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

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Abstract

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 paper shows the variation of green revenues during 2009-2016. We document a smooth increase in average green revenues over 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. We find 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. We also find 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.

Keywords: Green Revenue; Clean Innovation; Technology Spillover; Climate Change

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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, Newell, and Stavins, 2002; Dechezleprêtre and Sato, 2017). However, innovators are not always beneficiaries because the economic benefits of clean innovation largely rely on technology commercialisation, which does not necessarily happen inside the same firms where new technologies are invented (Teece, 2006; McGahan and Silverman, 2006). 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 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, most existing literature examines the economic impacts of clean innovation based on the aggregated firm-level data (Popp, 2019), 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

[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.

green economic activities (Jacobs, Singhal, and Subramanian, 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 linkage between firms and measure clean technology spillovers when evaluating the economic benefits of clean innovation (Dechezleprêtre, Martin, and Mohnen, 2017; Barbieri, Marzucchi, and Rizzo, 2020). 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 more than 14000 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. Nearly 3500 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 field of clean technologies. 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 such 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, Muckley, and Neelakantan, 2021). This paper builds on this strand of literature by providing a new piece of evidence on the relationship between clean innovation on firms' economic benefits from green commercial activities.

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, Schankerman, and Van Reenen, 2013; Lychagin et al., 2016). Some studies pay attention to possible spillovers of firms' clean technologies, but heavily rely on patenting activities to capture spillover linkages and have not fully differentiated the spillovers across different spaces (Dechezleprêtre, Glachant, and Ménière, 2013; Aghion et al., 2016; Dechezleprêtre, Martin, and Mohnen, 2017; Barbieri, Marzucchi, and Rizzo, 2020). 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.

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, Singhal, and Subramanian, 2010; Eccles, Ioannou, and Serafeim, 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 2 describes the data used in our study. Section 3 presents the construction of key variables and our empirical strategies. Section 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 5 concludes.

2 Data

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 over 14000 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

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 1: FTSE Russell Green Revenue Classification System

Notes: The FTSE Russell Green Revenues Data Model develops a new green taxonomy - Green Revenue Classification System, containing 10 green sectors and 64 subsectors. For more details on each sector, please refer to https://www.ftserussell.com/data/sustainability-and-esg-data/green-revenues-data-model.

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 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

[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.

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. Nearly 3500 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]

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.

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

[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 A1.

[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 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 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.

for a clearer interpretation (shown in Figure 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

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

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, 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.

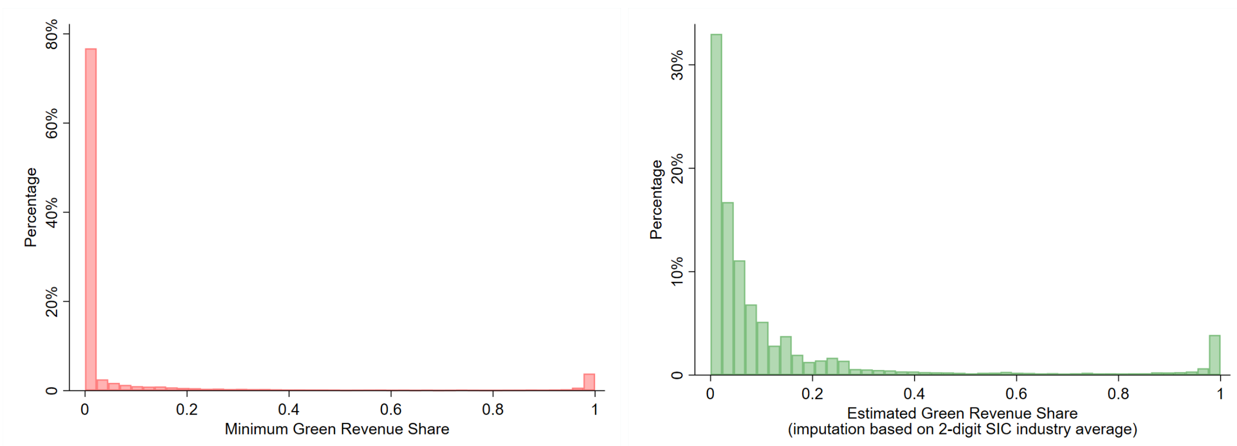

Figure 3: Distribution of Minimum and Estimated Green Revenue Share

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 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.

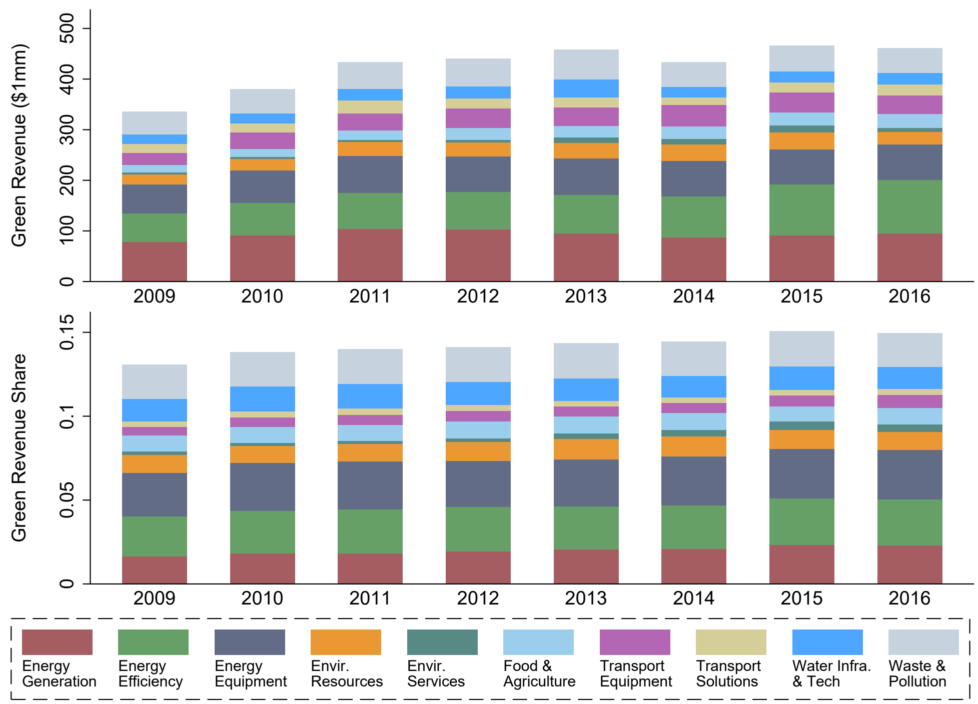

Figure 4: Trend and Composition of Green Revenue and Green Revenue Share

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.

Figure 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 held steady thereafter. The bottom half displays the average green revenue

[7]Figure 4 excludes firms that are not identified as engaged in green business as they do not have any green revenues.

share in each firm. Although the absolute value of green revenue increases, the share of green revenue remains stable over 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.

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, Hurtado-Albir, and Volpe, 2018). To ensure the relevance between technologies in the Y02 category and green business in the FTSE GR data, we link each Y02 category to related FTSE GR green subsectors for a more precise check and measure 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

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

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 Empirical Methodology

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 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 stock of clean patents. More specifically, we retrieve patent documents starting from 1970 and calculate patent stocks using a perpetual inventory method with a 15% depreciation rate (Hall, Jaffe, and Trajtenberg, 2005). The clean patent stock $CleanTechStock$ in year t is $CleanTechStock_t = CleanPat_t + (1 - \delta)CleanPat_{t-1}$, where $CleanPat$ is the new clean patent applications in yeat t and δ denotes depreciation rate. In addition to the count of clean patents as the quantity measure, we also construct clean patent stocks based on patent citations, international patent families and triadic patent families to address the issue of patent quality.[9]

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 5. It is not surprising that firms' green revenues generally increase with their own clean innovation,

[9]International patent family is defined as the patent family that covers a set of applications filed in more than one country. Triadic patent family is defined as a set of patent applications within one patent family that have been submitted to the USPTO, EPO, and JPO three patent offices.

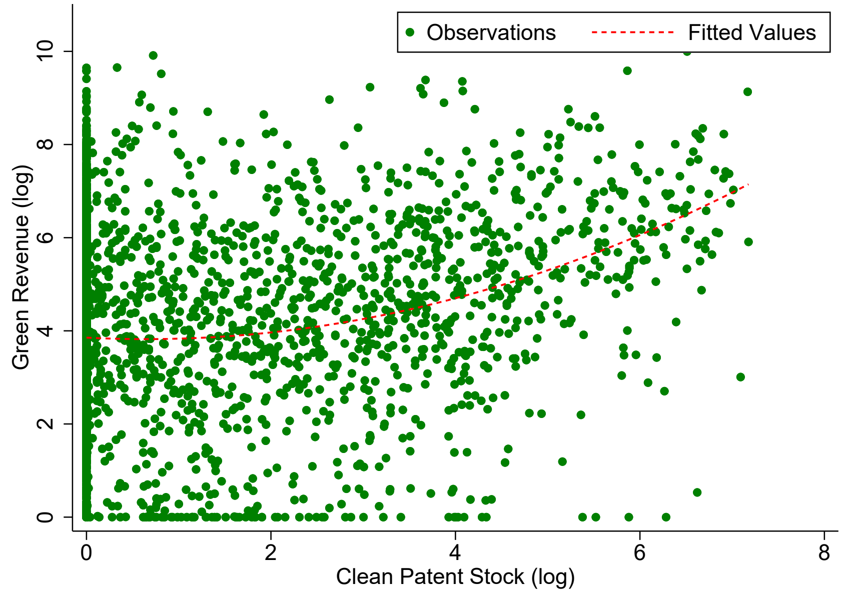

Figure 5: Scatter Plot of Green Revenue and Clean Innovation

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.

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 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:

$$CleanSpill_{it} = \sum_{j \neq i} w_{ijt} \cdot CleanTechStock_{jt} \tag{1}$$

where $CleanTechStock_{jt}$ is the cumulative stock of clean patents that other firms j pos-

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

sess 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.

3.1.1 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:

$$w_{ijt}^{TechSpace} = CL_{ijt} \cdot TechProx_{ijt}^{Jaffe} = CL_{ijt} \cdot \frac{T_{it}T_{jt}'}{\sqrt{T_{it}T_{it}'}\sqrt{T_{jt}T_{jt}'}} \tag{2}$$

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, Schankerman, and Van Reenen (2013) (BSV) develops an alternative Mahalanobis-

[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.

distance index of technological proximity that takes into account the relatedness between different 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.

3.1.2 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, Schankerman, and Van Reenen (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:

$$w_{ijt}^{ProdMktSpace} = ProdMktProx_{ijt} = \frac{S_{it}S'_{jt}}{\sqrt{S_{it}S'_{it}}\sqrt{S_{jt}S'_{jt}}} \quad (3)$$

Analogous to the vector T_{it} in Eq (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 contrast, the spillover indicator based on the overlap of green products between firms can better cover the technology spillovers that lead to technology commercialisation.

3.1.3 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

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

capture where innovation activities emerge.[16] More specifically, the geographic proximity between a pair of firms i and j is calculated as:

$$w_{ijt}^{GeogSpace} = GeogProx_{ijt} = \frac{L_{it}L_{jt}'}{\sqrt{L_{it}L_{it}'}\sqrt{L_{jt}L_{jt}'}} \tag{4}$$

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]

3.1.4 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, Perruchas, and Consoli, 2020). 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, Lavie, and Messeni Petruzzelli, 2017). The lower risk and higher value of commercial applications encourage firms to put more focus on business 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

[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.

specifically, a firm-level clean technology maturity can be constructed as:

$$CleanTechMat_{it} = \sum_{g=1}^{G} GR\_Ratio_{igt} \cdot (\frac{1}{P} \sum_{p=1}^{P} TechAge_{ipt}) \tag{5}$$

A straightforward measure of $TechAge_{ipt}$ is the age of patent p owned by firm i up to year t, and P represents the number of firm i's clean patents categorised into the technology classes which are linked to green subsector g.[18] 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, Lavie, and Messeni Petruzzelli, 2017). Prior arts that a patent cites describe the composition of knowledge that this focal patent draws on. 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.

3.1.5 Summary Statistics

Table 1 presents the basic descriptive statistics of all sample firms and green firms (firms are identified as involved in the green business). The firms in our sample are relatively large and the green firms are much larger than other firms. When it comes to innovation activities, green firms emerge to be much more active among the full sample of firms (both in total patenting and clean patenting).

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

Table 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, Schankerman, and Van Reenen (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".

Furthermore, we specifically compare the mean and important quartiles of key variables between green and non-green firms, as shown in Figure 6. We can see that green firms play a much bigger role in both aspects of markets and technologies. Since green revenue information is available only for green firms, our analysis mainly focuses on green firms, while non-green firms are still taken into account when computing spillovers and other industry- or country-level indicators.

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:

$$Y_{itjc} = \beta_0 + \beta_1 CleanTech_{i,t-1} + X_{i,t-1} + \gamma_i + \delta_{jt} + \lambda_{ct} + \varepsilon_{ijct} \tag{6}$$

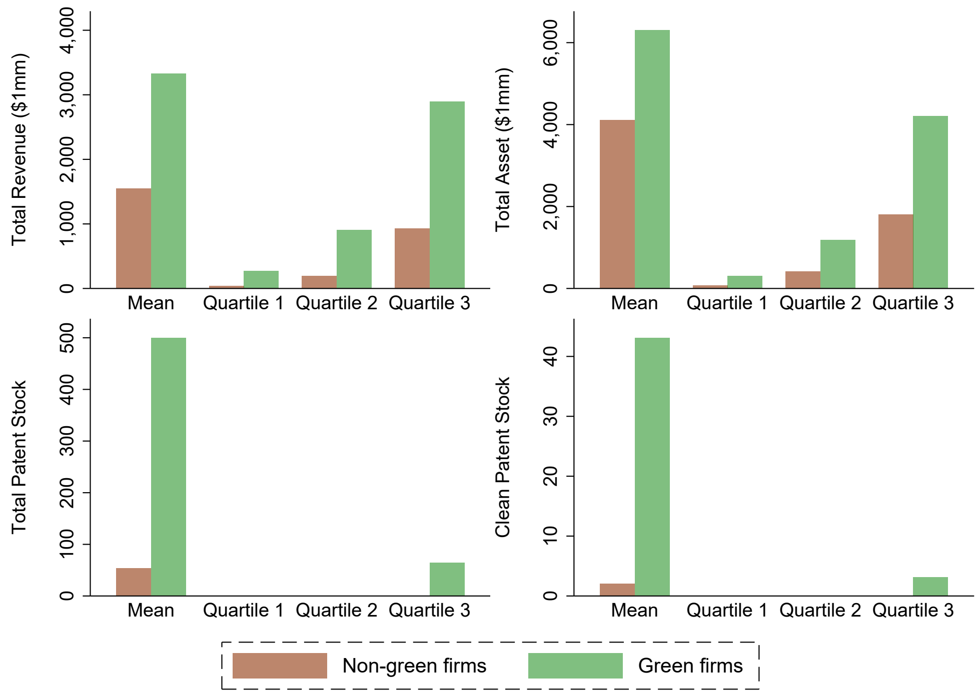

Figure 6: Comparison between Green and Non-Greene Firms

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). 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 (6) cannot capture the spillover effects of other firms' clean technologies. Hence, the clean technology pools of other firms should be also added to the regression model:

$$Y_{it} = \beta_0 + \beta_1 CleanTech_{i,t-1} + \beta_2 CleanSpill_{i,t-1} + X_{i,t-1} + \gamma_i + \delta_{jt} + \lambda_{ct} + \varepsilon_{ijct} \quad (7)$$

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.

4 Empirical Results

4.1 Baseline Results

Table 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.

Table 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.

Since firms' green revenues may also benefit from other firms' clean technologies, we next estimate the clean technology spillovers by Eq (7). Table 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 technologies of other neighbouring firms close in the technological space. This result suggests the existence of spillovers across the technological space.

Table 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.

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, Schankerman, and Van Reenen, 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 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 A1, which shows similar results as Table 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.

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 (5) to our regression.

Table 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.

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 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

Table 4: Clean Technology Maturity and Green Revenue

Dependent Variable:	Green Revenue			
Innovation Measured by:	Patent Count		Patent Citation	
Technology Maturity Measured by:	PatAge (1)	BkwAge (2)	PatAge (4)	BkwAge (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.

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. The results suggest that in alternative energy, energy efficiency, and sustainable transport, firms mainly benefit from others' technologies when they have a large overlap in green product markets.

Table 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.

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-samples to examine the role of firm size and technology capacity in the relationship between green revenues and clean technologies. Table 6 presents the corresponding results.

We first divide firms into two groups based on their firm sizes: one group with market

Table 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.

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 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 6 echo the opinion that firms' complementary assets play an important role in how much firms can benefit from innovation (Teece, 1986; Pisano, 2006)

4.5 Robustness Checks

First, Bloom, Schankerman, and Van Reenen (2013) (BSV) develops an alternative measure of technological proximity that takes into account the relatedness between different technology classes. [19] 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:

$$w_{ijt}^{TechSpace} = CL_{ijt} \cdot TechProx_{ijt}^{BSV} = CL_{ijt} \cdot \frac{T_{it}\Omega T_{jt}'}{\sqrt{T_{it}T_{it}'}\sqrt{T_{jt}T_{jt}'}} \tag{8}$$

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. [20] We re-estimate our models by using the BSV's technological proximity. The results for this robustness check are kept in Table A2, 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, Webster, and Jensen, 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

[19]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.

[20]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.

patent families, respectively. The results for the two innovation indicators are presented separately in Columns (1) to (3) and (4) to (6) of Table A3. 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 A4. 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 A4. 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.

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 public support to clean innovation is needed to spread the economic benefits of clean technologies and achieve the green transition.

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Appendix A Additional Figures and Tables

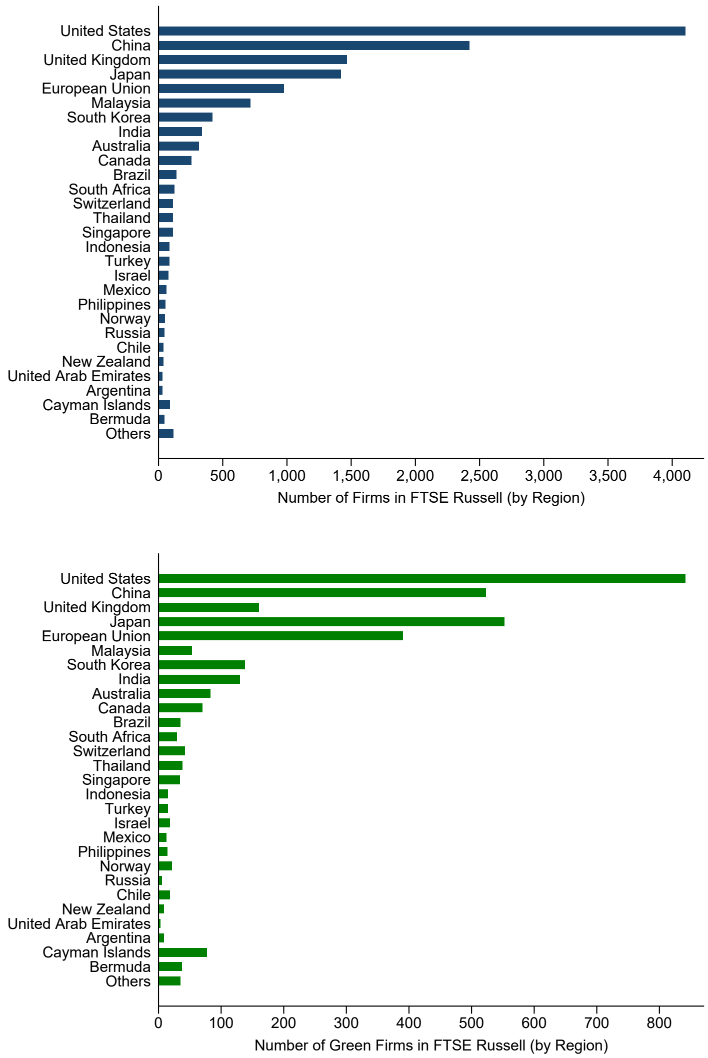

Figure A1: Geographic Distribution of Firms in FTSE Russell Dataset

Notes: The upper panel shows the number of firms covered by FTSE Russell in each region. The lower panel shows the number of firms covered by FTSE Russell and identified as green firms in each region. 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.

Table A1: 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 A2: 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)
Spill_TechSpace(BSV)$_{t-1}$	0.035***	0.037**	0.026***	0.026**
	(0.012)	(0.016)	(0.009)	(0.011)
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 A3: 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)-64) 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 A4: 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.