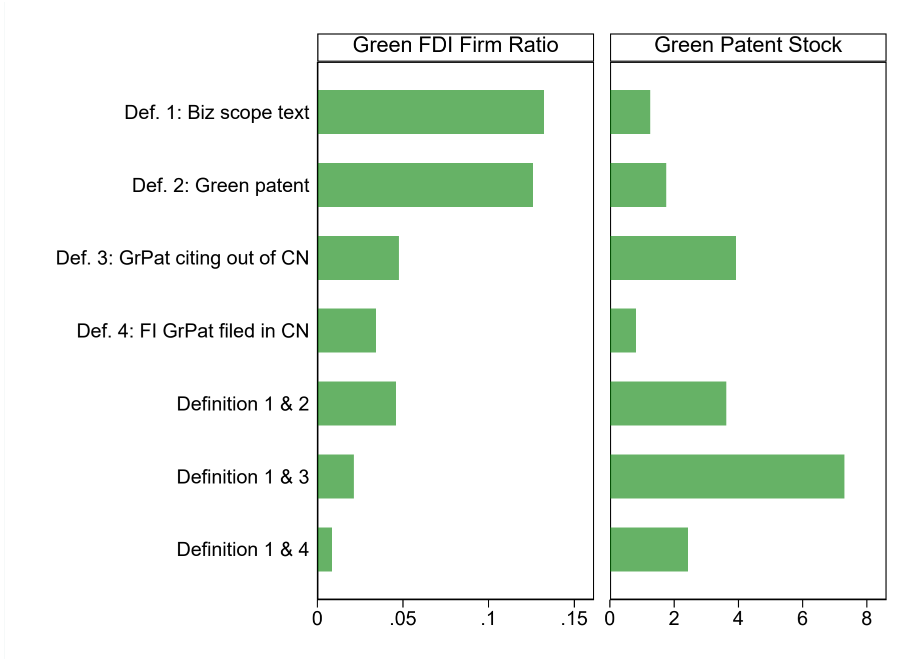


Figure 4.1: Comparison of Different Green FDI Definitions

Notes: The value in the left panel is the ratio of foreign-invested firms defined as green FDI firms to all foreign-invested firms in China. The value in the right panel is the average stock of green patents (depreciation rate 15%) owned by green FDI firms. Green FDI definition 1 is whether the text description of FDI firms' business scope includes keywords related to environmental governance, clean production, clean energy, or green technology (Def. 1: Biz scope text). Green FDI definition 2 is whether FDI firms own green patents (Def. 2: Green patent). Green FDI definition 3 is whether FDI firms own green patents that cite prior arts from foreign countries outside China (Def. 3: GrPat citing out of CN). Green FDI definition 4 is whether FDI firms' foreign investors have filed green patents in China (Def. 4: FI GrPat filed in CN). Definition 1 & 2 indicates the intersection of Green FDI definitions 1 and 2. Definition 1 & 3 indicates the intersection of Green FDI definitions 1 and 3. Definition 1 & 4 indicates the intersection of Green FDI definitions 1 and 4.

technology level of green FDI. Overall, using text description of FDI business scope helps to have the largest coverage of FDI firms involving environmentally-friendly commercial activities, while using patenting activities of FDI firms is conducive to capturing FDI specialisation in green technologies and possible technology transfers.

This study uses the first approach (keywords searching in the text description of foreign-invested firms' business) to define whether a foreign-invested firm is green FDI because environmentally-friendly commercial activities cover the transfers in green technologies and provide a business basis for possible green technology transfers. In contrast, green FDI definition based on patent activities may not reflect well the business focus of a foreign-invested firm even if this firm owns a few green patents.[7] Although the first definition of

[7]Since there is currently no consensus on green FDI definition in both academic and policy research, more discussions on how to properly define green FDI are still strongly needed.

green FDI is used in the main analysis, other alternative definitions of green FDI are also examined in robustness checks.

Figure 4.2 compares foreign-invested firms identified as green FDI firms and other foreign-invested firms (non-green FDI firms). The four graphs reveal the differences between green FDI and non-green FDI firms with respect to economic and technological characteristics. The generic factors such as the size of assets, size of labour, or overall technology capacities still cannot explain well the huge discrepancy of green technologies between green and non-green FDI firms.[8] Hence, only focusing on generic FDI in analyses, even controlling generic factors, may bring considerable noise in estimating the contributions of FDI to green knowledge transfer in the host countries. By developing specific definitions of green FDI, this paper can remove the noise from non-green FDI and refine the estimation of how much FDI contributes to green knowledge spillovers in China.[9]

4.2.4 FDI Opening-up Policy in China

Which industry is opened up to FDI and how much the opening-up is allowed in China are regulated by the *Catalogue for the Guidance of Foreign Investment Industries*, compiled by the National Development and Reform Commission and Ministry of Commerce of China. Since the first edition of the Catalogue appeared in 1995, the Catalogue was modified every few years to adapt to the need of the increasingly globalised Chinese economy. Figure 4.3 displays the timeline of the Catalogue that develops from the first edition to the seventh edition. Each new edition of the Catalogue contains the modifications of which products become more open to FDI and which ones become less open. The several modifications of the Catalogue offer a series of policy shocks that can be used as an instrumental variable and help to identify the knowledge spillovers from green FDI. Since the sample period covers 2000-2013, this study takes advantage of the FDI changes in the 3rd edition (2002), 4th edition (2004), 5th edition (2007), and 6th edition (2011).

As displayed in Figure 4.3, the Catalogue regulates FDI opening-up at the product level and classifies products into four categories: (1) Products where FDI is supported; FDI in such products enjoys preferential investment policies such as tax credits, the lower interest

[8] The abnormal drop in firms' assets in 2010 is probably caused by the measurement issues of production and financial variables including output, asset, sales, wages, and material inputs in the data compilation of ASIE for 2010 by the National Bureau of Statistics of China (Brandt et al., 2014). However, the key dependent and independent variables in this paper are constructed by the information on innovation and foreign direct investment, which are not built upon ASIE. Hence, the potential measurement issues in the data of ASIE for 2010 do not influence the estimations in this paper.

[9] The definition of green FDI used in Figure 4.2 is based on the first approach, i.e., text description of FDI firms' business. There are much larger discrepancies in green technologies between green and non-green FDI firms when using other green FDI definitions.

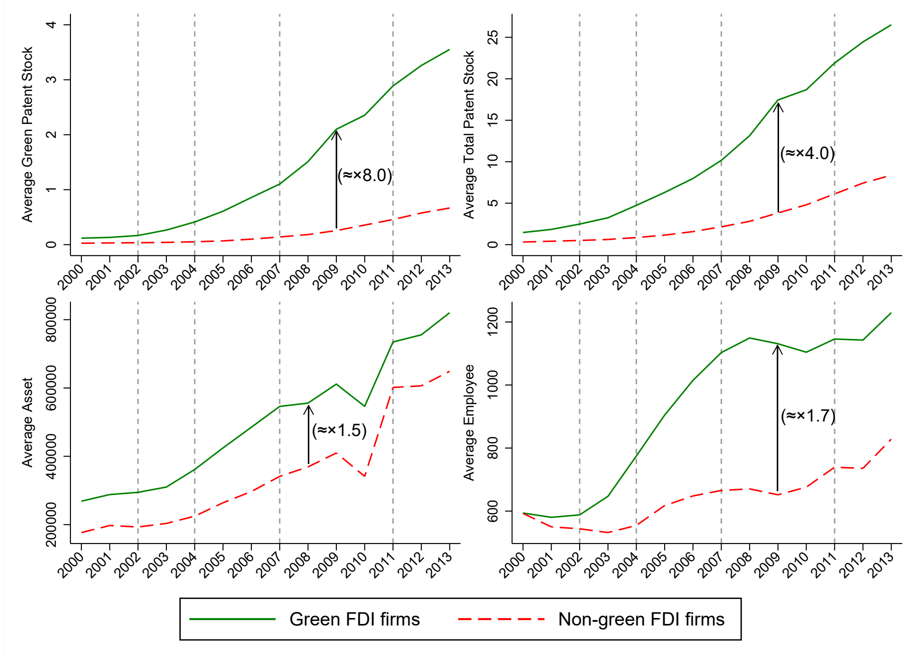


Figure 4.2: Green FDI vs. Non-green FDI

Notes: The four plots present the trends of the average green patent stock, average total patent stock, average asset, and average employee of green FDI firms (solid) and non-green FDI firms (dash). The four vertical lines indicate the time points of the four waves of FDI opening-up policy changes: 3rd Edition FDI Catalogue published in 2002, 4th Edition FDI Catalogue published in 2004, 5th Edition FDI Catalogue published in 2007, 6th Edition FDI Catalogue published in 2011. Each updated edition opened up more products and industries to FDI. Further details of the FDI opening-up policy changes are discussed in Section 4.2.4.

of loans and the cheaper land rents. (2) Products where FDI is permitted; FDI in such products is not subject to extra restrictions. (3) Products where FDI is restricted; FDI in such products is subject to restrictions such as ownership limits or more scrutiny. (4) Products where FDI is prohibited; FDI in such products are completely banned. FDI is most welcome in product category (1) while least welcome in product category (4).

By comparing each edition of the Catalogue, I can identify whether a product becomes more open or less open to FDI. According to the changes in FDI opening-up regulations at the product level, there are three possible scenarios for each product during each modification of the Catalogue: (1) FDI becomes more open, i.e., a product is changed from a less FDI-welcome to a more FDI-welcome category. (2) FDI becomes less open, i.e., a product is changed from a more FDI-welcome to a less FDI-welcome category. (3) No change in the openness to FDI, i.e., a product does not have any change in the openness to FDI before and after a modification of the Catalogue. Since this study focuses on green FDI, I identify products relevant to environmental governance, clean production, clean energy or green technology as green products based on the Catalogue. Each green product is classified into the three possible scenarios of the change in FDI openness according to the modification of four Catalogue versions (3rd to 6th edition) during 2000-2013.

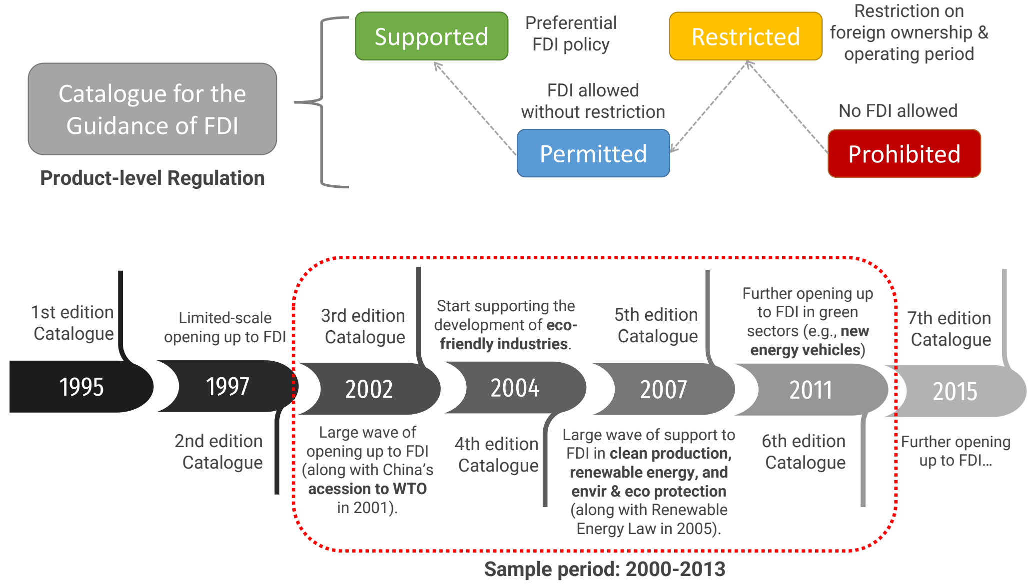


Figure 4.3: FDI Opening-up Policy Change in China

Notes: The Catalogue classifies products into four categories: FDI in "supported" category can enjoy preferential investment policies, FDI in "permitted" category is not subject to restrictions, FDI in "restricted" category is subject to extra investment restrictions, and FDI in "prohibited" category is not allowed. In each wave of the Catalogue update, a large number of products are moved from a less FDI-welcome category to a more FDI-welcome category, while very few products are moved from a more FDI-welcome category to a less FDI-welcome category. Our sample period (2000-2013) covers four waves of the Catalogue update (3rd, 4th, 5th, 6th edition Catalogue).

However, the changes in the Catalogue are at the product level, while the firm-level data by ASIE do not provide detailed product information of each firm but only industry classifications.[10] Hence, I need to aggregate the changes in FDI opening-up regulations from the product level to the industry level. Following Lu et al. (2017), I use the Industrial Product Catalogue from the National Bureau of Statistics of China to map each product classification to the four-digit industry classification. It is worth noting that multiple products from the Catalogue may be mapped to one industry classification. Hence, the aggregation process generates four industry categories during each modification of the Catalogue:

(1) Green FDI No-change Industry: All green products mapped to the industry keep unchanged in the openness to FDI.

(2) Green FDI Encouraged Industry: For all green products belonging to the industry,

[10]Product classifications in the Catalogue for the Guidance of Foreign Investment Industries are more disaggregated than the four-digit Chinese industry classifications.

there is at least one green product becoming more open to FDI, while no green products becoming less open to FDI.

(3) Green FDI Disencouraged Industry: For all green products belonging to the industry, there is at least one green product becoming less open to FDI, while no green products becoming more open to FDI.

(4) Green FDI Mixed Industry: For all green products belonging to the industry, there is at least one green product becoming more open to FDI, while also at least one green product becoming less open to FDI.

Figure 4.4 visualises the definition of four industry categories in a Catalogue change. Since this study covers four waves of the Catalogue changes, first, I only designate an industry as "Green FDI No-change Industry" only when all green products mapped to the industry keep unchanged in the openness to FDI throughout the four waves of the Catalogue changes. Second, an industry is classified as "Green FDI Encouraged Industry" only after at least one green product mapped to the industry becomes more open to FDI in one modification of the Catalogue, while no green product becomes less open to FDI in all later modifications of the Catalogue. Third, an industry is classified as "Green FDI Disencouraged Industry" only after at least one green product mapped to the industry becomes less open to FDI in one modification of the Catalogue, while no green product becomes more open to FDI in all later modifications of the Catalogue. All other industries are assigned to "Green FDI Mixed Industry".

Among the 506 four-digit Chinese industries, 293 industries do not contain any green products or contain green products that do not change the openness to FDI throughout the sample period, categorised as "Green FDI No-change Industry"; 192 industries contain green products that become more open to FDI while no green products that become less open to FDI throughout the sample period, categorised as "Green FDI Encouraged Industry"; 21 industries are categorised as "Green FDI Disencouraged Industry" or "Green FDI Mixed Industry".[11] Since this study mainly focuses on the knowledge spillover effect of green FDI on green innovation of domestic firms, the analysis only includes "Green FDI No-change Industry" and "Green FDI Encouraged Industry" and excludes the other two industry groups.

[11] Each wave of the modification of the Catalogue for the Guidance of Foreign Investment Industries since 2002 is basically opening up more products to FDI because of the commitments made by the Chinese central government for the accession to WTO in 2001. Therefore, there are very few industries categorised as "Green FDI Disencouraged Industry" and "Green FDI Mixed Industry".

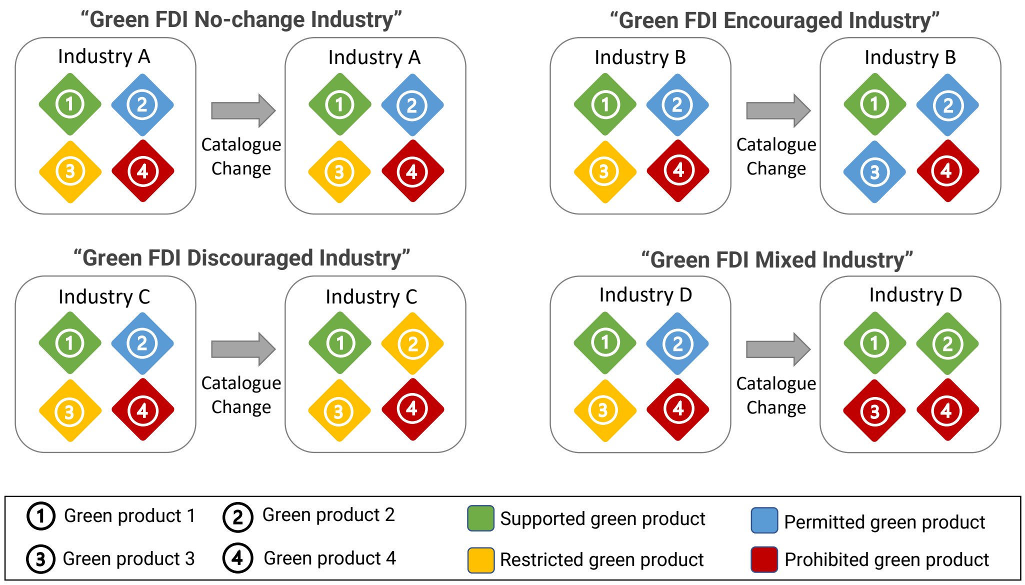


Figure 4.4: FDI Policy Change Aggregation from a Product Level to an Industry Level

Notes: This figure illustrates how to define the "Green FDI No-change Industry", "Green FDI Encouraged Industry", "Green FDI Disencouraged Industry", and "Green FDI Mixed Industry" based on the change of FDI openness at the product level during a wave of the Catalogue change. An industry is defined as "Green FDI No-change Industry" if all green products mapped to the industry keep unchanged in the openness to FDI. An industry is defined as "Green FDI Encouraged Industry" if it includes at least one green product becoming more open to FDI while no green product becoming less open to FDI. An industry is defined as "Green FDI Disencouraged Industry" if it includes at least one green product becoming less open to FDI while no green product becoming more open to FDI. An industry is defined as "Green FDI Mixed Industry" if it includes at least one green product becoming more open to FDI while at least one green product becoming less open to FDI. "More open to FDI" stands for a product is changed from a less FDI-welcome to a more FDI-welcome category (e.g., from restricted to permitted), and "less open to FDI" stands for a product is changed from a more FDI-welcome to a less FDI-welcome category (e.g., from restricted to prohibited).

4.3 Empirical Strategy

4.3.1 Econometric Specification

In most FDI literature, the spillover effect of FDI is tested by estimating the relationship between the presence of foreign-invest firms in the host countries and the performance of other domestic firms (Aitken and Harrison, 1999; Javorcik, 2004). Following this idea, I start with the regression model that examines whether green innovation of domestic firms is enhanced by the knowledge stocks resulting from green FDI firms.[12] More specifically,

[12] One implied assumption of this specification is that green FDI brings new knowledge to foreign-invested firms, and then the knowledge stocks in those foreign-invested firms spread to other domestic firms and promote domestic green innovation. Such assumption is tested and reported in Table 4.A.2, where the results show that the entry of green FDI leads to more green innovation in foreign-invested firms except using the fourth definition of green FDI.

for domestic firm f in four-digit industry i located in province p at year t, the baseline model is:

$$E[Y_{fipt}|GrFDIKnow_{it}, X_{ft}] = exp(\beta_0 + \beta_1 GrFDIKnow_{it} + \beta_2 X_{ft} + \gamma_f + \lambda_t + \delta_i + \eta_p), \tag{4.1}$$

where Y_{fipt} denotes green innovation of domestic firm f in industry i, province p and year t, measured by the number of green patent families filed in China in the main results.[13] Domestic firm f includes firms that are only invested by domestic investors in China and do not contain any foreign-invested firms. X_{ft} is a vector of time-varying firm characteristics, including asset, employee, and sales revenue. γ_f, λ_t, δ_i and η_p denote firm, year, industry, and province fixed effects. The standard errors are clustered at the four-digit industry level. Since the dependent variable Y_{fipt} is a count variable, I use the conditional fixed effects Poisson regression (FE Poisson) and compute coefficients by Poisson Pseudo Maximum Likelihood (PPML) estimators.

$GrFDIKnow_{it}$ is the main regressor of interest, which consists of three indicators that capture how much the domestic firms in industry i are exposed to the knowledge from green FDI firms that belong to the same industry i, the downstream industries of i, and the upstream industries of i, respectively. First, the exposure of domestic firms to the knowledge from green FDI firms within the same industry i is measured by the aggregation of knowledge stocks of green FDI firms operating in industry i (named as "horizontal green FDI knowledge stocks"). Specifically, for industry i at year t, it is constructed as:

$$GrFDIKnow_{it}^{Hori} = \sum_{j \; for \; all \; j \in i} I(GrFDI_{jt}) \times GrPatStock_{jt}, \tag{4.2}$$

where $I(GrFDI_{jt})$ is a binary indicator equalling one if foreign-invested firm j received green FDI at year t or before (i.e., green FDI firms), and zero otherwise. $GrPatStock_{jt}$ is the stock of green patents filed by foreign-invested firm j, adjusted with a 15% yearly depreciation rate (Hall et al., 2005). The summation of $I(GrFDI_{jt}) \times GrPatStock_{jt}$ within industry i aggregates green patent stocks of all foreign-invested firms that have received green FDI up to year t (i.e., green FDI firms).[14]

[13] Other green patent measures are used in the discussion on innovation heterogeneity, including the number of green invention patent families, the number of green utility patent families, the number of forward citations received by green patent families, the number of green patent families cited by patents outside China, and the number of patent family in the fields of alternative energy, sustainable transportation, and energy conservation.

[14] The term $I(GrFDI_{jt}) \times GrPatStock_{jt}$ reflects the stock of green patents filed by foreign-invested firm j at year t given that firm j has received green FDI up to year t. If a foreign-invested firm j has not received green FDI up to year t, $I(GrFDI_{jt}) \times GrPatStock_{jt}$ would be zero. In other words, the summation does

Second, the exposure of domestic firms in industry i to the knowledge from green FDI firms that belong to the downstream industries of i can help to capture how much domestic firms can benefit from the knowledge of downstream green FDI. Built upon Javorcik (2004), for domestic firms in industry i, such exposure is measured by the weighted aggregation of knowledge stocks of green FDI firms operating in all downstream industries of i (named as "downstream green FDI knowledge stocks"). For industry i at year t, it is constructed as:

$$GrFDIKnow_{it}^{Down} = \sum_{k\,if\,k\neq i} \alpha_{ik} GrFDIKnow_{kt}^{Hori} \tag{4.3}$$

where k stands for a downstream industry of industry i. $GrFDIKnow_{kt}^{Hori}$ is the knowledge stocks of green FDI firms operating in i's downstream industry k at year t. As one industry i can have multiple downstream industries, the knowledge stocks of green FDI firms in each downstream industry need to be further aggregated to measure the total exposure of domestic firms in industry i to knowledge from downstream green FDI. The weight α_{ik} determines the importance of each downstream industry k to industry i's selling activities, representing the share of industry i's output supplied to its downstream industry k.

Third, for domestic firms in industry i, their exposure to the knowledge of upstream green FDI can be measured by the weighted aggregation of knowledge stocks of green FDI firms operating in all upstream industries of i (named as "upstream green FDI knowledge stocks"). Similarly, such exposure can be constructed as:

$$GrFDIKnow_{it}^{Up} = \sum_{m\,if\,m\neq i} \beta_{im} GrFDIKnow_{mt}^{Hori} \tag{4.4}$$

where m stands for an upstream industry of industry i. $GrFDIKnow_{mt}^{Hori}$ is the knowledge stocks of green FDI firms operating in i's upstream industry m at year t. Similar to the previous case in Eq (4.3), since one industry can have multiple upstream industries, the knowledge stocks of green FDI firms in each upstream industry need to be further aggregated to measure the total exposure of domestic firms in industry i to knowledge from upstream green FDI. The weight β_{im} is used to determine the importance of each upstream industry m to industry i's purchase activities, representing the share of industry i's input purchased from its upstream industry m. The input-output linkage between industries is obtained from China's 2007 Input-Output Table.[15]

not take into account the green patent stocks of foreign-invested firms that have not received green FDI up to year t, as their $I(GrFDI_{jt}) \times GrPatStock_{jt}$ are zero.

[15] The inter-industry Input-Output Table in China is published every five years. Considering the sample period covers 2000-2013, this study uses the input-output information in the middle point of the sample period in the analysis.

$GrFDIKnow_{it}$ represents $GrFDIKnow_{it}^{Hori}$, $GrFDIKnow_{it}^{Down}$, and $GrFDIKnow_{it}^{Up}$. Hence, the coefficient β_1 in Eq (4.1) captures the relationship between domestic firms' green innovation and knowledge stocks of green FDI firms that belong to the same industry i, to industry i's downstream industries, and to industry i's upstream industries, respectively. However, this relationship cannot be interpreted as the impacts of green FDI yet as $GrFDIKnow_{it}^{Hori}$, $GrFDIKnow_{it}^{Down}$, and $GrFDIKnow_{it}^{Up}$ are not uncorrelated with the error term, even conditional on a group of control variables and fixed effects.[16]

To tackle the endogeneity issue, inspired by Lu et al. (2017), I resort to the variations across industries in the changes of FDI opening-up policy in China as an instrumental variable for the knowledge stocks of green FDI firms. The instrumental variable serves as a quasi-random shock that determines whether a larger scale of green FDI enters a specific industry and consequently leads to more knowledge stocks of green FDI firms within the industry.[17] Specifically, industry i is assigned to the treatment group if it is categorised as the "Green FDI Encouraged Industry", and assigned to the control group if it is categorised as the "Green FDI No-change Industry", based on the category definition in Section 4.2.4. The treatments occur in 2002, 2004, 2007 and 2011, by the timeline of the four waves of the FDI Catalogue changes in China. For the endogenous variable $GrFDIKnow_{it}^{Hori}$, the first-stage estimation of the instrumental variable is based on a difference-in-differences (DID) strategy:

$$GrFDIKnow_{it}^{Hori} = \beta_0 + \beta_1 GrFDIOpen_{it}^{Hori} + \beta_2 X_{ft} + \gamma_f + \lambda_t + \delta_i + \eta_p + \varepsilon_{fipt}, \quad (4.5)$$

where $GrFDIOpen_{it}^{Hori}$ is a binary variable that indicates whether industry i is categorised as a "Green FDI Encouraged Industry" at year t. The intuition behind the instrumental variable is that an industry i receives more green FDI if green products in this industry become more open to FDI, and consequently the domestic firms are more exposed to the knowledge stocks of green FDI firms within the same industry i.

The instrumental variable for the knowledge stocks of green FDI firms in downstream industries $GrFDIKnow_{it}^{Down}$ can be constructed by computing the overall openness of green FDI in industry i's downstream industries, similar to Eq (4.3). Specifically, $GrFDIOpen_{it}^{Down} = \sum_{k\, if\, k\neq i} \alpha_{ik} GrFDIOpen_{kt}^{Hori}$, where α_{ik} represents the weights of industry i's exposure

[16] For example, the decision of whether a green FDI enters an industry in China might be driven by a selective strategy based on their own and the invested entities' competitiveness. Additionally, the increase in knowledge stocks of green FDI firms could also be influenced by the innovation capacities of domestic firms rather than solely relying on knowledge from foreign investors.

[17] The decision regarding whether an industry becomes more open to green FDI is determined by the previous negotiation of China's accession to WTO and high-level government policies. These factors are much less influenced by the strategies of foreign investors or the capacities of invested domestic firms.

to its each downstream industry k. Similarly, the instrumental variable for the knowledge stocks of green FDI in upstream industries $GrFDIKnow_{it}^{Up}$ can be constructed as: $GrFDIOpen_{it}^{Up} = \sum_{m\, if\, m \neq i} \beta_{im} GrFDIOpen_{mt}^{Hori}$, where β_{im} represents the weights of industry i's exposure to its each upstream industry k. With controlling the endogeneity of $GrFDIKnow_{it}$ by using instrumental variables, the coefficient β_1 in Eq (4.1) captures the impacts of knowledge stocks resulting from green FDI firms on domestic firms' green innovation. Such impacts by green FDI firms' knowledge stocks from the same industry (as domestic firms), downstream industries, and upstream industries can be interpreted as the knowledge spillover effects of green FDI via horizontal, downstream and upstream linkages, respectively.

Table 4.1: Summary Statistics

Variables	N	Mean	SD	Min	Max
Panel A: Innovation Indicator					
Total Patent Family Count	387059	0.824	24.300	0.000	5607
Green Patent Family Count	387059	0.104	4.504	0.000	2023
Total Patent Family Citation	387059	2.265	126.200	0.000	35059
Green Patent Family Citation	387059	0.305	11.100	0.000	2229
Panel B: Green FDI Knowledge Stock					
Horizontal GrFDI Know (Text)	387059	28.330	116.000	0.000	1971
Horizontal GrFDI Know (GrPat)	387059	52.290	142.000	0.000	2020
Horizontal GrFDI Know (GrPatOutCN)	387059	34.800	124.900	0.000	1933
Horizontal GrFDI Know (FIGrPatCN)	387059	3.292	20.070	0.000	254.4
Downstream GrFDI Know (Text)	387059	24.300	41.470	0.000	384.7
Downstream GrFDI Know (GrPat)	387059	44.450	70.350	0.000	550.7
Downstream GrFDI Know (GrPatOutCN)	387059	31.380	58.000	0.000	526.8
Downstream GrFDI Know (FIGrPatCN)	387059	4.284	9.345	0.000	143.9
Upstream GrFDI Know (Text)	387059	21.190	38.960	0.013	431.6
Upstream GrFDI Know (GrPat)	387059	36.230	59.930	0.121	528.1
Upstream GrFDI Know (GrPatOutCN)	387059	24.700	48.950	0.002	467.7
Upstream GrFDI Know (FIGrPatCN)	387059	1.448	3.407	0.000	48.02
Panel C: Other Firm Atrributes					
Firm Age	386089	26.340	13.750	3.000	66
Output (1 million Yuan)	356787	286.200	2562.000	0.001	258799
Asset (1 million Yuan)	386077	300.400	3015.000	0.001	276431
Sale Revenue (1 million Yuan)	386078	283.500	2750.000	0.001	258206
Employee	384310	517.000	2450.000	1.000	161654

Notes: Panel A shows the indicators of innovation. Panel B presents the knowledge stocks of green FDI by different definitions and channels. In Panel B, *Horizontal* denotes the knowledge stocks resulting from green FDI firms within the same industry, *Downstream* indicates the knowledge stocks resulting from green FDI firms in downstream industries, and *Upstream* represents the knowledge stocks resulting from green FDI firms in upstream industries. "Text" denotes the first green FDI definition: whether the text description of FDI business scope includes keywords related to environmental governance, clean production, clean energy, or green technology. "GrPat" is the second green FDI definition: whether FDI firms own green patents. "GrPatOutCN" stands for the third green FDI definition: whether FDI firms own green patents that cite prior arts from foreign countries. "FIGrPatCN" represents the fourth green FDI definition: whether FDI firms' foreign investors have filed green patents in China. Panel C reports other firm-level attributes.

Table 4.1 presents the summary statistics of key variables in the following analyses, including innovation indicators, measures of knowledge stocks of green FDI, and other firms' characteristics. Panel A shows that green patents take around 10% to 20% of total patents in each firm on average, and the low value of means and much larger standard deviations suggest that a large share of domestic firms do not have patenting activities. The fact that patenting activities happen at a small group of firms further justifies the use of Poisson regression rather than OLS for estimation of the baseline model Eq (4.1). Panel B displays the difference in the knowledge stock of green FDI firms across different green FDI definitions. In the main analyses, I focus on the green FDI definition based on the "Text" approach, i.e., defined by the text description of FDI business scope. Results of using other green FDI definitions are discussed in the robustness checks. Panel C shows that firms in the sample are relatively large, with total assets equivalent to around 300 million Yuan and output equivalent to around 286 million Yuan. Such large sizes result from the fact that ASIE mostly covers firms above annual sales above 5 million Yuan rather than small size firms in China. Therefore, the conclusion of this paper is more applicable to the knowledge spillover effects on large size domestic firms in the host countries, and one should be cautious in extrapolating the conclusion to small size domestic firms.

4.3.2 Validity of Instrumental Variable

The validity of the DID instrumental variable heavily relies on the exclusion restriction condition, which requires: (1) the green products opened up to FDI are randomly selected in the FDI opening-up policy; (2) no other major channels through which the FDI opening-up policy affects the domestic firms' green innovation other than the increasing presence of green FDI firms' knowledge stocks.

Unfortunately, the selection of when and which green products become more open to FDI is likely to be non-random. One defence for the quasi-random selection of products is that the FDI opening-up policy in China was generally aligned with the agreement from lengthy negotiations of China's accession to WTO, which was not largely determined by China and still uncertain prior to the accession (Lu et al., 2017; Chen et al., 2022). However, the Chinese government might still wield considerable influence on the implementation of the opening-up policy and cherry-pick specific green products to be opened up at specific desired timelines due to specific industrial factors.[18] In such cases, the selection of whether

[18]For instance, if there is an important technology discovery regarding a green product in a particular industry, the government might choose to protect that industry for a longer period and therefore delay its opening-up to green FDI. Moreover, other green industrial policies promoting domestic green innovation could also lead to a synergistic effect, impacting the timing of opening-up to green FDI.

and when a green product is opened up to FDI is not random, and the validity of the instrumental variable is impaired.

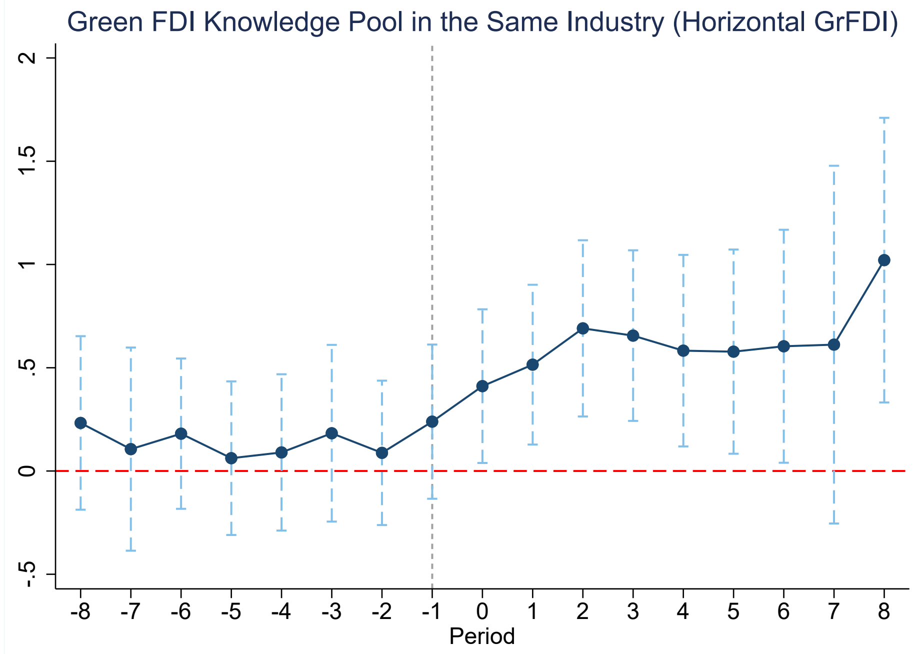


Figure 4.5: Dynamic Effect of Green FDI Opening-up Policy Changes

Notes: Dependent variable is the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), which is measured in logarithms. The dot indicates the point estimates for each period before and after the industry-level green FDI opening-up policy changes, i.e., if the industry becomes "Green FDI Encouraged Industry" (includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). The intercept indicates the 95% confidence interval. The estimation is based on the two-stage DID strategy designed by Gardner (2022). Specific numbers of coefficients are shown in Table 4.A.5.

I adopt two strategies to alleviate this concern. First, I conduct an event study and plot the dynamic effects based on the DID model in Eq (4.5), to examine whether there is a significant difference in green FDI firms' knowledge stocks between the treatment and control groups prior to the time points when an industry encourages green FDI. It is worth noting that the DID model in Eq (4.5) is a staggered DID setting, under which the coefficients of the treatments may not be reliable measures of the treatment effects if directly estimated by the ordinary least squares (OLS) (Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Gardner, 2022). I use the two-stage DID strategy designed by Gardner (2022) to estimate the dynamic effects of Eq (4.5).[19] The estimated coefficients

[19]The two-stage DID requires a clear binary DID setting as the estimation in the first stage is targeted to the units never treated. However, it is unable to apply this strategy to the indicators of the openness to downstream and upstream green FDI $GrFDIOpen_{it}^{Down}$ and $GrFDIOpen_{it}^{Up}$ because they are the aggregations of the treatment variables across multiple downstream and upstream industries. I therefore compare the results of the horizontal knowledge spillover effects between the conventional DID and

over periods before and after the treatments are displayed in Figure 4.5. The plot indicates that the treatment and control groups are balanced in green FDI firms' knowledge stocks in the pre-treatment periods. In contrast, the treatment group experiences a gradual and persistent increase in green FDI firms' knowledge stocks in the post-treatment periods and generates a significant difference compared with the control group. The specific magnitude of corresponding coefficients is displayed in Table 4.A.5.

Second, inspired by Gentzkow (2006), I control for industrial factors that explain as much as possible whether an industry encourages green FDI (i.e., the selection of the treatment group).[20] However, a manual search and selection of key industrial factors involve considerable subjective judgement, which cannot well ensure most of the key determinants are covered. I resort to the least absolute shrinkage and selection operator (LASSO) to perform an automatic variable selection, to largely avoid the subjective bias in the selection of key factors. Specifically, I add to the model 14 pre-open (prior to 2002, i.e., the first wave of the Catalogue change during the sample period 2000-2013) industry-level factors that have abundant pre-open observations and capture most of the important dimensions of industrial development.[21] The variable selection process ultimately singles out 8 industrial factors as the key determinants (number of firms, output, average number of employees, average wage, HHI, new product intensity, R&D expense, and green patent stock), which possess the largest explanatory power to the selection of the treatment group while avoiding the overfitting of the model.[22] Then I add the interaction terms between year fixed effects λ_t and the 8 industry-level key determinants in pre-open periods (average in 2000 and 2001) to the regression models to control for endogenous selection of which industry

two-stage DID, which are shown in Table 4.A.3 in the Appendix. The horizontal spillover results of the two-stage DID are very close to the results of conventional DID, which suggests the results of downstream and upstream knowledge spillover effects can be reliable even if they are unable to be estimated by the two-stage DID strategy.

[20] While it may not completely eliminate the possibility of other policy confounders, this approach can control for the majority of potential confounders that influence the selection of the treatment assignment and enhance the exogeneity of the estimation as much as possible.

[21] The 14 industry factors include the number of firms, the average age of firms, output, sales, capital, the average number of employees, average wage per employee, new production intensity, export, export intensity, Herfindahl-Hirschman Index (HHI), R&D expense, total patent stock, green patent stock. They are taken average over 2000 and 2001.

[22] Among three major methods of the LASSO, I choose the adaptive method because it provides nearly the lowest deviance while further reducing the overfitting issue compared with the cross-validation method. The plug-in method does not perform well in the variable selection.

encourages green FDI.[23] The results are discussed in the robustness checks and do not challenge the conclusion.

There is another considerable concern that the FDI opening-up policy may affect the domestic firms' green innovation via other channels beyond the increasing presence of green FDI firms' knowledge stocks. For example, when an industry encourages green FDI, it not only increases the knowledge stocks of green FDI firms but also the knowledge stocks of non-green FDI. The non-green FDI firms' knowledge stocks may indirectly influence domestic firms' green innovation. To control this additional channel, I construct the knowledge stocks of non-green FDI firms in the horizontal, downstream, and upstream industries.[24] Then I add the measures of the non-green FDI firms' knowledge stocks as additional covariates to the regression models, to control for the possible impacts via the non-green FDI channel.

The second possible channel is associated with firm sorting behaviour. Firms may decide to adjust their operating industries in response to the FDI policy changes when certain industries become more open to FDI. The green innovation of domestic firms is likely to be influenced by some firms moving in or out of certain industries. I remove all of the firms that change industries throughout the sample period to avoid the possible channel via the firm sorting behaviour. I discuss the robustness checks of the two tests that eliminate additional channels through which the FDI opening-up policy may affect domestic firms' green innovation, and the two tests do not change the main results.

[23] There are two reasons of adding the interactions between year fixed effects and pre-open key determinants rather than directly adding the time-varying key determinants as controls to the model: (1) Some key determinants have missing values in several periods (e.g., R&D expense, export), and therefore using these time-varying control variables will largely shrink the observations. (2) These time-varying key determinants are very likely to be also affected by the treatments. Such reverse impacts by the treatments may open new spurious paths between the treatments and the outcomes and therefore deliver poorer estimates of the causal effects, which is known as the "bad control" problem (Zeldow and Hatfield, 2021; Callaway, 2022; Caetano et al., 2022). Hence, adding more time-varying control variables probably affected by the treatments leads to higher possibilities of bringing in extra biases of the estimations. The strategy of using interaction terms not only confine key determinants to pre-treatment periods but also takes into account the changes of key determinants in future periods, which is an alternative way to capture the time-variation of key controls while avoiding the "bad control" problem.

[24] The construction of non-green FDI knowledge stocks is similar to Eq (4.2), (4.3), and (4.4), and the only change is the binary indicator from $I(GrFDI_{jt})$ to $I(NonGrFDI_{jt})$, which denotes if foreign-invested firm j having received non-green FDI at year t.

4.4 Empirical Results

4.4.1 Main Results

Table 4.2 summarises the main results for the knowledge stocks of green FDI and green innovation of domestic firms. I start with estimating the baseline model Eq (4.1) without using the instrumental variables. Columns (1) to (3) reports the correlation between green FDI firms' knowledge stocks and domestic firms' green patent family count. The explanatory variable in Columns (1) to (3) represents the knowledge stocks of green FDI firms in the same (horizontal) industry, the downstream industries, and the upstream industries, respectively. The coefficients in the first three columns are statistically insignificant and seemingly indicate that domestic green innovation is not associated with knowledge resulting from green FDI firms. However, the coefficients in Columns (1) to (3) do not tease out the impacts of green FDI firms' knowledge stocks but contain many unclear factors that both influence green FDI and domestic green innovation, even if conditional on a group of control variables and fixed effects. Such endogeneity problems create difficulties in identifying how much green FDI firms' knowledge stocks affect domestic firms' green innovation.

Therefore, I correct the endogeneity problems by using instrumental variables of green FDI firms' knowledge stocks. The corresponding results are reported in Columns (4) to (6) of Table 4.2. The explanatory variable in the first-stage estimation captures the openness of an industry covering green products to FDI after the changes in the FDI opening-up policy in China. Column (4) in the first-stage estimation shows that the instrument $GrFDIOpen_{it}^{Hori}$ has a positive and statistically significant effect on $GrFDIKnow_{it}^{Hori}$, confirming the relevance of the instrument that more knowledge stocks of green FDI firms exist in an industry if this industry becomes more open to green FDI. Moreover, I report the Cragg-Donald Wald F-statistic and Kleibergen-Paap rk Wald F-statistic to detect the weak instrumental variable problem. Cragg-Donald Wald F-statistic is valid when errors are independent and identically distributed (i.i.d), while Kleibergen-Paap rk Wald F-statistic is valid when errors are not i.i.d. The result in Column (4) shows that the Cragg-Donald statistic and Kleibergen-Paap statistic are both larger than the 10% critical value by Stock and Yogo (2002), rejecting the null hypothesis that the instrumental variable for horizontal green FDI firms' knowledge stocks is subject to the weak IV problem. After being instrumented, the explanatory variable of Column (4) in the second-stage estimation identifies the impact of green FDI firms' knowledge stocks on domestic firms' green patent counts. The coefficient suggests that knowledge stocks of green FDI within the same

Table 4.2: Knowledge Stocks of Green FDI Firms and Green Innovation of Domestic Firms

Dependent Variable:	Green Patent Family Count					
Knowledge Stock of:	Horizontal GrFDI (1)	Downstream GrFDI (2)	Upstream GrFDI (3)	Horizontal GrFDI (4)	Downstream GrFDI (5)	Upstream GrFDI (6)
				Second-stage Estimation		
GrFDI Know	0.148	0.026	0.237	0.000	0.732**	2.512*
	(0.091)	(0.149)	(0.236)	(0.263)	(0.357)	(1.393)
Observations	51,296	51,296	51,296	51,296	51,296	51,296
				First-stage Estimation Dependent Variable: GrFDI Know		
GrFDI Open				0.845***	1.570***	0.376*
				(0.157)	(0.385)	(0.208)
Observations				384,297	384,297	384,297
CD Wald F-statistic				33165	55003	15849
KP Wald F-statistic				29.07	16.60	9.131
Estimation	Poisson	Poisson	Poisson	Poisson&IV	Poisson&IV	Poisson&IV
Firm Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y

Notes: Dependent variable is firm green patent family count. Columns (1) to (3) show results for Poisson regression. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stocks indicators are in logarithms. Columns (4) to (6) show results for two-stage IV estimation: the first-stage estimation is OLS, and the second-stage estimation is Poisson regression. $GrFDIOpen$ is the instrumental variable used in the first-stage estimation and captures if the same industry (Horizontal GrFDI), downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI) are identified as "Green FDI Encouraged Industry" (i.e., includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). CD Wald F-statistic denotes Cragg-Donald Wald F-Statistic, and KP Wald F-statistic denotes Kleibergen-Paap rk Wald F-statistic. Stock-Yogo critical values for weak identification test (Cragg-Donald and Kleibergen-Paap rk Wald F statistics) are 16.38 at 10% and 8.96 at 15% maximal IV size. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

industry has an insignificant effect on the green innovation of domestic firms. The muted horizontal knowledge spillover effects of green FDI echoes the mixed conclusions in the existing literature of whether domestic firms benefit from or suffer from FDI in the same industry. (Aitken and Harrison, 1999; Javorcik, 2004; Newman et al., 2015; Lu et al., 2017; Chen et al., 2022). On one hand, domestic firms may benefit from foreign entrants by observing, imitating, or reverse-engineering the new products and technologies brought by FDI. On the other hand, the entry of FDI may crowd out domestic firms in the market due to the advantages of new products or technologies and lead to the market-stealing effect. The two simultaneous but opposite effects may be offset and lead to an insignificant effect of knowledge stocks resulting from green FDI firms within the same industry.

Column (5) reports the results for knowledge stocks of green FDI firms in downstream industries. After being instrumented, the coefficient in Column (5) in the second-stage estimation reports a positive and statistically significant effect of green FDI firms' knowledge stocks from downstream industries on domestic firms' green patents. This finding suggests the knowledge spillovers from downstream green FDI to domestic firms and a 1% increase in downstream green FDI firms' knowledge stocks can lead to roughly 0.732% increase in green patents of domestic firms.[25] Such finding implies that domestic firms can benefit from green FDI firms' knowledge by becoming suppliers to green FDI firms, which echoes some flagship industrial policies in China, such as public procurement and local content requirement in renewable energy industries. Although not specialising in green products initially, Chinese domestic firms took advantage of their lower cost of manufacturing and entered the supply chains as suppliers of components to foreign companies. During the integration into the supply chains of green products, domestic firms can benefit from absorbing green knowledge resulting from FDI firms. This process helps domestic firms gradually build up their own green innovation capacities, take a more important role in the supply chains, develop new green products with more competitiveness, and ultimately dominate local and penetrate global green markets.

Column (6) presents the results for knowledge stocks of green FDI firms in upstream industries. In the first-stage estimation, the coefficient shows a much weaker correlation between the openness of upstream industries to green FDI $GrFDIOpen_{it}^{Up}$ and the knowledge stocks of green FDI firms in upstream industries $GrFDIKnow_{it}^{Up}$. Although the Cragg-Donald statistic is larger than the 10% critical value, the Kleibergen-Paap statistic is only larger than the 15% critical value but smaller than the 10% critical value. The Kleibergen-Paap statistic offers a more valid test as the standard errors in my regression are clustered at the industry level and are not i.i.d. The weak identification test raises the concern of the weak instrumental variable problem for the knowledge stocks of green FDI firms in upstream industries. After being instrumented, the coefficient in Column (6) displays a slightly positive and statistically significant effect of upstream green FDI firms' knowledge stock on domestic firms' green innovation. This finding indicates that domestic firms may learn green technologies embedded in the intermediate goods supplied by green FDI firms. The inputs supplied by upstream green FDI may be accompanied by additional services or technical supports that also facilitate the knowledge absorption of domestic customers and users. Such learning may as well generate green knowledge spillovers from

[25] Since the independent variable is transformed into the logarithm and the estimated model is Poisson regression, the estimated coefficients can be interpreted as the elasticity of the outcome variable (domestic firms' green patents) with respect to the independent variable (green FDI firms' knowledge stocks).

foreign-invested suppliers to domestic firms. However, the possible existence of the weak instrumental variable problem threatens the solidity of the estimation and reminds the caution in concluding the knowledge spillovers from upstream green FDI. Further tests are conducted in the robustness checks.

4.4.2 Robustness Checks

I conduct a battery of robustness checks on the main results to examine the stability of the coefficient estimates.

Non-random instrumental variables. As discussed in Section 4.3.2, the selection of when and which industries become more open to green FDI may be non-random and violates the parallel trend assumption of using the DID instrumental variable. I use two strategies to tackle this issue. First, I conduct an event study to check if there is a significant difference in the pre-treatment periods. Figure 4.5 shows the estimated coefficients across periods. There is no evidence of significant difference existing in the pre-treatment periods, which provides support for the parallel trend assumption. Second, I use the LASSO to extract key determinants that sufficiently explain the non-random selection in which industries become more open to green FDI during the changes in the FDI opening-up policy. Then I add interaction terms between year fixed effects and the key determinants to control for endogenous selection of the treatment group while avoiding the "bad control" problem as far as possible. The corresponding results, shown in Table 4.A.6, are similar to the main results in Table 4.2.

Instrumental variables affecting outcomes via other channels. The instrument, the FDI opening-up policy, may affect domestic firms' green innovation via the other channels beyond the key endogenous variable green FDI firms' knowledge stocks, according to the discussion in Section 4.3.2. My robustness checks eliminate two typical channels to alleviate this concern. First, I add the measures of the non-green FDI firms' knowledge stocks as additional controls to remove the possible effect of the FDI opening-up policy on the outcomes via non-green FDI. The corresponding results are shown in Table 4.A.7. The results are generally similar to the main results in Table 4.2, except the insignificant coefficient of the instrumental variable $GrFDIOpen_{it}^{Up}$ for upstream green FDI firms' knowledge stocks $GrFDIKnow_{it}^{Up}$ in Column (3). The insignificant coefficient of the instrument in Column (3) and the Kleibergen-Paap statistic much lower than the 15% critical value suggest the weak instrumental variable problem for upstream green FDI knowledge stocks and hinder the further interpretation of knowledge spillovers from upstream green FDI. Second, I remove firms that change industries during the sample period to eliminate the possible effect of the FDI opening-up policy on the outcomes via firms' sorting behaviour. Such robustness test is based on the concern that some firms may adjust their operating industries in response to the openness of certain industries to green FDI, and ultimately influence green innovation of domestic firms. The corresponding results are reported in Table 4.A.8. The robustness check further supports the evidence of knowledge spillover effects of green FDI in downstream industries on domestic firms' green innovation.

Controlling for Subsidies. Some literature finds that a large scale of subsidy programmes are launched by Chinese central and local governments to support R&D activities of domestic firms (Li, 2012; Haley and Haley, 2013). Particularly, many subsidy programmes are targeted to renewable energy sectors such as solar and wind energy and catalyse firms' investment in the relevant technologies (Wang et al., 2012; Xiong and Yang, 2016). These subsidy programmes boost domestic firms' generic and green innovation while probably also affecting green FDI firms' knowledge stocks. Omitting such an important policy confounder may bias the results when I estimate the knowledge spillover effects of green FDI on domestic firms' green innovation. To relieve this concern, I include the total amount of subsidies that each firm receives as an additional control variable in the regressions.[26] The corresponding results are shown in Table 4.A.9. Although the sample size shrinks due to the incomplete coverage of firm-level subsidy information, the estimated coefficients are similar to the main results and do not change the conclusion.

Alternative thresholds of foreign ownership. The knowledge spillover effects of green FDI may vary due to the ratio of foreign ownership in green FDI firms. Two important ownership thresholds may have influences. First, a foreign-invested firm with foreign ownership less than 25%, though contains foreign investment, is not entitled to preferential corporate taxation offered for FDI according to China's Foreign Investment Law. This difference in the FDI preferential policy may impact the knowledge spillover effects of green FDI. I therefore reconstruct the knowledge stocks of green FDI by defining $I(GrFDI_{jt}) = 1$ if foreign-invested firm j is identified as a green FDI firm and has foreign ownership greater than 25% at year t in Eq (4.2). The corresponding results are reported in Columns (1) to (3) of Table 4.A.10. Second, the majority foreign ownership (greater than 50%) can ensure the foreign investors' absolute control in the operation and management of FDI firms. This controlling position may alleviate the worries of foreign investors about the enforced tech-

[26]It would be ideal to extract each specific subsidy policy regarding R&D and green sectors in China, but Chinese subsidy policies are implemented by governments at different levels and it is very challenging to collect data on a wide variety of subsidy programmes. Moreover, there is currently no available firm-level dataset that differentiates the subsidies based on the purposes of subsidies. Although not perfect, firms' total amount of subsidies can still be a feasible proxy that to some extent controls the effect of subsidies on domestic firms' green innovation.

nology transfer to domestic partners and impact the green knowledge spillovers via FDI. To capture the knowledge stocks of green FDI firms under the majority foreign ownership, I re-define that $I(GrFDI_{jt}) = 1$ only if foreign ownership greater than 50% in the construction of green FDI firms' knowledge stocks. The corresponding results are reported in Columns (4) to (6) of Table 4.A.10. The coefficients in Columns (2) and (5) further support the main results that the knowledge stocks of downstream green FDI firms generate knowledge spillovers to domestic firms, while results in Columns (3) and (6) further warn that the upstream green FDI may not generate clear knowledge spillovers.

Alternative definitions of green FDI. This study constructs four approaches to defining green FDI as discussed in Section 4.2.3. I use the first approach to define green FDI in the main analyses, i.e., keywords searching in the text description of foreign-invested firms' business. To check the robustness, I use other developed definitions to define green FDI and reconstruct the knowledge stocks of green FDI firms. Specifically, I use the second approach (whether foreign-invested firms own green patents), third approach (whether foreign-invested firms own green patents that cite prior arts from foreign countries), fourth approach (whether foreign investors have filed green patents in China), and the intersection of the first and second approach to defining green FDI in $I(GrFDI_{jt}) = 1$ from Eq (4.2), respectively. The corresponding second-stage estimation results are presented in Table 4.A.11. The coefficient estimates based on different green FDI definitions, though vary in coefficient magnitude, do not significantly change the main conclusion.

4.4.3 Heterogeneity of Innovation

In this subsection, I investigate the knowledge spillover effects of green FDI on the quality of domestic green innovation, and on innovation in different technological fields.

There are three categories under the Chinese patent system: invention, utility model, and design patents (Wei et al., 2017). The invention patent requires a more substantial improvement related to practical, inventive, and new technical innovations. The utility model patent corresponds to the improvement in technical solutions to the shape or structure of an object. The design patent only involves the external appearance of products. Among the three categories, the invention patent contains the highest requirement of novelty, and inventiveness, which stands for a higher quality than other categories. I distinguish green invention and utility model patents as separate dependent variables.[27] With the number of green invention and utility model patent families as dependent variables, Panel A and B

[27] The design patent is not related to environmental governance, clean production, climate mitigation or adaptation functionality. Hence, the analysis excludes the design patent.

in Table 4.3 report the corresponding results. The coefficients in Column (2) indicate that the knowledge stocks of green FDI firms in downstream industries promote domestic firms' green invention patents but do not has a clear effect on green utility patents. This finding suggests that the knowledge spillovers from downstream green FDI contribute more to the most innovative green patents of domestic firms.

Table 4.3: Heterogeneity of Green Innovation Quality

Knowledge Stock of: *Second-stage Estimation*	Horizontal GrFDI (1)	Downstream GrFDI (2)	Upstream GrFDI (3)
Panel A: Dependent Variable: Green Invention Patent Family			
GrFDI Know	0.139	1.305*	4.086**
	(0.383)	(0.673)	(1.833)
Observations	30,581	30,581	30,581
Panel B: Dependent Variable: Green Utility Patent Family			
GrFDI Know	0.007	0.101	1.383
	(0.199)	(0.370)	(1.388)
Observations	39,080	39,080	39,080
Panel C: Dependent Variable: Green Patent Family Cititation			
GrFDI Know	0.285	0.877***	4.011***
	(0.260)	(0.313)	(1.325)
Observations	43,145	43,145	43,145
Panel C: Dependent Variable: Green Patent Family Cited by Patents outside China			
GrFDI Know	0.450	1.186***	4.144**
	(0.320)	(0.330)	(1.816)
Observations	12,356	12,356	12,356
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Sector FE	Y	Y	Y
Province FE	Y	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable is firm green invention patent family count in Panel A, green utility patent family count in Panel B, green patent family citation in Panel C, and green patent family cited by patents outside China in Panel D. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. The first-stage estimation results are not shown in the table for the sake of brevity. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

The number of forward citations received by patents is another widely-used indicator of patent quality (Hall et al., 2005). Hence, I use the domestic firms' green patent family citations as the dependent variable to examine how knowledge stocks of green FDI affect domestic green innovation quality. The corresponding results are kept in Panel C of Table 4.3. The positive and statically significant coefficient in Column (2) suggests that downstream green FDI firms' knowledge stocks promote domestic high-quality green innovation.

Although overall citations can reflect the value of patents, the citations across borders may indicate a distinct value compared with the citations within borders because the cross-border citations imply a wider applicability and commercial value. Particularly, most of the Chinese patents are only used within China and do not contribute much to the global technology frontier. This also casts a doubt on the quality of Chinese patents. To better capture the quality of green innovation, I extract green patent families that receive citations outside China, which indicates a clear technology diffusion across borders. Panel D in Table 4.3 shows the results. The similar results as Panel C further justify the knowledge spillover effects of downstream green FDI.

Table 4.4: Heterogeneity across Green Technological Fields

Knowledge Stock of: *Second-stage Estimation*	Horizontal GrFDI (1)	Downstream GrFDI (2)	Upstream GrFDI (3)
Panel A: Dependent Variable: Alternative Energy Patent Family			
GrFDI Know	0.509**	0.867**	5.424***
	(0.253)	(0.398)	(1.877)
Observations	21,304	21,304	21,304
Panel B: Dependent Variable: Sustainable Transportation Patent Family			
GrFDI Know	0.296	0.432**	2.460**
	(0.210)	(0.201)	(1.156)
Observations	9,635	9,635	9,635
Panel C: Dependent Variable: Energy Conservation Patent Family			
GrFDI Know	-0.083	0.424	1.765
	(0.308)	(0.440)	(1.852)
Observations	30,429	30,429	30,429
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Sector FE	Y	Y	Y
Province FE	Y	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable is alternative energy patent family count in Panel A, sustainable transportation patent family count in Panel B, and energy conservation patent family count in Panel C. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. The first-stage estimation results are not shown in the table for the sake of brevity. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Due to the variance in innovation features and business models, green FDI firms' knowledge spillovers may have heterogenous impacts on domestic green innovation across green technological fields. I break down green patents into a more disaggregated level and focus on three main fields: alternative energy, sustainable transportation, and energy conservation. The results are presented in Table 4.4. The statistically significant coefficients in Panel A indicate that domestic innovation in alternative energy is enhanced by the knowledge stocks of green FDI in the same industry, downstream and upstream industries. The effects on domestic sustainable transportation innovation are not salient by green FDI firms' knowledge within the same industry. In contrast, there is no evidence that green FDI can effectively promote domestic innovation in energy conservation.

4.4.4 Mechanisms of Green FDI Knowledge Spillovers

In this subsection, I explore what mechanism factors can explain the difference in knowledge spillover effects of green FDI.

Local vs. non-local green FDI. The effects of green FDI firms' knowledge stocks on domestic firms' green innovation may vary with the geographic distance. Domestic firms located in the regions close to green FDI firms may benefit from a stronger knowledge spillover from green FDI due to the lower cost of communication and shared local talent pool. To test whether the distance to green FDI firms makes a difference, I define a binary variable, $LocalFDI$, which indicates whether the knowledge stocks are from green FDI firms located in the same province as the domestic firms. The corresponding results of the second-stage estimation are reported in the Panel A of Table 4.5. The interaction term of green FDI firms' knowledge stocks $GrFDIKnow$ and the dummy variable $LocalFDI$ captures whether local knowledge stocks of green FDI firms contribute more to domestic firms' green innovation. The result in Column (2) suggests that domestic firms' green innovation significantly benefit more from local green FDI if domestic firms become local suppliers of green FDI firms, while the results in Columns (1) and (3) indicate local green FDI firms' knowledge does not contribute to domestic green innovation if green FDI is in the same industry or upstream industries.

Technological Proximity. The main results have shown that domestic firms' green innovation significantly benefits from the knowledge stocks of green FDI firms in the downstream industries. The knowledge spillovers across industries may vary with the knowledge similarity of the industries. A closer technology background between a pair of industries indicates innovation activities between the two industries are more relevant. The higher relevance of knowledge basis between industries can facilitate knowledge spillovers and absorptions. Hence, if the knowledge stocks of green FDI firms derive from the downstream industries that are closer in technological spectrums, the knowledge spillovers from such downstream green FDI may contribute more to domestic firms' green innovation.

To capture the effect of technological proximity on green FDI knowledge spillovers, I start

Table 4.5: Mechanisms of Green FDI Knowledge Spillovers

Dependent Variable:	Green Patent Family Count		
Knowledge Stock of:	Horizontal GrFDI	Downstream GrFDI	Upstream GrFDI
Second-stage Estimation	(1)	(2)	(3)
Panel A: Local FDI vs. Non-local FDI			
GrFDI Know	-0.052	0.413*	0.589
	(0.192)	(0.229)	(0.400)
GrFDI Know×Local FDI	-0.085	0.899*	1.526
	(0.426)	(0.498)	(1.035)
Observations	102,386	102,591	102,594
Panel B: Technological Proximity between Industries			
GrFDI Know	N/A	0.680*	1.440
		(0.369)	(0.963)
GrFDI Know×FDI IndTechProx	N/A	0.059*	-0.080
		(0.032)	(0.053)
Observations		102,596	102,596
Panel C: Environmental Regulation Stringency of Green FDI Origin Countries			
GrFDI Know	-0.111	0.428*	0.550
	(0.479)	(0.239)	(0.376)
GrFDI Know×FDI OriginEPS	0.009	0.292*	0.619
	(0.132)	(0.163)	(0.424)
Observations	102,596	102,596	102,596
Firm Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Province FE	Y	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable is firm patent family count. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. $LocalFDI$ is a binary variable indicating if the knowledge stock is from green FDI firms within the same province. $FDI\ IndTechProx$ is a binary variable indicating if the knowledge stock is from green FDI firms in other industries with large technological proximity (above the median value). $FDI\ IndTechProx$ is not applicable for Horizontal GrFDI as technological proximity is always 1 for the same industry. $FDI\ OriginEPS$ is a binary variable indicating if the knowledge stock is from green FDI that originates from countries with environmental policy stringency index higher than China. The first-stage estimation results are not shown in the table for the sake of brevity. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

with computing the technological proximity across industries, built upon the approach proposed by Jaffe (1986):

$$TechProx_{idt} = \frac{T_{it}T'_{dt}}{\sqrt{T_{it}T'_{it}}\sqrt{T_{dt}T'_{dt}}} \tag{4.6}$$

where T_{it} is industry i's patent portfolio vector up to year t,[28] defined as $T_{it} = (T_{i1,t}, T_{i2,t}, ..., T_{iC,t})$,

[28] Industry d denotes another industry paired with industry i during the calculation.

in which $T_{ic,t}$ is the share of patents of industry i in technology class c up to year t.[29] The proximity indicator ranges between 0 and 1, showing the similarity of a pair of industries' patent distributions across technology classes.

Then I divide each industry pair into high and low groups depending on whether the technological proximity of an industry pair is larger or smaller than the median value. I define a binary variable, $FDI\ IndTechProx$ indicates whether the knowledge stocks derive from green FDI in the industries with high technological proximity (above the median value) to the domestic firms' industry or in the industries with the low technological proximity (below the median value). The interaction term of $GrFDIKnow$ and $FDI\ IndTechProx$ tests whether technological proximity matters in cross-industry knowledge spillovers of green FDI firms.[30] The corresponding results of the second-stage estimation are presented in the Panel B of Table 4.5. Similarly, the second-stage estimation result in Column (2) suggests that knowledge from downstream green FDI contributes more to domestic firms' green innovation when such downstream green FDI come from the industries close to domestic firms' industries in terms of technological proximity. The results in Column (3) indicate that industrial technological proximity does not play a role in knowledge spillovers from upstream green FDI.

Environmental regulations in origin countries of green FDI. While environmental regulations can drive green technological changes within the jurisdictions, they may also play a role in knowledge spillovers across borders (Popp, 2006). Once green knowledge has been developed to comply with a specific environmental regulation in one country, it may be transferred to other countries with lower regulation stringency due to its competitive advantage compared to other potential competitors in the lower-regulating countries (Dechezleprêtre et al., 2015). This provides an incentive for foreign investors to apply their green knowledge in the host countries. Therefore, the discrepancy of the environmental regulation stringency may affect the knowledge spillovers via green FDI.

To examine the role of environmental regulation stringency, I define a binary indicator $FDIOriginEPS$ to indicate whether the knowledge stocks are from green FDI that originates from countries with environmental policy stringency higher than China. The environmental policy stringency of green FDI origin countries is measured by the Environmental Policy Stringency (EPS) index, collected from the OECD Statistics database.[31] The in-

[29] Technology classes in the analysis rely on International Patent Classification (IPC) 4-digit code.

[30] The effect of the knowledge stocks of green FDI firms within the same industry (Horizontal GrFDI) is not considered in this analysis as the technological proximity is always 1 between the same industry.

[31] The Environmental Policy Stringency (EPS) index covers all OECD countries and other main non-OECD economies including Brazil, China, India, Indonesia, Russia, and South Africa.

teraction term of $GrFDIKnow$ and $FDIOriginEPS$ captures whether environmental regulation stringency plays an important role in knowledge spillovers of green FDI. The corresponding results of the second-stage estimation are displayed in the Panel C of Table 4.5. The coefficient in Column (2) indicates that domestic firms' green innovation benefit from stronger knowledge spillovers from downstream green FDI that originates from countries with higher environmental regulation stringency.

4.5 Conclusion

There has been a lack of attention to how to define and measure green FDI. Such neglect leads to considerable noise in quantifying how much FDI contributes to green knowledge spillovers. This partly explains why there is no consensus on the effects of FDI on pollution, energy efficiency, or clean technologies in the host countries. However, these mixed findings may bring troubles for policymaking in many governments of developing countries, because on one hand they are keen to attract FDI to enhance efficiency or absorb technologies, but on the other hand they are facing the ambiguities of how much FDI can contribute to their green economies.

This paper contributes to the literature by developing new definitions of green FDI by utilising the characteristics of FDI projects. Based on the newly defined green FDI, I examine the impacts of green FDI firms' knowledge stocks on domestic firms' green innovation. I further develop an instrumental variable for green FDI firms' knowledge stocks based on the changes in FDI opening-up policy in China to better identify the knowledge spillovers of green FDI. The results show that green innovation of domestic firms does not benefit from the knowledge of green FDI firms within the same industry, but mostly benefits from the knowledge of green FDI firms in downstream industries. Specifically, a 1% increase in downstream green FDI firms' knowledge stocks contributes to roughly 0.732% increase in domestic firms' green patents. Such knowledge spillovers from downstream green FDI imply that domestic firms absorb green knowledge when they perform as suppliers of green FDI firms. Using different indicators of green innovation, I find that the knowledge spillovers from downstream green FDI contribute more to high-quality domestic green innovation. I further explore some features of knowledge spillovers from downstream green FDI and find that the knowledge spillovers vary with the location of green FDI, the technological proximity between industries, and the environmental regulation stringency of green FDI origin countries. Most of the results remain valid in the robustness checks.

This paper answers how FDI performs as one of the important drivers in the rapid development of green industries in China. During the engagement in supply chains led by foreign companies, Chinese domestic firms strongly focus on the build-up of their own scales and innovation capabilities, to establish the basis of large-scale production, new technology innovation, and competitiveness in the markets. Such model of a rapid expansion in green industries, though along with some debatable measures such as subsidies, public procurement and local content requirement, may provide other emerging economies with some implications for a faster path to the green transition. More rapid progress in green knowledge spillovers and the green transition is critical to achieving global climate targets.

4.A Additional Tables

Table 4.A.1: Keywords for Green FDI Definition by the Text-mining of Firms' Business Description

Fields	Keywords
Environmental protection (general)	Environmental protection, environmental governance, environmental treatment, environmental monitoring, environmental testing, environmental countermeasures, environmental restoration, environmental purification, environmental improvement, environmental sanitation, sanitation machinery, environmental engineering, environmental equipment, environmental technology, environmental science, environmental research, new environmental materials, environmental test equipment, low-carbon technology, low-carbon science, low-carbon industry, low-carbon products, green products, green technology, environmentally-friendly, eco-friendly
Pollution control	Pollution control, low-carbon emission; air treatment, flue gas purification, exhaust gas purification, carbon capture, emission control, emission reduction, exhaust gas purification, scrubber, filter material, air purification, dust remover, dust removal equipment, air improvement; water treatment, water governance, water filter, water purifier, water quality monitoring, water quality improvement, wastewater treatment, wastewater reuse, seawater desalination, brackish water desalination, reclaimed water recycle, reclaimed water treatment, filter membrane; soil remediation, soil pollution, soil remediation, desertification prevention, soil erosion control, soil erosion prevention, soil conditioning, ecological restoration
Clean energy	Clean energy, low-carbon energy, new energy, alternative energy, clean fuel, renewable energy, sustainable energy; wind energy, wind power, wind turbines, power generation blades; solar energy, solar electric energy, photovoltaic, solar thermal, wind-solar hybrid; hydropower, hydroelectric power, tidal power, ocean power, geothermal energy; cogeneration, thermoelectric production; hydrogen fuel, hydrogen energy, hydrogen storage; biofuels, biomass fuel, biomass energy, bioenergy, biodiesel
Energy efficiency & management	Energy efficiency, energy management, energy saving, low-energy consumption; compact fluorescent lamp, diode, heat pumps; electric control systems, distribution switch control, low-voltage switchgear, transformers, inductors, transformers, rectifiers, sensors, boosters, electricity meters, sensitive components, electrical control system, uninterruptible power supply, integration of electromechanical equipment, relays, circuit breakers
Battery & sustainable vehicle	Lithium battery, lithium ion battery, lithium polymer battery, nickel metal hydride battery, power battery, fuel cell, green battery, environmentally friendly battery, pollution-free battery; electric vehicle, dual fuel car, hybrid car, charging pile
Sustainable agriculture	Sustainable agriculture, green agriculture, pollution-free agriculture, organic agricultural, organic farming, low-impact farming, eco-agriculture; biomass resource utilization, biofertilizer, drip irrigation, water saving irrigation, genetic engineering
Resource saving & waste management & recycling	Resource saving, recycling, resource recovery, resource regeneration, resource conservation, resource protection, renewable resource, resource regeneration, comprehensive utilization of resources, recycled material recovery, waste resource recovery; waste management, waste treatment power generation, waste incineration power generation, biogas power generation, waste heat recovery, waste heat power generation, waste gas treatment; leftover material production, comprehensive utilization of biology, comprehensive utilization of ash and slag, utilization of waste plastics, exhaust gas turbine, waste liquid treatment, scrap steel, waste dismantling, scrap metal, oil and gas recovery, comprehensive utilization of electricity
Materials and components for renewable energy & energy efficiency & sustainable buildings	Rare metals, rare earths, lithium, cobalt, tantalum, tungsten, platinum, silica, silicon rectifiers, graphite, uranium, permanent magnet materials, high temperature insulation, thermoelectric materials, inorganic heat conduction, monocrystalline silicon, polycrystalline silicon, cross-linked polyethylene, fluorine-free, rare earth hydrogen storage, photoelectric new materials, low-carbon materials, semiconductors, electronic ceramics, UHMWPE fiber, organic heat carrier, glass fiber, optical fiber, liquid crystal display, liquid crystal cell, silicon wafer, single chip, thin film, polyester film, optoelectronic film, electronic glass, optoelectronics, nanocomposite, nanotechnology, ultra-thin glass; lightweight building materials, fire-resistant materials, heat insulation materials, heat preservation materials, thermal insulation materials, fireproof materials, temperature control system equipment, coated glass, adjustable light transmittance glass, glass ceramics, exterior wall insulation, aerated concrete, insulation system materials
Automation & intelligence	Automation control, intelligent control, smart grid, smart city, digital control, power automation, distribution automation, intelligent network, building intelligence, electric power automation, industrial automation

Notes: The table lists the keywords of business activities regarding environmental governance, clean production, clean energy, and green technology. The keywords are used for text-mining the description of foreign-invested firms' business scope, which is the first approach to defining green FDI. If a foreign-invested firm's business description includes keywords listed in the table, this foreign-invested firm is defined as green FDI.

Table 4.A.2: Entry of Green FDI and Green Innovation of Foreign-invested Firms

Dependent Variable:	Green Patent Family	
	Patent Count	Patent Citation
	(1)	(2)
GrFDI (Text)	0.649*	0.713**
	(0.390)	(0.351)
GrFDI (GrPat)	2.324***	2.115***
	(0.387)	(0.349)
GrFDI (GrPatOutCN)	1.047***	1.142***
	(0.225)	(0.229)
GrFDI (FIGrPatCN)	-0.117	-0.266
	(0.935)	(0.765)
Observations	28,645	24,352
Firm Controls	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
Industry FE	Y	Y
Province FE	Y	Y

Notes: The table shows the results for the correlation between the entry of green FDI to foreign-invested firms and their green innovation. Dependent variable is firm green patent family count and citation. $GrFDI$ is a dummy variable that indicates whether foreign-invested firms receive green FDI. The regressions for using different green FDI definitions are separately conducted: "Text" is the first green FDI definition: whether the text description of FDI business scope includes keywords related to environmental governance, clean production, clean energy, or green technology. "GrPat" is the second green FDI definition: whether FDI firms own green patents. "GrPatOutCN" stands for the third green FDI definition: whether FDI firms own green patents that cite prior arts from foreign countries. "FIGrPatCN" represents the fourth green FDI definition: whether FDI firms' foreign investors have filed green patents in China. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.3: Robustness Checks on Two-stage DID

Knowledge Stock of:	Horizontal GrFDI	
	(1)	(2)
Panel A: Second-stage Estimation (Dependent Variable: Green Patent Family)		
	Patent Count	Patent Citation
GrFDI Know	0.000	0.285
	(0.263)	(0.260)
Observations	51,296	43,145
Panel B: First-stage Estimation (Dependent Variable: GrFDI Know)		
GrFDI Open	0.845***	0.845***
	(0.157)	(0.157)
Observations	384,297	384,297
Firm Controls	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
Industry FE	Y	Y
Province FE	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable in Panel A is firm green patent family count and citation. $GrFDIKnow$ is the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), which is measured in logarithms. Panel B shows the results for the first-stage estimation, which is OLS. Dependent variable in Panel B is the knowledge stock of green FDI firms, which is the main exploratory variable in the second-stage estimation. $GrFDIOpen$ is the instrumental variable used in the first-stage estimation and captures if the same industry (Horizontal GrFDI) is identified as "Green FDI Encouraged Industry" (i.e., includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). CD Wald F-statistic denotes Cragg-Donald Wald F-Statistic, and KP Wald F-statistic denotes Kleibergen-Paap rk Wald F-statistic. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.4: Results for Baseline Model (OLS)

Dependent Variable:	Green Patent Family Count					
Knowledge Stock of:	Horizontal GrFDI (1)	Downstream GrFDI (2)	Upstream GrFDI (3)	Horizontal GrFDI (4)	Downstream GrFDI (5)	Upstream GrFDI (6)
				Second-stage Estimation		
GrFDI Know	0.010***	0.010***	0.020***	0.011**	0.027**	0.050
	(0.002)	(0.003)	(0.004)	(0.006)	(0.012)	(0.039)
Observations	384,297	384,297	384,297	384,297	384,297	384,297
				First-stage Estimation Dependent Variable: GrFDI Know		
GrFDI Open				0.845***	1.570***	0.376*
				(0.157)	(0.385)	(0.208)
Observations				384,297	384,297	384,297
CD Wald F-statistic				33165	55003	15849
KP Wald F-statistic				29.07	16.60	9.131
Estimation	OLS	OLS	OLS	2SLS	2SLS	2SLS
Firm Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y

Notes: Dependent variable is firm green patent family count. Columns (1) to (3) show results for OLS regression. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. Columns (4) to (6) show results for 2SLS estimation. $GrFDIOpen$ is the instrumental variable used in the first-stage estimation and captures if the same industry (Horizontal GrFDI), downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI) are identified as "Green FDI Encouraged Industry" (i.e., includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). CD Wald F-statistic denotes Cragg-Donald Wald F-Statistic, and KP Wald F-statistic denotes Kleibergen-Paap rk Wald F-statistic. Stock-Yogo critical values for weak identification test (Cragg-Donald and Kleibergen-Paap rk Wald F statistics) are 16.38 at 10% and 8.96 at 15% maximal IV size. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.5: Results for Dynamic Effects

GrFDI Open	Horizontal GrFDI Know
Pre-Open Period 8	0.233
	(0.214)
Pre-Open Period 7	0.106
	(0.250)
Pre-Open Period 6	0.181
	(0.185)
Pre-Open Period 5	0.062
	(0.189)
Pre-Open Period 4	0.090
	(0.193)
Pre-Open Period 3	0.183
	(0.218)
Pre-Open Period 2	0.088
	(0.178)
Pre-Open Period 1	0.239
	(0.190)
Post-Open Period 0	0.411**
	(0.189)
Post-Open Period 1	0.515***
	(0.197)
Post-Open Period 2	0.691***
	(0.217)
Post-Open Period 3	0.656***
	(0.210)
Post-Open Period 4	0.583**
	(0.236)
Post-Open Period 5	0.578**
	(0.252)
Post-Open Period 6	0.604**
	(0.287)
Post-Open Period 7	0.612
	(0.441)
Post-Open Period 8	1.021***
	(0.351)
Observations	384,301
Firm Controls	Y
Firm FE	Y
Year FE	Y
Industry FE	Y
Province FE	Y

Notes: The table shows the coefficients for each point estimate in the dynamic effect plot Figure 4.5. Dependent variable is the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), which is measured in logarithms. *PreOpen Period t* is a time dummy variable indicating t periods before the industry becomes "Green FDI Encouraged Industry" (i.e., the industry includes green products becoming more open to FDI while no green product becoming less open to FDI during FDI regulation changes). *PostOpen Period t* is a time dummy variable indicating t periods after the industry becomes "Green FDI Encouraged Industry". Firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects are included. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.6: Robustness Checks on Adding Key Determinants

Knowledge Stock of:	Horizontal GrFDI	Downstream GrFDI	Upstream GrFDI
	(1)	(2)	(3)
Panel A: Second-stage Estimation (Dependent Variable: Green Patent Family Count)			
GrFDI Know	0.077	0.546**	3.903***
	(0.246)	(0.276)	(1.310)
Observations	51,296	51,296	51,296
Panel B: First-stage Estimation (Dependent Variable: Green FDI Knowledge Stock: GrFDI Know)			
GrFDI Open	0.638***	1.506***	0.357**
	(0.132)	(0.348)	(0.170)
Observations	384,297	384,297	384,297
CD Wald F-statistic	22360	47319	11305
KP Wald F-statistic	23.24	18.73	9.455
Firm Controls	Y	Y	Y
Key Determinants	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Province FE	Y	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable in Panel A is firm green patent family count. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. Panel B shows the results for the first-stage estimation, which is OLS. Dependent variable in Panel B is the knowledge stock of green FDI, which is the main exploratory variable in the second-stage estimation. $GrFDIOpen$ is the instrumental variable used in the first-stage estimation and captures if the same industry (Horizontal GrFDI), downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI) are identified as "Green FDI Encouraged Industry" (i.e., includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). The interaction terms between year fixed effects and eight industry-level key determinants that affect the openness to green FDI are included as controls. CD Wald F-statistic denotes Cragg-Donald Wald F-Statistic, and KP Wald F-statistic denotes Kleibergen-Paap rk Wald F-statistic. Stock-Yogo critical values for weak identification test (Cragg-Donald and Kleibergen-Paap rk Wald F statistics) are 16.38 at 10% and 8.96 at 15% maximal IV size. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.7: Robustness Checks on Controlling Non-green FDI

Knowledge Stock of:	Horizontal GrFDI (1)	Downstream GrFDI (2)	Upstream GrFDI (3)
Panel A: Second-stage Estimation (Dependent Variable: Green Patent Family Count)			
GrFDI Know	-0.118	0.996**	3.692**
	(0.350)	(0.411)	(1.460)
Observations	51,296	51,296	51,296
Panel B: First-stage Estimation (Dependent Variable: Green FDI Knowledge Stock: GrFDI Know)			
GrFDI Open	0.642***	1.245***	0.317
	(0.158)	(0.398)	(0.222)
Observations	355,108	384,297	384,297
CD Wald F-statistic	25493	26077	2889
KP Wald F-statistic	23.93	9.789	2.869
Firm Controls	Y	Y	Y
Non-GrFDI Control	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Province FE	Y	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable in Panel A is firm green patent family count. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. Panel B shows the results for the first-stage estimation, which is OLS. Dependent variable in Panel B is the knowledge stock of green FDI, which is the main exploratory variable in the second-stage estimation. $GrFDIOpen$ is the instrumental variable used in the first-stage estimation and captures if the same industry (Horizontal GrFDI), downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI) are identified as "Green FDI Encouraged Industry" (i.e., includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). The knowledge stock of non-green FDI is added as a control variable. CD Wald F-statistic denotes Cragg-Donald Wald F-Statistic, and KP Wald F-statistic denotes Kleibergen-Paap rk Wald F-statistic. Stock-Yogo critical values for weak identification test (Cragg-Donald and Kleibergen-Paap rk Wald F statistics) are 16.38 at 10% and 8.96 at 15% maximal IV size. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.8: Robustness Checks on Removing Firm Sorting

Knowledge Stock of:	Horizontal GrFDI	Downstream GrFDI	Upstream GrFDI
	(1)	(2)	(3)
Panel A: Second-stage Estimation (Dependent Variable: Green Patent Family Count)			
GrFDI Know	0.003	0.842**	2.469
	(0.349)	(0.385)	(1.555)
Observations	27,930	27,930	27,930
Panel B: First-stage Estimation (Dependent Variable: Green FDI Knowledge Stock: GrFDI Know)			
GrFDI Open	0.867***	1.620***	0.437*
	(0.157)	(0.375)	(0.240)
Observations	232,093	232,093	232,093
CD Wald F-statistic	18679	31812	10302
KP Wald F-statistic	30.54	18.63	7.487
Firm Controls	Y	Y	Y
Drop Sorting Firms	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Province FE	Y	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable in Panel A is firm green patent family count. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. Panel B shows the results for the first-stage estimation, which is OLS. Dependent variable in Panel B is the knowledge stock of green FDI firms, which is the main exploratory variable in the second-stage estimation. $GrFDIOpen$ is the instrumental variable used in the first-stage estimation and captures if the same industry (Horizontal GrFDI), downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI) are identified as "Green FDI Encouraged Industry" (i.e., includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). Firms changing industries during the sample period are removed. CD Wald F-statistic denotes Cragg-Donald Wald F-Statistic, and KP Wald F-statistic denotes Kleibergen-Paap rk Wald F-statistic. Stock-Yogo critical values for weak identification test (Cragg-Donald and Kleibergen-Paap rk Wald F statistics) are 16.38 at 10% and 8.96 at 15% maximal IV size. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.9: Robustness Checks on Subsidies as Control

Knowledge Stock of:	Horizontal GrFDI (1)	Downstream GrFDI (2)	Upstream GrFDI (3)
Panel A: Second-stage Estimation (Dependent Variable: Green Patent Family Count)			
GrFDI Know	0.106	0.859**	3.142**
	(0.285)	(0.347)	(1.471)
Observations	36,874	36,874	36,874
Panel B: First-stage Estimation (Dependent Variable: Green FDI Knowledge Stock: GrFDI Know)			
GrFDI Open	0.749***	1.448***	0.361*
	(0.149)	(0.374)	(0.197)
Observations	320,445	320,445	320,445
CD Wald F-statistic	24101	37410	8449
KP Wald F-statistic	25.12	15.01	6.017
Firm Controls	Y	Y	Y
Subsidy Control	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Province FE	Y	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable in Panel A is firm green patent family count. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. Panel B shows the results for the first-stage estimation, which is OLS. Dependent variable in Panel B is the knowledge stock of green FDI firms, which is the main exploratory variable in the second-stage estimation. $GrFDIOpen$ is the instrumental variable used in the first-stage estimation and captures if the same industry (Horizontal GrFDI), downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI) are identified as "Green FDI Encouraged Industry" (i.e., includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). Total amount of subsidies received by each firm is added as an additional control variable. CD Wald F-statistic denotes Cragg-Donald Wald F-Statistic, and KP Wald F-statistic denotes Kleibergen-Paap rk Wald F-statistic. Stock-Yogo critical values for weak identification test (Cragg-Donald and Kleibergen-Paap rk Wald F statistics) are 16.38 at 10% and 8.96 at 15% maximal IV size. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.10: Robustness Checks on Alternative Foreign Ownership Thresholds

Ownership Thershold:	Foreign Ownership > 25%			Foreign Ownership > 50%		
Knowledge Stock of:	Horizontal GrFDI	Downstream GrFDI	Upstream GrFDI	Horizontal GrFDI	Downstream GrFDI	Upstream GrFDI
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second-stage Estimation (Dependent Variable: Green Patent Family Count)						
GrFDI Know	-0.069	0.717**	1.892	-0.071	0.561**	1.179
	(0.288)	(0.342)	(1.412)	(0.238)	(0.261)	(0.965)
Observations	51,296	51,296	51,296	51,296	51,296	51,296
Panel B: First-stage Estimation (Dependent Variable: Green FDI Knowledge Stock: GrFDI Know)						
GrFDI Open	0.780***	1.507***	0.385	0.990***	2.004***	0.590
	(0.133)	(0.322)	(0.261)	(0.181)	(0.263)	(0.393)
Observations	384,297	384,297	384,297	384,297	384,297	384,297
CD Wald F-statistic	29401	53916	1548	45653	85352	1143
KP Wald F-statistic	34.59	21.90	4.575	30.06	58.21	3.417
Firm Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y

Notes: Panel A shows the results for the second-stage estimation, which is Poisson regression. Dependent variable in Panel A is firm green patent family count. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. Panel B shows the results for the first-stage estimation, which is OLS. Dependent variable in Panel B is the knowledge stock of green FDI firms, which is the main exploratory variable in the second-stage estimation. $GrFDIOpen$ is the instrumental variable used in the first-stage estimation and captures if the same industry (Horizontal GrFDI), downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI) are identified as "Green FDI Encouraged Industry" (i.e., includes green products more opened up to FDI while no green products less opened up to FDI during FDI regulation changes). Only firms with foreign ownership larger than 25% are regarded as FDI in Columns (1)-(3) and firms with foreign ownership larger than 50% are regarded as FDI in Columns (4)-(6) when constructing the knowledge stock of green FDI firms. CD Wald F-statistic denotes Cragg-Donald Wald F-Statistic, and KP Wald F-statistic denotes Kleibergen-Paap rk Wald F-statistic. Stock-Yogo critical values for weak identification test (Cragg-Donald and Kleibergen-Paap rk Wald F statistics) are 16.38 at 10% and 8.96 at 15% maximal IV size. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

Table 4.A.11: Robustness Checks on Alternative Green FDI Definitions

Dependent Variable:	Green Patent Family Count		
Knowledge Stock of: *Second-stage Estimation*	Horizontal GrFDI (1)	Downstream GrFDI (2)	Upstream GrFDI (3)
GrFDI Know (GrPat)	-0.058	1.029**	2.251*
	(0.509)	(0.482)	(1.263)
GrFDI Know (GrPatOutCN)	-0.082	0.510*	1.296
	(0.264)	(0.285)	(0.866)
GrFDI Know (FIGrPatCN)	-0.112	0.496*	0.718
	(0.440)	(0.287)	(0.460)
GrFDI Know (Text&GrPat)	0.000	0.732***	2.512*
	(0.263)	(0.357)	(1.393)
Observations	51,296	51,296	51,296
Firm Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Province FE	Y	Y	Y

Notes: The table shows the results for the second-stage estimation, which is Poisson regression. Dependent variable is firm green patent family count. $GrFDIKnow$ is classified into three types: the knowledge stocks of green FDI firms in the same industry (Horizontal GrFDI), in downstream industries (Downstream GrFDI), and upstream industries (Upstream GrFDI). All knowledge stock indicators are in logarithms. The regressions for using alternative green FDI definitions are separately conducted: "GrPat" is the second green FDI definition: whether FDI firms' own green patents. "GrPatOutCN" stands for the third green FDI definition: whether FDI firms own green patents that cite prior arts from foreign countries. "FIGrPatCN" represents the fourth green FDI definition: whether FDI firms' foreign investors have filed green patents in China. "Text&GrPat" means the intersection of the first and second definitions of green FDI: whether the text description of FDI business scope includes keywords related to environmental governance, clean production, clean energy, or green technology, and owns green patents. The first-stage estimation results are not shown in the table for the sake of brevity. All columns contain firm control variables, firm fixed effects, year fixed effects, industry fixed effects, and province fixed effects. Standard errors in the parentheses are clustered at the industry level. ***, **, *, indicate significance at 1% level, 5% level, and 10% level, respectively.

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