Environmental Regulation promotes Green Technological Diversification: Evidence from Chinese Cities

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Papers in Evolutionary Economic Geography

22.26

Utrecht University Human Geography and Planning

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Abstract: Green technological diversification is crucial to regional green transition, but green technologies tend to be more radical and complex. This means that they require significant efforts to scale, and we need to understand all possible levers for green technological change. Based on patenting activities in Chinese cities from 2003 to 2016, this paper finds that cities with tighter environmental regulations tend to branch into new green technology spaces. Moreover, environmental regulations help cities enter more complex green domains, and this association varies across different green types and regions. This study provides significant implications for the green transition and diversification literature.

Keywords: Environmental regulation; Technology diversification; Green innovation; Relatedness; Complexity

JEL codes: B52; Q55; Q56; R11

1. Introduction

The urgency to mitigate environmental degradation and climate change is often considered the most pressing challenge of our times. Green technologies, which promise to have few or zero adverse effects on the environment (Oltra & Saint Jean, 2009), are regarded as a potential way to achieve a win-win situation between the economy and the environment (Popp, 2019). Though green innovations have higher social value, more economic benefits, and broader potential applications across various technological areas than non-green innovations (Popp & Newell, 2012; Nemet, 2012), the process of diversifying into green tech domains is challenging and risky due to the knowledge and environmental externalities of green innovation. Helping regions, especially underdeveloped areas, jump the technological trajectories and create new, more complex green technology development paths is essential for fostering sustainable development and reducing regional inequality.

In the regional diversification literature, the ability of a region to develop a new technology hinges on its existing knowledge and capabilities related to this specific technology. Regions gradually diversify by leveraging related, preexisting economic activities, which are path-dependent (Balland & Rigby, 2017; Dong et al., 2022). As a dimension of knowledge, the complexity of economic activities has received increasing attention in regional diversification studies since both technological composition and values are vital to the regional knowledge basket (Hidalgo & Hausmann, 2009; Balland & Rigby, 2017; Balland et al., 2022). According to them, economic activities with a high level of complexity are more exclusive and harder to replicate, transmit, and copy (Simon, 1991), which is essential for creating a long-term competitive advantage for regions (Kogut & Zander, 1992; Hidalgo & Hausmann, 2009; Balland & Rigby, 2017).

Considering the vital role of green innovation, the regional diversification literature has recently contributed to our understanding of the green innovation space (Li et al., 2020; Barbieri et al., 2020; Santoalha et al., 2021). These studies focused on the role of relatedness (Tanner, 2014; van den Berge et al., 2019; Barbieri et al., 2020) and the difference between green and non-green diversification (Barbieri et al., 2020). However, this strand of literature often overlooks the impact of policies. The processes of green transition include more path-breaking and complex technology, and market participants hesitant to develop this kind of innovation without external sources due to its environmental and knowledge externalities (Aghion et al., 2016; Popp, 2019). Therefore, recent diversification literature has explored the role of external policy shock in the processes of path-breakthrough green diversification (Markard et al., 2012; Rogge & Reichardt, 2016), but they ignore the role of technological complexity.

In the environmental policy area, scholars have discussed how environmental policy affects green innovation and moves a city's technological frontier forward. Proponents of the "Porter Hypothesis" consider that environmental regulations encourage more technological innovations (Porter & Van der Linde, 1995; Aghion et al., 2016), while critics contend that environmental regulations improve the abatement cost and squeeze out new technologies (Popp & Newell, 2012; Noailly & Smeets, 2015). Though this strand of research deepens our understanding of how external factors affect the innovation process, it mainly explores the number of green technologies and tends to ignore the embedded knowledge and technological structure, undermining the dynamic evolutionary process of diversification. In practice, many countries have introduced policies to promote domestic green technologies. For example, France launched the France Recovery Plan in 2020, allocating 30 billion euros to ecological transformation, and supporting various green technologies. On a global scale, China's green transformation is also closely tied to advancements in green technologies and supportive environmental policies.

With this in mind, this study investigates whether environmental policies can help cities embrace a more complex green technology and whether they contribute to or hinder regional disparities. We conduct our study by using China's authorized patent data from 2003 to 2016. First, we find that environmental regulations foster cities' expansion into new green technology spaces in general. Second, environmental regulations stimulate cities to enter more complex domains of green technologies. Third, there is significant heterogeneity in the consequences of environmental regulations regarding the types of green innovations and different regions. Therefore, environmental regulations might exacerbate regional inequalities in economic development and the environment.

In doing so, we bridge the knowledge gap in environmental policy and diversification literature. Since diversifying into more complex green innovation is more challenging, a few recent studies have focused on how external factors affect green diversification (Markard et al., 2012; Rogge & Reichardt, 2016). However, this body of literature is mainly about how the embedded knowledge structure is related to the green diversification process or whether supporting policies that provide subsidies and reduce costs could alter the path-dependent process. In addition, they mainly investigate how the external linkages can alter the path-dependent innovation process by considering the relatedness density. Despite this emerging focus, a substantial knowledge gap persists between regional diversification research and environmental policy research. In particular, there is little evidence of the capacity of environmental regulations to facilitate the adoption of complex green technologies in cities. We argue that analyzing whether diversifying into more complex technology can be improved by environmental regulation is particularly important due to the role of complexity in regions' long competitiveness. The point of environmental regulation forcing innovation is addressed in the previous answer related to the "Porter Hypothesis". However, this study moves beyond the existing "Porter hypothesis" literature focusing on the aggregated output of innovation by introducing a technology's complexity and knowledge value.

2. Literature Review

2.1 Diversification, Relatedness and Complexity

Jane Jacobs (1969) was the first to propose that diversification can provide opportunities for regional production knowledge restructuring and thus drive economic growth. Subsequently, a series of studies argued that diversification can help promote regional economic growth through knowledge spillovers (Glaeser et al., 1992; van Oort, 2004). Evolutionary economic geography inherits the basic viewpoint and believes that the diversification process in a city depends on the preexisting knowledge of related technologies. Hidalgo et al. (2018) characterized this pattern as the "principle of relatedness", which indicates that specializations in a new technology field relate to the existing capabilities and knowledge repository of cities (Uhlbach et al., 2022). Therefore, new technologies are often not created from scratch, but rather a path-dependent incremental process due to high risk and switching costs (Neffke et al., 2011). This path-dependent process is supported by many empirical studies at various geographical scales (Colombelli et al., 2014; Boschma & Capone, 2015; Dong et al., 2022).

Recent studies also placed much emphasis on the complexity of economic activities. Hidalgo & Hausmann (2009) argued that more advanced products and services require the convergence of diverse expertise, which in turn requires complex coordination capabilities that are developed over time in a cumulative, path-dependent, and continuous manner. Therefore, those economies that are already active in complex activities also have the best opportunities and prerequisite regions to gain further competitiveness in other more complex fields. At the sub-national level, studies have confirmed that complex activities will be more unequally distributed and less ubiquity. They argued that few regions can specialize in the most complex production processes, while many regions focus on less complex or even simple activities (Balland & Rigby, 2017; Balland et al., 2020; Mewes &Broekel, 2020).

2.2 Green Diversification

Due to the increasing emphasis on green transformation, the regional diversification literature has gained some insights into understanding green innovation space (Barbieri et al., 2020; Santoalha et al., 2021). Studies indicate that relatedness drives green diversification. For example, Montresor & Quatraro (2020) showed a positive impact of the relatedness of green and non-green knowledge on new green technology specialization. Perruchas et al. (2020) found that countries are more likely to achieve green diversification related to their capacity combinations based on 63 country cases in the European region. However, another branch of research emphasized the specificity of the green innovation process (Quatraro & Scandura, 2019; Zeppini & den Bergh, 2011), suggesting that the combination of “distant” technological pieces is more likely to lead to a paradigmatic shift from a non-green regime to a greener one (Nightingale, 1998; Fleming, 2001). In addition, many studies indicated that green technologies tend to be more complex and involve novel recombinations (Barbieri et al., 2020), which requires more external economic support and diversified knowledge sources (Cooke, 2010; Tanner, 2016). Recent research has claimed that strong policy interventions are required to achieve sustainability goals and develop new green technologies (Rogge & Reichardt, 2016; Lindberg et al., 2019). Public policies play a crucial role, as seen in Santoalha & Boschma's (2021) research on supportive environmental policies in seven European countries.

In summary, literature on green diversification largely focuses on the inherent characteristics of green innovation. A few recent studies examine how public policies influence the path-dependent processes of green diversification, but this body of work primarily emphasizes supportive policies that provide subsidies and reduce costs. Furthermore, these studies often overlook the knowledge value embedded in green technologies, which is essential for a region's long-term sustainable development and competitive advantage. Given that advancing green transition into more complex and valuable domains is challenging without external support, it is worth exploring whether and how external sources influence this process. However, there is limited evidence on the capacity of environmental policies to facilitate the adoption of complex green technologies across cities.

2.3 The Effect of Environmental Regulation on Innovation

While society is enthusiastic about the green and innovative path for sustainability, it suffers from two kinds of market failures (Popp, 2019; Aghion et al., 2016). The first one is environmental externalities, where the social benefits of pollution reduction aren't reflected in prices, leading to insufficient incentives for firms and consumers to reduce pollution. The second one is the externality of knowledge, which means the knowledge of the new innovation becomes public once the innovators want to reap the benefits of innovations. Such public knowledge will induce more followers and lead to copies of current innovations, which benefits the public but not the innovator. Due to these two market failures, market participants lack the incentives to invest in green innovations without proper policy interventions.

Considering the insufficient incentives for green innovations by market forces, academics have become more interested in how environmental regulation affects green innovations. Proponents of the “Porter Hypothesis” consider that environmental regulations encourage innovators to develop more technological innovations, aiming to enhance their long-term competitiveness under the pressure of regulatory policies (Porter & Van der Linde, 1995; Aghion et al., 2016). Numerous studies have confirmed the positive relationship between environmental regulation and technologies (Tchorzewska et al., 2022), with recent literature focusing on clarifying which type of policy tools is most effective and has a sustained incentive effect on innovation (Bergek et al., 2013; Popp, 2019). Conversely, opponents argue that environmental regulation inhibits green innovation. Such studies are mainly based on the cost perspective and emphasize that environmental regulation will bring high governance and compliance costs, “crowding out” enterprises’ willingness and resources for innovation (Popp & Newell, 2012; Noailly & Smeets, 2015). Popp (2006, 2019) pointed out that environmental regulations punishing companies that do not meet regulatory requirements will reduce innovation.

In summary, this strand of literature mainly examines how environmental policies influence the aggregate innovation output across different research scales. Yet, it often overlooks the role of embedded knowledge structures in the green diversification process. While studies have argued that the impact of environmental regulations on innovation depends on existing technologies, most studies tend to ignore the relatedness and complexity of specific technologies with others, as well as city-specific green technological characteristics (e.g., comparative technological advantage, technological maturity). However, such cross-technology relatedness and knowledge value are crucial for cities to foster further innovation.

3. Hypothesis Development

Regional development is constrained by preexisting knowledge bases, which generates a strong path-dependent process (Boschma & Frenken, 2011). Such path-dependence has been a significant obstacle for less developed regions branching into new technology spaces (Hidalgo et al., 2007; Kogler et al., 2017). This pattern is especially true for the most complex technologies, which, as a result, tend to concentrate intensely in large cities (Balland et al., 2020). However, the lack of related knowledge to a region can be compensated by extra-regional linkages, thereby facilitating the diversification process by providing missing knowledge pieces (Aghion et al., 2016; Dong et al., 2022).

A big question, however, concerns environmental regulations. They are fundamental to fighting climate change and environmental degradation, but understanding whether they create or hinder economic opportunities is essential to receiving societal support. Porter & Van de first proposed the "Porter hypothesis" in 1995, arguing that environmental regulations could positively affect innovation. The rationale behind this is that technologies induced by environmental regulation are expected to offset abatement costs by making their processes more efficient, reducing waste, and enhancing productivity. In this context, environmental regulations stimulate innovators to develop new technologies (Xu et al., 2023; Lin & Xie, 2023), helping regions enter new technological domains. The Porter Hypothesis has been tested at various scales in the literature (Dechezleprêtre & Glachant, 2014; Rexhäuser & Löschel, 2015; Costantini et al., 2017; Zhu et al., 2019; Xu et al., 2023). Additionally, certain environmental regulations provide resources and subsidies to innovators, further reducing the risks associated with entering new technological domains and encouraging innovation.

Therefore, we propose the first hypothesis regarding the effect of environmental regulations on both green and non-green technologies:

H1: *Cities with tighter environmental regulations are more likely to diversify into new technologies.*

Though environmental regulation plays a vital role in diversifying both non-green and green technology spaces, it will undoubtedly affect green diversification to a larger extent. This is for two reasons. Firstly, green technologies exhibit both environmental and knowledge externalities. Environmental regulation can address these market failures by offering subsidies and internalizing these externalities to encourage investment in green technologies (Rogge & Schleich, 2018; Popp, 2019). Secondly, green technologies are generally in the early stage of their life cycle, presenting greater risks and uncertainties. Experts in this field face challenges due to the complex knowledge required and the uncertainties involved (Consoli et al., 2016; Braungart et al., 2007), involving higher risk (Barbieri et al., 2020) and the need for diverse knowledge inputs (Dong et al., 2020; Rennings & Rammer, 2009).

Therefore, diversifying into green technology space needs more external sources (Braungart et al., 2007; Barbieri et al., 2020). The environmental regulation intervention could provide such sources and reduce uncertainties by altering consumer preference and regulating the production process (Barwick et al., 2019), forming a positive feedback loop between green production and consumption. More specifically, to fulfill the environmental regulations to avoid punishment, enterprises will attempt to produce green by replacing the equipment with fewer pollutants, utilizing cleaner energy, and so on. In addition, by improving public awareness of environmental issues, environmental regulations will enhance consumers' preference for clean products (Barwick et al., 2019; Popp et al., 2011), further stimulating green production. This positive feedback loop between green production and consumption could create a bigger green market, making green innovations more profitable, hence reducing the relative risks of investing in these radical and complex technologies.

Therefore, we develop our second hypothesis as below:

H2: *Environmental regulations are more likely to encourage cities to enter green technologies than non-green ones.*

In the realm of green technologies, complexity is a significant factor influencing the likelihood of adoption. On the one hand, the complexity of green technology can affect its cost-effectiveness, which in turn influences how businesses and industries react to environmental policies. Complex green technologies might offer more significant long-term comparative advantage and entry barriers, but the higher upfront investment costs could be an issue. Environmental policy interventions can provide resources and capital vital for advancing sophisticated green technologies. This illustrates why environmental policy can be particularly effective for complex green technologies.

On the other hand, the support and guidance provided by governments are strategically targeted and not randomly allocated. Local governments often focus on investing in more complex technologies to boost long-term competitiveness and environmental performance. Subsidies, support, and guidance from the government can enable innovators to reallocate their financial resources towards acquiring the necessary knowledge and capabilities to delve into more advanced and complex technological fields.

Therefore, we propose our third hypothesis:

H3: *Environmental regulations foster cities to develop more complex green technologies.*

4. Data and Methodology

4.1 Data and Variable Definition

4.1.1 Technology-related Variables

We obtained information on Chinese patents from IncoPat, which sources its original data from the China National Intellectual Property Administration (CNIPA). IncoPat contains data on patents from 102 countries and territories. All Chinese inventions were applied from September 1985, including the patent title, abstract, application date, and grant date. We compiled the application number, name of applicants, address of applicants, and 4-digit International Patent Classification (IPC) class of invention patents. These patent applications were approved before June 2017. Therefore, we applied the patent data of 637 4-digit IPC sub-classes from 2003 to 2016 in the analysis. Since the grants of patent rights attest to the validity of the applicants' technological innovation efforts, we only counted patent applications that were ultimately authorized. We excluded patent applications that were denied official grants because they cannot reflect a city's success in entering technical fields. Our original dataset encompasses over 1.6 million authorized patents. Utilizing this raw data, we calculated the number of patent applications at the 4-digit IPC class of each city by year. Ultimately, our analysis results in 637 distinct categories based on the IPC 4-digit code classification, spanning 284 cities from 2003 to 2016.

(1) Green innovation

According to the description of the World Intellectual Property Organization (WIPO), green innovations are defined as: "protecting the environment, being less polluting, using all resources in a more sustainable manner, recycling more of their wastes and products, and handling residual waste in a more acceptable manner than the technologies for which they were substitutes." This definition is also widely used in the literature (Zhu et al., 2019; Xu et al., 2023). Green innovation includes seven subcategories based on whether its IPC 4-digit subclass is included in the Green Inventory by WIPO. Considering the relationship with the ER index we constructed, we excluded the nuclear energy category since it is mainly innovated by certain institutions in China, and whether it belongs to green innovation remains to be discussed (Popp et al., 2019). Finally, we identified six subcategories of alternative energy production (Alter_ener), agriculture/forestry (Agri_fore), administrative, regulatory or design aspects (Ard), waste management (Waste), energy conversation (Energy_con), and transportation (Trans) as the green innovations. Green patent authorizations, numbering 390,418, account for approximately 24.20% of the total authorizations (1,613,332)

(2) Revealed comparative advantage (RCA)

To determine whether a city has an advantage in a certain technology, we employed the revealed comparative advantage (RCA). RCA is calculated by the location quotient, which is the share of cities' specialization in the average national level of specialization in a specific technology. Formally, the RCA of each technology subcategory in each city is specified as follows:

$$RCA_{i,c,t} = \begin{cases} = 1, if \ \dfrac{Teconology_{i,c,t}/\sum_i Teconology_{i,c,t}}{\sum_C Teconology_{i,c,t}/\sum_c \sum_i Teconology_{i,c,t}} \geq 1 \\ = 0, if \ \dfrac{Teconology_{i,c,t}/\sum_i Teconology_{i,c,t}}{\sum_C Teconology_{i,c,t}/\sum_c \sum_i Teconology_{i,c,t}} < 1 \end{cases} \quad (1)$$

Here, i, c and t stand for technology, city and year, respectively. $Technology_{i,c,t}$ is the number of patents granted of subclass i in city c in time t. $RCA_{i,c,t}$ equals one if the ratio of a specific technology i to all technology invented by a city is higher than that of the national average level and equals zero otherwise.

(3) Relatedness ($\varphi_{i,j,t}$) and relatedness density ($Density_{i,c,t}$)

We followed Hidalgo et al. (2007) and defined relatedness between technology i and j as the minimum of the conditional probability that two technologies whose RCAs both equal one in the same cities. The calculation is as follows:

$$\varphi_{i,j,t} = \min\{P(RCA_{i,c,t} = 1 | RCA_{j,c,t} = 1),\ P(RCA_{j,c,t} = 1 | RCA_{i,c,t} = 1)\} \quad (2)$$

A higher value of $\varphi_{i,j,t}$ implies that the two technologies tend to be developed in the same region. Relied on the relatedness constructed in Equation (2), technology relatedness density ($Density_{i,c,t}$) is measured as the weighted average RCA of all other technologies in a specific city weighted by their relatedness with this particular technology and is calculated as follows:

$$Density_{i,c,t} = \frac{\sum_j RCA_{j,c,t}\varphi_{i,j,t}}{\sum_j \varphi_{i,j,t}} \tag{3}$$

Higher density indicates that in city c, this certain technology is encircled by many other highly developed technologies.

(4) Technology Complexity Index (TCI) and Knowledge Complexity Index (KCI)

To measure the Knowledge Complexity Index (KCI) of regions and the Technology Complexity Index (TCI) of economic activities, Hidalgo & Haussmann (2009) created a "Method of Reflections" based on the hypothesis that cities with more complex knowledge structures create exclusive products that are infrequently produced by other economic systems. This approach has been used in a variety of contexts, including exports (Reynolds et al., 2018), patents (Balland et al., 2019), employment (Farinha et al., 2019), and so forth.

The Knowledge Complexity Index (KCI) gauges the level of knowledge present in a city's economic activity (in our case, technology), which reflects the city's knowledge and productivity (Balland & Rigby, 2017; Balland et al., 2019; Dong et al., 2020). The Technology Complexity Index (TCI), which measures a technology's knowledge intensity, is the technology counterpart of KCI (Balland & Rigby, 2017; Sweet & Eterovic, 2019). According to the complexity principle, cities with a more complex knowledge structure produce unique goods that are infrequently produced by other cities. Therefore, the complexity is simultaneously determined by two factors: (i) a city's diversity, i.e., the number of RCA technologies a city possesses; (ii) a product's ubiquity, i.e., the number of cities with RCA in a specific technology. For instance, a type of technology is considered to be more complex if it can only be produced in a small number of cities, i.e., with high exclusiveness of technology. A city has greater knowledge complexity if it has RCA in many different technological fields.

The formal calculation is:

$$Diversity_{c,t} = K_{c,0,t} = \sum_c M_{i,c,t} \tag{4}$$

$$Ubiquity_{i,t} = K_{i,0,t} = \sum_i M_{i,c,t} \tag{5}$$

Where $M_{i,c,t}$ is a city-technology adjacency matrix. $M_{i,c,t}$ equals 1 if $RCA_{i,c,t}$ takes 1, and equals 0 otherwise. Higher diversity means a city can invent more exclusive technologies that are less likely to be invented and imitated by other cities, leading to a tendency for a city's technological portfolio to be more complex. A technology with low ubiquity can only be specialized in a few places since the knowledge and skills needed to develop it are infrequently available, making the technology more complicated. Cities must become more specialized in less ubiquitous technologies if they want to receive high complexity scores.

KCI and TCI can be calculated across iterations by merging diversity and ubiquity:

$$KCI_{c,t} = K_{c,n,t} = \frac{1}{k_{c,0}} \sum_i M_{i,c,t} TCI_{i,n-1,\mathrm{t}} \tag{6}$$

$$TCI_{i,t} = K_{i,n,t} = \frac{1}{k_{i,0}} \sum_c M_{i,c,t} KCI_{c,n-1,\mathrm{t}} \tag{7}$$

A higher value of $KCI_{c,t}$ suggests a city is more complex in its technology portfolio, and a higher value of $TCI_{i,t}$ indicates the knowledge intensity of technology is higher.

Then, we made the difference between TCI_i and KCI_c to quantify the relative complexity of technology i to city c's specialization basket. A positive $GCI_{i,c}$ represents that technology i has a higher level of complexity than city c's average.

$$GCI_{i,c} = TCI_i - KCI_c \tag{8}$$

4.1.2 Environmental Regulation

The key independent variable is environmental regulation *(ER)* stringency. Considering the availability of city-level data and the challenges of the single indicator and objective score (Dechezlepretre & Sato, 2017), this study uses the comprehensive index method and follows. Wang & Feng (2014) and Du et al. (2021) to construct a comprehensive index of environmental regulation at city level by the entropy weighting method. We select some sub-indicators (described in Appendix A online) that are related to the stringency of environmental regulation, including the product per unit of smoke and dust produced by the secondary industry, the product per unit of wasted water produced by the secondary industry, smoke, and dust removal rate, industrial solid waste utilization rate, sewage treatment rate, and garbage harmless treatment rate. The raw data is from China's environmental statistical yearbook.

The concept of the entropy weight method is that the greater the degree of dispersion and differentiation of a sub-indication can contain more information, the higher the weight it will get (Huang et al., 2018; Yuan et al., 2019). The calculation process is as follows:

We started to standardize each raw sub-indicator j (j=1,2,...,m) to eliminate the effects of various dimensions.

$$x^*_{j,c,t} = \frac{x_{j,c,t} - min(x_{j,t})}{max(x_{j,t}) - min(x_{j,t})} \quad (9)$$

Where $x_{j,c,t}$ is the sub-indicator *j* related to environmental regulation of city *c* (*c*=1,2,..n) at time *t*, $min(x_{j,t})$ and $max(x_{j,t})$ are the smallest and largest values of a specific indicator *j* at time *t* among all cities, respectively.

Then, we calculated the entropy $e_{j,t}$ based on the contribution of each standardized indicator $y_{j,c,t} = \frac{x^*_{j,c,t}+1}{\sum_{c=1}^{n}(x^*_{j,c,t}+1)}$:

$$e_{j,t} = -\frac{1}{log(n)}\sum_{c=1}^{n} y_{j,c,t} log(y_{j,c,t}) \quad (10)$$

The divergence coefficient $d_{j,t}$ will be:

$$d_{j,t} = 1 - e_{j,t} \quad (11)$$

The larger $d_{j,t}$, the more important the indicator. The weight of indicator *j* at time *t* is:

$$w_{j,t} = \frac{d_{j,t}}{\sum_{j=1}^{m} d_{j,t}} \quad (12)$$

The environmental regulation stringency index will be the weighted sum of the selected sub-indicators:

$$ER_{c,t} = \sum_{j=1}^{m} w_j x^*_{j,c,t} \quad (13)$$

Figure 1 shows the geographical distribution of the mean environmental regulation index at the city level from 2003-2016 across cities. Generally, we find ER decreases from east to west. Cities with stricter ER mainly concentrate in northern and eastern coastal areas, while those with a lower level of ECI are mainly distributed in southwestern and northeastern areas.

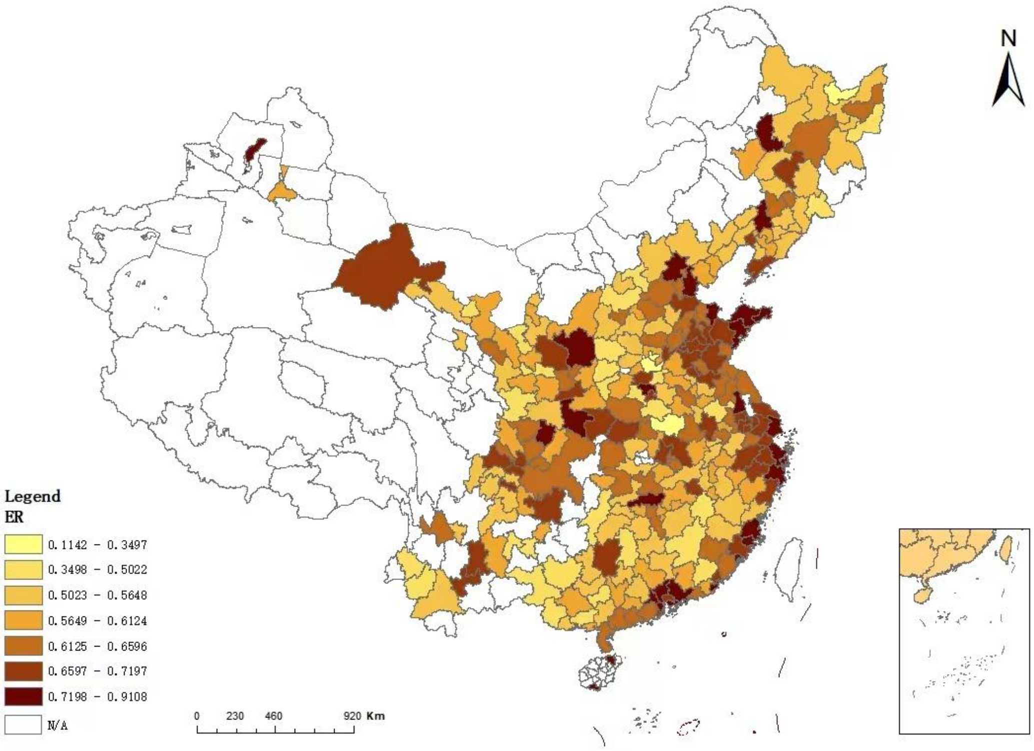

Figure 1. The geographical distribution of the environmental regulation index across cities (2003-2016)

Figure 2 exhibits a geographical distribution of the mean knowledge complexity index (KCI) at the city level from 2003-2016. Cities with higher KCI are mainly located in eastern coastal areas, and the four municipalities (Beijing, Shanghai, Chongqing, and Tianjin), as well as Jiuquan[1] in northwest China.

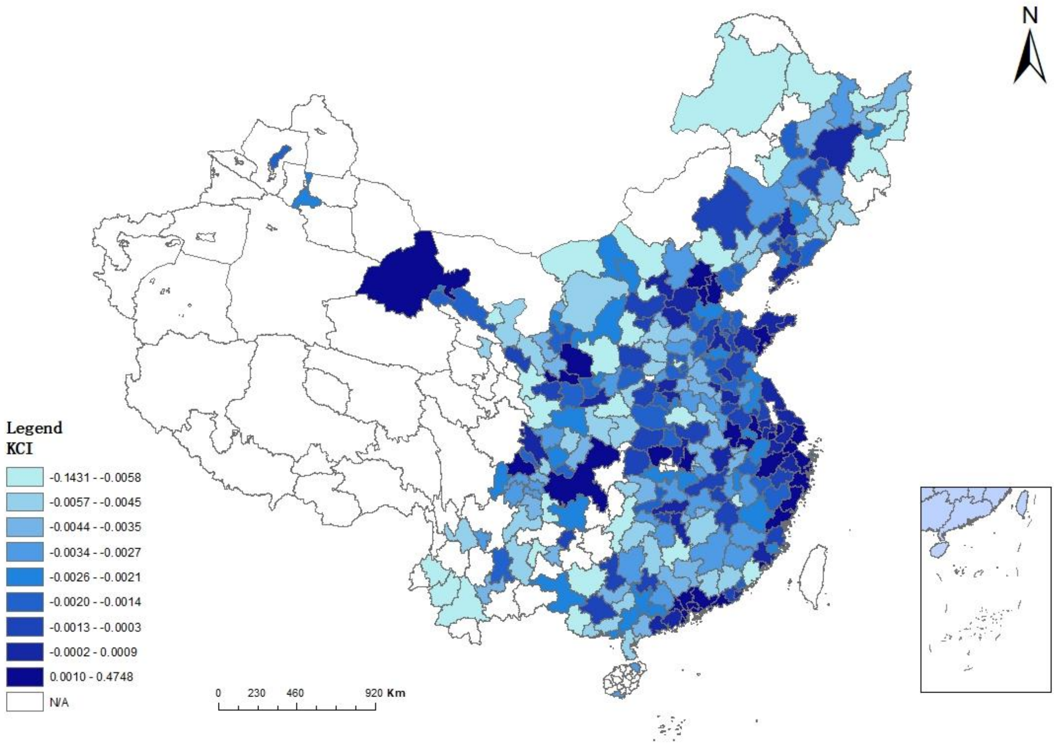

Figure 2. The geographical distribution of knowledge complexity across cities (2003-2016)

4.1.3 Control Variables

We followed Dong et al. (2020) and used the following market fundamentals from the China City Statistic Yearbooks as control variables, including gross domestic product per capita (*GDP_pc*), foreign direct Investment (*FDI*), population density (*Pop_Den*), total population (*Pop*) and industrial structure (*Ind,* measured by the secondary employment to the total employment). These factors could capture the differences between cities in economic development, openness, size, and agglomeration economies.

Besides the above market fundamentals, we further considered the demand pull and technology push as the drivers of green technologies. As for the demand-pull, we have added the following controls as the proxy for demand push: (i) *GDP_pc***:** Literature has found that the level of economic development could affect the innovation process by affecting people's demand for green products and the investment in research and development (Arranz et al., 2019). (ii) *Pm25***:** We used ambient fine particulate matter (PM2.5) as a proxy for the air quality in a city. Since a more polluted environment could also stimulate people's demand for green products (Sun et al., 2017), we used PM2.5 from the "Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) with GWR" as another proxy for the demand.

In addition to the technology-city level push captured by relatedness density (*Density)* measuring the role of the prior technological development and path dependency (Hidalgo et al., 2007; Rexhäuser & Löschel, 2015; Boschma & Capone, 2015), we further included the city innovation ability (*Inno*) during 2003-2016 from "*China's cities and industries' innovation ability report 2017*" as the technology-push at the city level of additional controls. The variables' descriptive statistics are shown in Table1.

Table 1 Descriptive statistics

Variables		Obs	Mean	Std. Dev.	Min	Max
Entry	Entry probability to new technology space	1,047,055	0.059	0.236	0	1
Density	Relatedness density	1,047,055	7.044	7.314	0	100
GCI	Difference between TCI and KCI	1,047,055	0.047	0.176	-1	1
ER	Environmental regulation	1,047,055	0.610	0.139	0.050	0.968
Gdp_pc	Gross domestic product per capita (10,000 Yuan)	1,047,055	2.404	2.910	0.120	49.305
Pop	Total population (10,000)	1,047,055	417.545	236.575	14.55	1438.7
Pop den	Population density (per person/m2)	1,047,055	423.805	284.492	4.7	11564
FDI	Foreign direct investment (10,000 US dollars)	1,047,055	45687.800	116784.000	0	2113444
Ind	Secondary employment to the total employment (%)	1,047,055	41.986	14.233	4.46	84.4
Inno	City innovation ability	1,047,055	7.346	36.929	0.01	1061.37
pm25	ambient fine particulate matter	1,047,055	47.670	17.772	8.155	112.340

4.2 Model Specification

By employing a linear probability model with fixed effects, the basic model specification examines whether environmental regulation is related to the likelihood that a city will specialize in a new specific technology (Balland et al., 2019; Dong et al., 2022) as below:

$$Prob(Entry_{i,c,t}= 1) = \alpha_0 + \alpha_1 * ER_{c,t-1} + \alpha_2 * Density_{i,c,t-1} + \beta * X_{c,t-1} + \delta_i + \partial_c + \mu_t + \varepsilon_{i,c,t} \quad (14)$$

The dummy variable $Entry_{i,c,t}$ takes 1 if city *c* does not have RCA in year *t-1* and then develops RCA in year *t* in the technology domain *i*. α_1 estimates how ER relates to the probability of entering a new specific technology. $Density_{,c,t-1}$ refers to the technological relatedness density. $X_{c,t-1}$ are city-specific control variables. We controlled for city and technology-fixed effects to absorb some technology-specific heterogeneities (δ_i, ∂_c) that might not be able to be observed in our controls. We also included year-fixed effects μ_t to control for some time-specific changes, such as policy shock.

To examine the hypothesis ***H2***, we included the cross-term *ER*Green* in Equation (14) as below:

$$Prob(Entry_{i,c,t}= 1) = \alpha_0 + \alpha_1 * ER_{c,t-1} + \alpha_2 * ER_{c,t-1} * Green_i + \alpha_3 * Density_{i,c,t-1} + \beta * X_{c,t-1} + \delta_i + \partial_c + \mu_t + \varepsilon_{i,c,t} \quad (15)$$

Where $Green_i$ is a dummy indicating whether a technology belongs to green technology or not ($Green_i$=1 if is a green technology and $Green_i$=0 otherwise). All control variables are defined in the same way as in Equation (14).

To test hypothesis ***H3***, we focused on the green categories and included the cross term of *GCI*ER* to estimate whether ER could help cities enter more complex green technology domains.

$$\begin{aligned} Prob(Entry_{i,c,t}= 1) &= \alpha_0 + \alpha_1 * ER_{c,t-1} + \alpha_2 * ER_{i,t-1} * GCI_{i,c,t-1} \\ &+ \alpha_3 * Density_{,c,t-1} + \alpha_4 * GCI_{i,c,t-1} + \alpha_5 * GCI\_sq_{i,c,t-1} \\ &+ \beta * X_{c,t-1} + \delta_i + \partial_j + \mu_t + \varepsilon_{i,c,t} \quad (16) \end{aligned}$$

α_1 is expected to be positive, and α_2 is expected to be positive in Equation (16). $GCI_{i,c,t-1}$ captures the difference between technology and knowledge complexity of city c at year $t-1$. Considering that the city tends to step into new technology spaces with similar complexity to its existing knowledge portfolio (Dong et al., 2022), we included its quadratic term $GCI\_sq_{i,c,t-1}$. This is because the capabilities inherent in complex technologies are rare and challenging to replicate, placing them beyond the reach of most cities. These cities often lack the necessary capabilities and knowledge required to develop such technologies (Balland et al., 2018). As a result, it becomes more difficult for a city to enter a technology space that is more complex than its existing technological infrastructure. Conversely, technologies that are less complex are typically less competitive and more susceptible to being superseded by more complex technologies that offer greater added value. Consequently, regions are more inclined to adopt new technologies that align with the level of complexity of their current technological framework. Therefore, α_5 is expected to be negative to indicate the inverse U-shape relationship between GCI and entry probability. All variables and fixed effects are defined in the same way as in Equation (14).

5. Results and Discussions

5.1 Baseline Result

Table 2 shows the overall effect of environmental regulation on the technology diversification process. In the most-baselined model (Column (1)) with city-level controls, the coefficient on environmental regulation (*ER*) is positive. Except for the industrial structures, all other controls are positively related to entering the new technology space. In Column (2), the significantly positive coefficient of *Density* indicates that the probability of specializing in new technologies is higher if this technology is more closely related to its existing technological infrastructure. This result is consistent with the previous relevant studies on diversification (Boschma & Capone, 2015; Balland et al., 2019). Since *Density* measures how the existing technology structure affects the entry probability, the coefficient on *Inno* turns negative after adding the *Density.* The result with the green dummy but without the IPC fixed effect are in Appendix B online.

Column (3) represents our preferred model and displays the estimated results derived from Equation (14), incorporating a variety of fixed effects specifications. The coefficient on environmental regulation (*ER*) is positive, suggesting that stricter environmental regulation (*ER*) improves the possibility of diversifying into new technology spaces. We can also see that most of the controls lose their significance after adding the fixed effects. To sum up, ***H1*** is supported.

Table 2 Baseline result

	(1)	(2)	(3)
Variables	Entry	Entry	Entry
ER	0.0258***	0.0234***	0.0265***
	(0.0016)	(0.0015)	(0.0022)
Density		0.0089***	0.0093***
		(0.0001)	(0.0001)
GDP	0.0026***	0.0019***	-0.0046
	(0.0004)	(0.0004)	(0.0063)
Ind	-0.0041***	-0.0026***	0.0145
	(0.0007)	(0.0007)	(0.0122)
Pop_Den	0.0037***	-0.0007*	0.0133
	(0.0004)	(0.0004)	(0.0177)
Pop	0.0031***	0.0046***	0.0000
	(0.0004)	(0.0004)	(0.0090)

FDI	0.0027***	0.0008***	0.0011
	(0.0001)	(0.0001)	(0.0022)
Inno	0.0206***	-0.0098***	-0.0166***
	(0.0002)	(0.0003)	(0.0008)
PM25	0.0114***	0.0071***	0.0002
	(0.0007)	(0.0007)	(0.0020)
Constant	-0.0526***	-0.0652***	-0.1597
	(0.0035)	(0.0035)	(0.1478)
Observations	1,047,055	1,047,055	1,047,050
R-squared	0.034	0.056	0.058
Year FE	NO	NO	YES
City FE	NO	NO	YES
IPC4 FE	NO	NO	YES
Adj R2	0.0338	0.0557	0.0573

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

Table 3 distinguishes the effect of environmental regulation on the green and non-green technology diversification process by adding the cross-term *ER*Green* (Equation (15)). We can see that the coefficient on *ER*Green* is significantly positive in all models with different settings, suggesting that environmental regulation's effect is larger for green technology space than for non-green technology space. This indicates that the stimulating effect of environmental policy is mainly driven by the effect on green technology, and environmental policies are more likely to encourage cities to enter green technology space than non-green technology space. The environmental policy intervention could provide such sources, reduce uncertainties, deal with this market failure, and incentivize the market to invest in green technologies. Such a result supports our hypothesis ***H2***.

Table 3 The effect of ER on Green and Non-green entry probability

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Entry	Entry	Entry	Entry	Entry	Entry
ER	0.0257***	0.0234***	0.0255***	0.0236***	0.0215***	0.0101***
	(0.0016)	(0.0015)	(0.0022)	(0.0016)	(0.0016)	(0.0029)
Green	0.0288***	0.0239***	0.0238***	0.0207***	0.0168***	-
	(0.0007)	(0.0007)	(0.0007)	(0.0027)	(0.0027)	
*ER*Green*				0.0132***	0.0117**	0.0121***
				(0.0046)	(0.0046)	(0.0043)
Density		0.0088***	0.0091***		0.0088***	0.0062***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
GDP	0.0025***	0.0019***	-0.0048	0.0025***	0.0019***	-0.0053
	(0.0004)	(0.0004)	(0.0063)	(0.0004)	(0.0004)	(0.0063)
Ind	-0.0041***	-0.0026***	0.0145	-0.0041***	-0.0026***	0.0169
	(0.0007)	(0.0007)	(0.0121)	(0.0007)	(0.0007)	(0.0133)
Pop_Den	0.0036***	-0.0007*	0.0118	0.0036***	-0.0007*	0.0096
	(0.0004)	(0.0004)	(0.0176)	(0.0004)	(0.0004)	(0.0237)

Pop	0.0031***	0.0046***	-0.0007	0.0031***	0.0046***	-0.0013
	(0.0004)	(0.0004)	(0.0089)	(0.0004)	(0.0004)	(0.0143)
FDI	0.0027***	0.0008***	0.0012	0.0027***	0.0008***	0.0014
	(0.0001)	(0.0001)	(0.0022)	(0.0001)	(0.0001)	(0.0030)
Inno	0.0207***	-0.0093***	-0.0160***	0.0207***	-0.0093***	-0.0064***
	(0.0002)	(0.0003)	(0.0008)	(0.0002)	(0.0003)	(0.0008)
PM25	0.0115***	0.0073***	0.0001	0.0115***	0.0073***	-0.0010
	(0.0007)	(0.0007)	(0.0020)	(0.0007)	(0.0007)	(0.0021)
Constant	-0.0570***	-0.0687***	-0.1492	-0.0557***	-0.0675***	-0.1083
	(0.0035)	(0.0035)	(0.1466)	(0.0035)	(0.0035)	(0.1953)
Observations	1,047,055	1,047,055	1,047,050	1,047,055	1,047,055	1,047,050
R-squared	0.036	0.057	0.059	0.036	0.057	0.091
Year FE	NO	NO	YES	NO	NO	YES
City FE	NO	NO	YES	NO	NO	YES
IPC4 FE	NO	NO	YES	NO	NO	YES
Adj R^2	0.0358	0.0570	0.0587	0.0358	0.0570	0.0904

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.2 Main Results: Heterogeneity in Knowledge Structure

This section focuses on green technology and explores how the technology structure, namely complexity, affects the role of ER based on Equation (16). Table 4 exhibits the result.

The coefficients of the square term of GCI (*GCI_sq*) are negative, indicating an inverse U-shaped link between the GCI and the chance of entering a new technology domain. It also implies that cities lean to diversify into technology spaces with similar complexity levels to the existing knowledge base, which is in line with the previous literature (Dong et al., 2022). Columns (2) and (4) show the estimated result about how complexity matters regarding the role of environmental regulations on technology. The significant and positive coefficient on *GCI*ER* indicates that environmental regulation helps cities diversify into more complex green technology spaces, which supports hypothesis ***H3.***

Table 4 Heterogeneity analysis in complexity within green technologies

	(1)	(2)	(3)	(4)
Variables	Entry	Entry	Entry	Entry
ER	0.0364***	0.0344***	0.0116*	0.0043
	(0.0045)	(0.0049)	(0.0064)	(0.0070)
*ER*GCI*		0.0611**		0.1048***
		(0.0302)		(0.0323)
GCI	-0.0568***	-0.0949***	0.0026	-0.0633***
	(0.0045)	(0.0189)	(0.0064)	(0.0209)
GCI_sq	-0.0873***	-0.0831***	-0.1415***	-0.1368***
	(0.0107)	(0.0110)	(0.0126)	(0.0126)
Density	0.0087***	0.0087***	0.0065***	0.0065***

	(0.0002)	(0.0002)	(0.0003)	(0.0003)
GDP	0.0024**	0.0025**	-0.0211	-0.0210
	(0.0011)	(0.0011)	(0.0240)	(0.0240)
Ind	-0.0020	-0.0022	0.0146	0.0141
	(0.0021)	(0.0021)	(0.0502)	(0.0502)
Pop_Den	-0.0079***	-0.0078***	0.0506	0.0501
	(0.0012)	(0.0012)	(0.0685)	(0.0686)
Pop	0.0108***	0.0107***	-0.0302	-0.0314
	(0.0012)	(0.0012)	(0.0447)	(0.0447)
FDI	0.0007*	0.0007*	0.0073	0.0073
	(0.0004)	(0.0004)	(0.0075)	(0.0075)
Inno	-0.0083***	-0.0082***	-0.0103***	-0.0101***
	(0.0008)	(0.0008)	(0.0022)	(0.0022)
PM25	0.0191***	0.0188***	0.0022	0.0012
	(0.0020)	(0.0020)	(0.0058)	(0.0058)
Constant	-0.0887***	-0.0864***	-0.2047	-0.1851
	(0.0100)	(0.0102)	(0.6170)	(0.6173)
Observations	165,072	165,072	165,057	165,057
Controls	YES	YES	YES	YES
Year FE	NO	NO	YES	YES
City FE	NO	NO	YES	YES
IPC4 FE	NO	NO	YES	YES
Adj R^2	0.0521	0.0521	0.0864	0.0865

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.3 Exclusion of the Potential Endogenous Issue

Considering that some unobserved factors could affect both environmental stringency and green innovation, environmental stringency could be endogenous. We adopt the approach of previous studies (Broner et al., 2012; Hering & Poncet, 2014) by employing the ventilation coefficient (VC) as an instrumental variable for ER. We follow the existing literature and use the interaction term of the VC and the national ER index as the instrumental variable (Nunn & Qian, 2014). The VC represents the impact of meteorological factors on the rate at which pollutants disperse in the air. The underlying rationale is that regions with slower dispersion of pollutants tend to enforce more stringent environmental regulations, while the meteorological conditions are not directly linked to green innovation. Table 5 shows the IV result.

The F-statistic for the first stage is larger than 10 in all columns, indicating our IV is not weakly identified. We can see that the result in Table 5 is consistent with Table 4. The coefficients on *ER* are positive in Columns (1)-(2) and *GCI*ER* are positive in Columns (3), indicating environmental regulation helps cities diversify into new green technology spaces, especially for the complex ones. To sum up, the above results prove our hypothesis ***H3***: Environmental regulations enable complex green diversification. Environmental regulation, as an external source, can provide “niches” for green technologies and alter the transition into complex green technology space.

Table 5 IV analysis

Variables	(1) Second stage	(2) Second stage	(3) Second stage
ER	0.0376***	0.0337***	-0.2397***
	(0.0115)	(0.0115)	(0.0441)
*ER*GCI*			2.3644***
			(0.3712)
GCI	0.0340***	0.0113	-1.4739***
	(0.0077)	(0.0080)	(0.2330)
GCI_sq		-0.1560***	-0.0462**
		(0.0153)	(0.0228)
Density	0.0071***	0.0071***	0.0077***
	(0.0003)	(0.0003)	(0.0004)
Observations	146,893	146,893	146,893
Controls	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES
IPC4 FE	YES	YES	YES
F-statistic for the First stage	1.4e+07	1.4e+07	263.626

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.4 Additional Analysis

5.4.1 Heterogeneity in Green Technologies Type

The different types of green innovations are expected to be affected by environmental regulations differently. Since the primary objectives of environmental regulations during the analysis period in China are to reduce emissions and enhance energy efficiency, enterprises serve as the primary targets of these regulations due to their substantial role in environmental impact. Consequently, technologies closely aligned with corporate behavior and more effective in reducing emissions and saving energy are expected to be more significantly influenced. By utilizing the detailed 4-digit IPC codes of each patent, we are able to distinguish different types of green patents and explore the heterogeneous effects of environmental regulations in Table 6, including six types of green i in Section 3.1.1.

We find *ER*GCI* is positive in Columns (1), (3), (4), and (5) at a 10% significant level, indicating environmental regulations foster alternative energy production (*Alter_ener*), administrative, regulatory or design aspects*(Ard)*, waste management (*Waste*), and energy conversation (*Energy_con*) enter more complex technology space. The above results mean that significant heterogeneous associations exist between ER and different types of green technology spaces. The complex technological space related to pollutant reduction, carbon emission control, and energy conversation is more likely to stand at the forefront of regulatory impact. Additionally, these technologies are primarily related to corporate behavior, which is the main group affected by the environmental policies implemented.

Table 6 Heterogeneity analysis across different green innovations

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Alter_ener	Agri_fore	Ard	Waste	Energy_con	Tran
ER	-0.0089	0.0122	0.0220	0.0039	-0.0190	0.0495***
	(0.0118)	(0.0363)	(0.0374)	(0.0097)	(0.0156)	(0.0155)
*ER*GCI*	0.1593***	-0.1666	0.2856*	0.1139***	0.1302*	-0.0088
	(0.0534)	(0.1708)	(0.1718)	(0.0436)	(0.0718)	(0.0730)
GCI	-0.1022***	0.1992*	-0.2583**	-0.0934***	0.0324	0.0235
	(0.0342)	(0.1199)	(0.1168)	(0.0280)	(0.0470)	(0.0491)
GCI_sq	-0.0964***	-0.1777	-0.2733***	-0.1439***	-0.2492***	0.0537
	(0.0158)	(0.1194)	(0.0902)	(0.0153)	(0.0392)	(0.0467)
Density	0.0043***	0.0113***	0.0001	0.0058***	0.0080***	0.0088***
	(0.0005)	(0.0021)	(0.0017)	(0.0004)	(0.0007)	(0.0008)
Observations	58,209	5,523	8,118	89,154	35,367	27,278
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
IPC4 FE	YES	YES	YES	YES	YES	YES
Adj R^2	0.0841	0.1348	0.0792	0.0871	0.0806	0.1032

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.4.2 Heterogeneity across Different Cities

The efficiency of environmental regulation (ER) is also influenced by city localities, such as fiscal resources, market demand, and financial access. Firstly, inventing new technologies requires external resources, i.e., capital and investment (Barbieri et al., 2020). Therefore, cities with greater fiscal capacity can provide innovators greater access to funding and R&D subsidies. Secondly, the demand for green innovation will affect the rewards and enthusiasm for green innovation. This demand is related to local economic conditions and environmental quality (Arranz et al., 2019). Regions with well-developed economies and a heightened awareness of environmental issues tend to have a higher demand for a green environment, product, and lifestyle. This, in turn, establishes a conducive environment for the proliferation of green technologies. Thirdly, the condition of the financial and loan market can affect the overall financial environment by lowering financial barriers and increasing access to capital. A developed loan market is essential for providing the necessary financial support and relieving credit constraints to green innovations, enabling them to overcome initial financial hurdles to innovate.

With these considerations, we conduct a heterogeneity analysis by categorizing cities into several groups based on different criteria in this section. Firstly, cities' fiscal capacities are indicated by fiscal revenues. Secondly, a city's economic status is measured by its GDP. Lastly, the health of the local financial and loan market is quantified by total savings and loans. Based on the median of these factors, we have divided the cities into two groups: i) cities with high and low fiscal ability; ii) cities with high and low economic development level; iii) cities with larger and smaller loan market development, and re-perform the analysis. The results are shown in Table 7. This categorization enables us to re-perform our analysis with a more differentiated perspective. Table 7 shows that only in cities with high fiscal ability, high economic development level and high loan market development, environmental regulations help cities enter the more complex green technology spaces.

Table 7 Heterogeneity analysis across different cities

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	High fiscal	Low fiscal	High gdp	Low gdp	High loan	Low loan
ER	0.0156	-0.0056	-0.0088	0.0070	0.0152	-0.0012
	(0.0125)	(0.0000)	(0.0184)	(0.0075)	(0.0121)	(0.0088)
*ER*GCI*	0.1245**	-0.0018	0.2554***	0.0337	0.1354***	-0.0340
	(0.0521)	(0.0000)	(0.0709)	(0.0359)	(0.0477)	(0.0441)
GCI	-0.0703**	-0.0314	-0.1665***	-0.0310	-0.0662**	-0.0137
	(0.0351)	(0.0000)	(0.0483)	(0.0229)	(0.0317)	(0.0275)
GCI_sq	-0.2086***	-0.0269	-0.2065***	-0.1011***	-0.1803***	-0.0483***
	(0.0209)	(0.0000)	(0.0302)	(0.0135)	(0.0194)	(0.0157)
Density	0.0065***	0.0071	0.0070***	0.0064***	0.0065***	0.0067***
	(0.0004)	(0.0000)	(0.0006)	(0.0004)	(0.0004)	(0.0005)
Observations	79,879	85,107	48,003	117,017	84,747	80,242
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
IPC4 FE	YES	YES	YES	YES	YES	YES
Adj R^2	0.0812	0.0855	0.0816	0.0822	0.0842	0.0823

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.4.3 Heterogeneity across Regions

China has significant regional disparities, with substantial differences in each region's capabilities, institutional backgrounds, fiscal resources, market demand, and access to finance. These disparities further influence the resources available to support the complex green transition. This section further re-performs the above analysis relying on the sub-sample of different regions in China, namely, the East, Middle, and West regions. The result is shown in Table 8.

The positive coefficient on *ER*GCI in* Columns (1) and (2) demonstrates that environmental regulations help cities enter the more complex green technology spaces in the East and Middle regions of China. In the West, the effect of environmental regulation is not significant. The rationale behind such different impacts is related to the regional capability and institutional background. The eastern area is relatively developed and has a higher level of innovation ability, and the residents here usually demand a better environment. The government here can provide support for investing in new and risky technology. Therefore, cities can more easily invent new and complex technology that has less harmful effects on the environment. The West region is less developed and tends to be the receiver of the high-polluting industries from the

East areas. The lower innovation ability makes them lack the necessary resources and knowledge to generate more complicated and less ubiquitous innovations, leading to a lower probability of entering more complex spaces.

Table 8 Heterogeneity in regions

Variables	(1) East	(2) Middle	(3) West
ER	0.0043	-0.0020	0.0030
	(0.0128)	(0.0123)	(0.0121)
*ER*GCI*	0.1218**	0.1677***	-0.0657
	(0.0609)	(0.0631)	(0.0536)
GCI	-0.1007**	-0.1172***	0.0595*
	(0.0413)	(0.0384)	(0.0348)
GCI_sq	-0.2080***	-0.0888***	-0.0867***
	(0.0238)	(0.0223)	(0.0240)
Density	0.0063***	0.0069***	0.0064***
	(0.0004)	(0.0006)	(0.0006)
Observations	70,917	50,357	43,783
Controls	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES
IPC4 FE	YES	YES	YES
Adj R^2	0.0814	0.0850	0.0980

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.4.4 Heterogeneity across Density

Numerous studies highlight the importance of external policy in enabling entry into less related technology spaces and achieving path-breaking innovations. Table 9 further considers whether the environmental regulation can achieve a path-breakthrough green innovation by adding the cross-term *Density*ER*. The significantly negative coefficient suggests that environmental regulation can alter the technology diversification process and help the city enter less related technology space. This finding underscores that environmental regulation enables regions to reduce the dependency on the existing knowledge base and move the city's technological frontier forward.

Table 9 Heterogeneity analysis across within green technologies

Variables	(1) Green	(2) Green
ER	0.0367***	0.0167**
	(0.0055)	(0.0085)
*ER*density*	-0.0015**	-0.0016*
	(0.0006)	(0.0009)
GCI	-0.0392***	0.0014
	(0.0039)	(0.0072)

GCI_sq	-0.0967***	-0.1436***
	(0.0100)	(0.0137)
Density	0.0087***	0.0076***
	(0.0004)	(0.0006)
Observations	200,882	165,057
Controls	NO	YES
Year FE	YES	YES
City FE	YES	YES
IPC4 FE	YES	YES
Adj R^2	0.0530	0.0864

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

5.5 Robustness Check

This section further conducts the following robustness checks to see whether our results are stable, as shown in Table 10.

Firstly, to ensure robustness in our analysis, we employed two additional indexes of environmental regulation stringency that are well-recognized in the literature. Beyond the entropy method-based environmental regulation index, the first alternate index is based on government attention to environmental protection *(ER2*), as indicated in their annual government work report (Zhang et al., 2024; Liu et al., 2023). These reports reflect the government's priority and commitment to environmental issues each year. The second index focuses on 113 key environmental protection cities in China *(ER3)*. These cities have been significantly affected by air pollution and have implemented stricter regulations to address it. These measures include monitoring air quality, controlling emissions from industrial and vehicular sources, and promoting cleaner energy usage. The positive interaction term of *ER2*GCI* and *ER3*GCI* in Columns (1) - (3) confirms that environmental regulations are indeed aiding cities in entering more complex green technological domains.

Secondly, considering that regional diversification is likely a prolonged process and the effects of environmental regulation may take time to manifest, we include a 5-year lag for the independent variable *ER* in our robustness check. This approach is intended to capture the delayed impacts of environmental regulation on technological diversification. The results are presented in Column (4) and show that environmental regulations help to develop more complex green technologies.

Thirdly, we define the *Density_co* using co-occurrences of two technologies on the same patent, giving a precise technological relatedness index instead of the Hidalgo et al. (2007) approach (Columns (5)). Using normalized co-occurrences of technologies within the same patent provides a precise technological relatedness index, whereas the Hidalgo et al. (2007) approach also considers additional factors, such as infrastructure and institutions, that might link two technologies. While the literature presents different methodologies, Boschma et al. (2015) demonstrate that results tend to be robust across these two approaches. In column (5), the positive coefficient on *Density_co* remains statistically significant. It indicates that cities are more likely to enter the technology space with higher density, and the diversification process is path-dependent. The interaction term of *ER*GCI* is positive, which confirms that environmental regulations help cities enter more complex green domains. Overall, the different settings of density do not affect the robustness of the result.

Lastly, considering the dependent variable *Entry* is a dummy, we re-perform the analysis with the Probit and Logit model. The results in Columns (6) and (7) are consistent with the alternative linear probability model in Table 4. The results prove that cities with stricter environmental regulations tend to develop more complex green technologies.

Table 10 Robustness check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Government attention	Key cities	Key cities	Lag 5 years	*Density_co*	Probit	Logit
ER					-0.0127*	0.2266***	0.6099***
					(0.0070)	(0.0768)	(0.1590)
*ER*GCI*					0.0668**	1.8590***	4.5670***
					(0.0321)	(0.2909)	(0.5814)
ER2	0.0001						
	(0.0030)						
*ER2*GCI*	0.0314***						
	(0.0118)						
ER3		0.0051***	-				
		(0.0015)	-				
*ER3*GCI*		0.0725***	0.0688***				
		(0.0074)	(0.0078)				
L5.ER				-0.0221			
				-0.0155			
*L5.ER*GCI*				0.1798***			
				-0.0628			
Density_co					0.0028***		
					(0.0001)		
Observations	174,274	214,012	213,995	105,857	165,057	164,851	164,851
Year FE	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
IPC4 FE	YES	YES	YES	YES	YES	YES	YES
Adj R2	0.0873	0.0839	0.0878	0.0802	0.0911	.	.

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

6. Conclusion

This study probes whether environmental regulations can help cities branch into a more complex technology space. Using China's annual patent data at the city level from 2003 to 2016, our results show that (i) environmental regulations foster cities to branch into new green technology spaces in general; (ii) environmental regulations help cities to develop more complex technology; (iii) the impact of environmental regulations on green innovation varies across different types of green technologies and cities.

In doing so, this study fills the research gap from the following perspectives. Though the literature identifies the role of green technologies in economic development strategies with environmental sustainability, there may not be enough incentives and capabilities to innovate in a green way. Therefore, some recent studies have started to explore how external variables affect the green diversification process. They find that the green diversification process is path-dependent and can be altered by external factors. However, they tend to ignore the role of technological complexity, while its importance is obvious since the value of knowledge complexity is vital to regional sustainable development. We argue that it is crucial to consider how environmental regulation is linked to more complex technological diversification since it is closely related to regions' long competitiveness. The prior studies related to the "Porter hypothesis" have identified that ER drives the amount of innovation (Aghion et al., 2016; Popp, 2019; Porter & Van der Linde, 1995) and have noticed the importance of path-dependency, while most empirical analyses focus on path-dependence from the same technology and ignore the cross-technology relatedness and the embedded knowledge value. There is still a gap in understanding the impact of environmental policies on the entry of complex green technologies in cities. By integrating a technology's complexity to measure the knowledge value and heterogeneity in technology structure, our study goes beyond the scope of the prior "Porter hypothesis" literature that mostly focuses on the aggregate output of innovation without considering the city-specific knowledge structures embedded in different technologies.

The result of this study has some practical implications. Firstly, our findings provide a scientific basis for local environmental policy-making. Local governments often face significant resistance from businesses and citizens when formulating environmental policies, as they often believe that environmental regulations will hinder their economic opportunities. However, our results indicate that such regulations can foster complex green diversification, ultimately contributing to regional development and long-term competitiveness. This evidence suggests that environmental policies can effectively resolve the perceived trade-off between economic growth and environmental protection.

Secondly, the regional heterogeneity analysis suggests a paradox: The less developed regions have a strong demand for complex green innovations, but they are short for green capability. Indeed, the lack of advanced knowledge and technology and the willingness to develop green technologies make it difficult to break the path-dependence. Due to long-term exposure to high-pollution environments, the less-developed regions face severe environmental degradation. Hence, lagging regions must create new green development paths. Our study demonstrates that environmental regulation might serve as a potential solution to the paradox, helping these regions overcome path-dependence and create more complex green technology development paths. In addition, local governments in underdeveloped regions could actively seek diversified funding support from higher-level governments and actively engage in green technology cooperation with developed cities.

Thirdly, while our analysis indicates that environmental regulation generally promotes the increase of urban complexity, it is important to recognize that it may also exacerbate regional inequality. This is because cities in developed regions tend to transfer high-polluting industries to less-developed regions under environmental regulations, further confining the less-developed regions in high-carbon and high-pollution regimes and worsening the Matthew effect in regional development. Though the Chinese government has implemented policies to foster regional collaboration, such as the Beijing-Tianjin-Hebei air protection project, the West-East gas transmission project, and so on, to address these issues, further research is needed to seek practical solutions to mitigate the Matthew effect. Moreover, it is also critical for governments and related agencies to formulate policies that balance equity and efficiency, such as implementing technology transfer and providing green technological assistance to less developed areas to achieve environmental justice and green transition across cities.

Lastly, the findings of this study offer broad implications for both central and local governments outside of China, especially in developing countries. It is crucial to avoid the flawed approach of "pollution first, treatment later" in China. Instead, developing countries could commit to a sustainable development strategy and balance the interests of green and traditional industries through green innovation. China's green transformation demonstrates that effective government intervention is a key factor in promoting green innovation. For example, China's global leading position in the new energy vehicle industry is largely attributed to policy tools such as tax cuts and subsidies from the central and local governments. For the central government, it is essential to guide urban sustainable green transformations based on regional conditions. Additionally, regional cooperation strategies should be implemented to address challenges related to environmental inequality. For local governments, it is important to develop targeted policy measures that reflect specific local circumstances. They should also actively seek assistance from higher-level governments and collaborate with other cities in developing green technologies.

This study has several limitations. First, the use of patent data presents certain drawbacks (Griliches, 1990), potentially biasing the results toward developed regions, as underdeveloped areas typically generate fewer patents (Pinheiro et al., 2022). Second, due to limitations in data availability, this study focuses exclusively on the effects of environmental regulations on green technological diversification within Chinese cities. Future research could address these gaps by adopting an international perspective to explore the effects of environmental regulations on green technological diversification and regional inequality across diverse national contexts.

Figures

Figure 1. The geographical distribution of the environmental regulation index across cities (2003-2016)

Figure 2. The geographical distribution of knowledge complexity across cities (2003-2016)

Notes

1. Jiuquan is known for modern spaceflight and the nuclear industry in China.

Acknowledgement

This paper is partially based on a working paper published in *Evolutionary Economic Geography* (http://econ.geo.uu.nl/peeg/peeg2226.pdf).

Disclosure Statement

No potential conflict of interest was reported by the authors.

Data availability statement

The data that support the findings of this study are available from the author upon reasonable request.

Funding

This work was supported by the National Social Science Fund of China under Grant 24CGL113; National Natural Science Foundation of China under Grant 72004199 and Central Universities Youth Research and Innovation Special Program under Grant S20230061.

Reference

Acemoglu, D., Akcigit, U., Hanley, D., & Kerr, W. (2016). Transition to Clean Technology. *Journal of Political Economy*, *124*(1), pp.52–104. https://doi.org/10.1086/684511

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & Van Reenen, J. (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. *Journal of Political Economy*, *124*(1), pp.1–51. https://doi.org/10.1086/684581

Albrizio, S., Kozluk, T., & Zipperer, V. (2017). Environmental policies and productivity growth: Evidence across industries and firms. *Journal of Environmental Economics and Management*, *81*, pp.209–226. https://doi.org/10.1016/j.jeem.2016.06.002

Arranz, N., F. Arroyabe, C., & Fernandez de Arroyabe, J. C. (2019). The effect of regional factors in the development of eco-innovations in the firm. *Business Strategy and the Environment*, *28*(7), pp.1406–1415. https://doi.org/10.1002/bse.2322

Balland, P.-A., & Rigby, D. (2017). The Geography of Complex Knowledge. *Economic Geography*, *93*(1), pp.1–23. https://doi.org/10.1080/00130095.2016.1205947

Balland, P.-A., Boschma, R., Crespo, J., & Rigby, D. L. (2019). Smart specialization policy in the European Union: Relatedness, knowledge complexity and regional diversification. *Regional Studies*, *53*(9), pp.1252–1268. https://doi.org/10.1080/00343404.2018.1437900

Balland, P.-A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., & Rigby, D. (2022). The new paradigm of economic complexity. *Research Policy*, *51*(3), p.104450. https://doi.org/10.1016/j.respol.2021.104450

Balland, P. A., Jara-Figueroa, C., Petralia, S., Steijn, M., Rigby, D., & Hidalgo, C. (2020) Complex Economic Activities Concentrate in Large Cities. *Nature Human Behavior*, *4,* pp.248–254. https://doi.org/10.1038/s41562-019-0803-3.

Barbieri, N., Perruchas, F., & Consoli, D. (2020). Specialization, Diversification, and Environmental Technology Life Cycle. *Economic Geography*, *96*(2), pp.161–186. https://doi.org/10.1080/00130095.2020.1721279

Barwick, P. J., Li, S., Lin, L., & Zou, E. (2019). From Fog to Smog: The Value of Pollution Information. In *NBER Working Papers.* No. 26541. National Bureau of Economic Research, Inc. https://ideas.repec.org/p/nbr/nberwo/26541.html

Bergek, A., Mignon, I., & Sundberg, G. (2013). Who invests in renewable electricity production? Empirical evidence and suggestions for further research. *Energy Policy*, *56*, pp.568–581. https://doi.org/10.1016/j.enpol.2013.01.038

Boschma, R. (2017). Relatedness as driver of regional diversification: A research agenda. *Regional Studies*, *51*(3), pp.351–364. https://doi.org/10.1080/00343404.2016.1254767

Boschma, R., & Capone, G. (2015). Institutions and diversification: Related versus unrelated diversification in a varieties of capitalism framework. *Research Policy*,

44(10), pp.1902–1914. https://doi.org/10.1016/j.respol.2015.06.013
Boschma, R., & Frenken, K. (2011). The emerging empirics of evolutionary economic geography. *Journal of Economic Geography*, *11*(2), pp.295–307. https://doi.org/10.1093/jeg/lbq053
Boschma, R., Balland, P.-A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, *24*(1), pp.223–250. https://doi.org/10.1093/icc/dtu012
Boschma, R., Heimeriks, G., & Balland, P.-A. (2014). Scientific knowledge dynamics and relatedness in biotech cities. *Research Policy*, *43*(1), pp.107–114. https://doi.org/10.1016/j.respol.2013.07.009
Braungart, M., McDonough, W., & Bollinger, A. (2007). Cradle-to-cradle design: Creating healthy emissions – a strategy for eco-effective product and system design. *Journal of Cleaner Production*, *15*(13–14), pp.1337–1348. https://doi.org/10.1016/j.jclepro.2006.08.003
Broner, F., Bustos, P., Carvalho, V.M. (2012). Sources of Comparative Advantage in Polluting Industries. *NBER Working Paper.* No. 18337. National Bureau of Economic Research, Inc. https://doi.org /10.3386/w18337
Brunnermeier, S. B., & Cohen, M. A. (2003). Determinants of environmental innovation in US manufacturing industries. *Journal of Environmental Economics and Management*, *45*(2), pp.278–293. https://doi.org/10.1016/S0095-0696(02)00058-X
Colombelli, A., Krafft, J., & Quatraro, F. (2014). The emergence of new technology-based sectors in European regions: A proximity-based analysis of nanotechnology. *Research Policy*, *43*(10), pp.1681–1696. https://doi.org/10.1016/j.respol.2014.07.008
Consoli, D., Marin, G., Marzucchi, A., & Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, *45*(5), pp.1046–1060. https://doi.org/10.1016/j.respol.2016.02.007
Cooke, P. (2010). Regional innovation systems: Development opportunities from the 'green turn.' *Technology Analysis & Strategic Management*, *22*(7), pp.831–844. https://doi.org/10.1080/09537325.2010.511156
Costantini, V., Crespi, F., & Palma, A. (2017). Characterizing the policy mix and its impact on eco-innovation: A patent analysis of energy-efficient technologies. *Research Policy*, *46*(4), pp.799–819. https://doi.org/10.1016/j.respol.2017.02.004
Davis, F. L., & Wurth, A. H. (2003). Voting Preferences and the Environment in the American Electorate: The Discussion Extended. *Society & Natural Resources, 16*(8), pp.729–740. https://doi.org/10.1080/08941920309195

De Marchi, V. (2012). Environmental innovation and R&D cooperation: Empirical evidence from Spanish manufacturing firms. *Research Policy*, *41*(3), pp.614–623. https://doi.org/10.1016/j.respol.2011.10.002
Dechezleprêtre, A., & Glachant, M. (2014). Does Foreign Environmental Policy Influence Domestic Innovation? Evidence from the Wind Industry.

Environmental and Resource Economics, 58, pp.391-413. https://doi.org/10.1007/s10640-013-9705-4

Dechezleprêtre, A., & Sato, M. (2017). The Impacts of Environmental Regulations on Competitiveness. *Review of Environmental Economics and Policy*, *11*(2), pp.183–206. https://doi.org/10.1093/reep/rex013

Dong, Z., Chen, W., & Wang, S. (2020). Emission reduction target, complexity and industrial performance. *Journal of Environmental Management*, *260*, p.110148. https://doi.org/10.1016/j.jenvman.2020.110148

Dong, Z., Li, Y., Balland, P.-A., & Zheng, S. (2022). Industrial land policy and economic complexity of Chinese Cities. *Industry and Innovation*, *29*(3), pp.367–395. https://doi.org/10.1080/13662716.2021.1990022

Du, K., Cheng, Y., & Yao, X. (2021). Environmental regulation, green technology innovation, and industrial structure upgrading: The road to the green transformation of Chinese cities. *Energy Economics*, *98*, p.105247. https://doi.org/10.1016/j.eneco.2021.105247

Farinha, T., Balland, P.-A., Morrison, A., & Boschma, R. (2019). What drives the geography of jobs in the US? Unpacking relatedness. *Industry and Innovation*, *26*(9), pp.988–1022. https://doi.org/10.1080/13662716.2019.1591940

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science, 47*(1), pp.117–132. https://doi.org/10.1287/mnsc.47.1.117.10671

Glaeser E. L., Kallal H., Scheinkman J et al. (1992). Growth in cities. *Journal of Political Economy, 100(6)*, pp.1126-1152. https://doi.org/10.1086/261856

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. Journal of Economic Literature, 28(4), p.1661. https://www.jstor.org/stable/2727442

Hering, L., & Poncet, S. (2014). Environmental policy and exports: Evidence from Chinese cities. *Journal of Environmental Economics and Management*, *68*(2), pp.296–318. https://doi.org/10.1016/j.jeem.2014.06.005

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(26), pp.10570–10575. https://doi.org/10.1073/pnas.0900943106

Hidalgo, C. A., Balland, P.-A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., Glaeser, E., He, C., Kogler, D. F., Morrison, A., Neffke, F., Rigby, D., Stern, S., Zheng, S., & Zhu, S. (2018). The Principle of Relatedness. In A. J. Morales, C. Gershenson, D. Braha, A. A. Minai, & Y. Bar-Yam (Eds.), *Unifying Themes in Complex Systems IX* (pp.451–457). Springer International Publishing. https://doi.org/10.1007/978-3-319-96661-8_46

Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The Product Space Conditions the Development of Nations. *Science*, *317*(5837), pp.482–487. https://doi.org/10.1126/science.1144581

Huang, W., Shuai, B., Sun, Y., Wang, Y., & Antwi, E. (2018). Using entropy-TOPSIS method to evaluate urban rail transit system operation performance: The China case. *Transportation Research Part A: Policy and Practice*, *111*, pp.292–303. https://doi.org/10.1016/j.tra.2018.03.025

Jacobs, J. (1969). The Economy of Cities. *New York*: Random House.

Kemp, R., Schot, J., & Hoogma, R. (1998). Regime shifts to sustainability through processes of niche formation: The approach of strategic niche management. *Technology Analysis & Strategic Management*, *10*(2), pp.175–198. https://doi.org/10.1080/09537329808524310

Kogler, D. F., Essletzbichler, J., & Rigby, D. L. (2017). The evolution of specialization in the EU15 knowledge space. *Journal of Economic Geography*, *17*(2), pp.345-373.

Kogler, D. F., Essletzbichler, J., & Rigby, D. L. (2017). The evolution of specialization in the EU15 knowledge space. *Journal of Economic Geography*, *17*(2), pp.345–373. https://doi.org/10.1093/jeg/lbw024

Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science*, *3*(3), pp.383–397. https://doi.org/10.1287/orsc.3.3.383

Lindberg, M. B., Markard, J., & Andersen, A. D. (2019). Policies, actors and sustainability transition pathways: A study of the EU's energy policy mix. *Research Policy*, *48*(10), p.103668. https://doi.org/10.1016/j.respol.2018.09.003

Liu, X., Cifuentes-Faura, J., Zhao, S., & Wang, L. (2023). Government environmental attention and carbon emissions governance: Firm-level evidence from China. *Economic Analysis and Policy*, *80*, pp.121–142. https://doi.org/10.1016/j.eap.2023.07.016

Markard, J., Raven, R., & Truffer, B. (2012). Sustainability transitions: An emerging field of research and its prospects. *Research Policy*, *41*(6), pp.955–967. https://doi.org/10.1016/j.respol.2012.02.013

Mewes, L., & Broekel, T. (2022). Technological complexity and economic growth of regions. *Research Policy*, *51*(8), p.104156. https://doi.org/10.1016/j.respol.2020.104156

Montresor, S., & Quatraro, F. (2020). Green technologies and Smart Specialisation Strategies: a European patent-based analysis of the intertwining of technological relatedness and key enabling technologies. *Regional Studies*, *54*(10), pp.1354–1365. https://doi.org/10.1080/00343404.2019.1648784

Neffke F., Henning M, Boschma R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography,* *87*(3), pp.237–265. https://doi.org/10.1111/j.1944-8287.2011.01121.x

Nemet, G. F. (2012). Inter-technology knowledge spillovers for energy technologies. *Energy Economics*, *34*(5), pp.1259–1270. https://doi.org/10.1016/j.eneco.2012.06.002

Nightingale, P. (1998). A cognitive model of innovation. *Research Policy*, *27*(7), pp.689–709. https://doi.org/10.1016/S0048-7333(98)00078-X

Noailly, J., & Smeets, R. (2015). Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level patent data. *Journal of Environmental Economics and Management*, *72*, pp.15–37. https://doi.org/10.1016/j.jeem.2015.03.004

Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *American Economic Review, 104*(6), pp.1630-1666. https://doi.org/10.1257/aer.104.6.1630

Oltra, V., & Saint Jean, M. (2009). Sectoral systems of environmental innovation: An application to the French automotive industry. *Technological Forecasting and Social Change*, *76*(4), pp.567–583. https://doi.org/10.1016/j.techfore.2008.03.025

Perruchas, F., Consoli, D., & Barbieri, N. (2020). Specialisation, diversification and the ladder of green technology development. *Research Policy*, *49*(3), p.103922. https://doi.org/10.1016/j.respol.2020.103922

Pinheiro, F. L., Balland, P. A., Boschma, R., & Hartmann, D. (2022). The dark side of the geography of innovation: relatedness, complexity and regional inequality in Europe. Regional Studies, pp.1–16. https://doi.org/10.1080/00343404.2022.2106362

Popp, D. (2006). International innovation and diffusion of air pollution control technologies: The effects of NO*X* and SO2 regulation in the US, Japan, and Germany. *Journal of Environmental Economics and Management*, *51*(1), pp.46–71. https://doi.org/10.1016/j.jeem.2005.04.006

Popp, D. (2019). Environmental Policy and Innovation: A Decade of Research. *NBER Working Paper.* No. 25631. National Bureau of Economic Research, Inc.
https://doi.org/10.3386/w25631

Popp, D., & Newell, R. (2012). Where does energy R&D come from? Examining crowding out from energy R&D. *Energy Economics*, *34*(4), pp.980–991. https://doi.org/10.1016/j.eneco.2011.07.001

Popp, D., Hafner, T., & Johnstone, N. (2011). Environmental policy vs. public pressure: Innovation and diffusion of alternative bleaching technologies in the pulp industry. *Research Policy*, *40*(9), pp.1253–1268. https://doi.org/10.1016/j.respol.2011.05.018

Porter ME & Van der Linde C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, *9*(4), pp.97-118. https://doi.org/10.1257/jep.9.4.97

Quatraro, F., & Scandura, A. (2019). Academic Inventors and the Antecedents of Green Technologies. A Regional Analysis of Italian Patent Data. *Ecological Economics*, *156*, pp.247–263. https://doi.org/10.1016/j.ecolecon.2018.10.007

Raven, R., Kern, F., Verhees, B., & Smith, A. (2016). Niche construction and empowerment through socio-political work. A meta-analysis of six low-carbon technology cases. *Environmental Innovation and Societal Transitions*, *18*, pp.164–180. https://doi.org/10.1016/j.eist.2015.02.002

Ren, S., Li, X., Yuan, B., Li, D., & Chen, X. (2018). The effects of three types of environmental regulation on eco-efficiency: A cross-region analysis in China. *Journal of Cleaner Production*, *173*, pp.245–255. https://doi.org/10.1016/j.jclepro.2016.08.113

Rennings, K., & Rammer, C. (2009). Increasing energy and resource efficiency through innovation-an explorative analysis using innovation survey data. *ZEW-Centre for European Economic Research Discussion*, No.09-056.

Rexhäuser, S., & Löschel, A. (2015). Invention in energy technologies: Comparing energy efficiency and renewable energy inventions at the firm level. *Energy Policy*, *83*, pp.206–217. https://doi.org/10.1016/j.enpol.2015.02.003

Reynolds, C., Agrawal, M., Lee, I., Zhan, C., Li, J., Taylor, P., Mares, T., Morison, J., Angelakis, N., & Roos, G. (2018). A sub-national economic complexity analysis of Australia's states and territories. *Regional Studies*, *52*(5), pp.715–726. https://doi.org/10.1080/00343404.2017.1283012

Rip, A., & Kemp, R. (1998). Technological change. In S. Rayner, & E. L. Malone (Eds.), *Human choice and climate change: Vol. II, Resources and Technology* (pp. 327-399). Battelle Press.

Rogge, K. S., & Schleich, J. (2018). Do policy mix characteristics matter for low-carbon innovation? A survey-based exploration of renewable power generation technologies in Germany. *Research Policy*, *47*(9), pp.1639–1654. https://doi.org/10.1016/j.respol.2018.05.011

Rogge, K. S., & Reichardt, K. (2016). Policy mixes for sustainability transitions: An extended concept and framework for analysis. *Research Policy*, *45*(8), pp.1620–1635. https://doi.org/10.1016/j.respol.2016.04.004

Santoalha, A., & Boschma, R. (2021). Diversifying in green technologies in European regions: Does political support matter? *Regional Studies*, *55*(2), pp.182–195. https://doi.org/10.1080/00343404.2020.1744122

Santoalha, A., Consoli, D., & Castellacci, F. (2021). Digital skills, relatedness and green diversification: A study of European regions. *Research Policy*, *50*(9), p.104340. https://doi.org/10.1016/j.respol.2021.104340

Schot, J., Hoogma, R., & Elzen, B. (1994). Strategies for shifting technological systems: The case of the automobile system. *Futures*, *26*(10), pp.1060–1076. https://doi.org/10.1016/0016-3287(94)90073-6

Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization Science, 2*(1), pp.125–134. https://doi.org/10.1287/orsc.2.1.125

Smith, A., & Raven, R. (2012). What is protective space? Reconsidering niches in transitions to sustainability. *Research Policy*, *41*(6), pp.1025–1036. https://doi.org/10.1016/j.respol.2011.12.012

Sun, C., Kahn, M. E., & Zheng, S. (2017). Self-protection investment exacerbates air pollution exposure inequality in urban China. *Ecological Economics*, *131*, pp.468–474. https://doi.org/10.1016/j.ecolecon.2016.06.030

Sweet, C., & Eterovic, D. (2019). Do patent rights matter? 40 years of innovation, complexity and productivity. *World Development*, *115*, pp.78–93. https://doi.org/10.1016/j.worlddev.2018.10.009

Tanner, A. N. (2014). Regional branching reconsidered: Emergence of the fuel cell industry in European regions. *Economic Geography*, 90(4), pp.403–427. https://doi.org/10.1111/ecge.12055

Tanner, A. N. (2016). The emergence of new technology-based industries: The case of fuel cells and its technological relatedness to regional knowledge bases. *Journal of Economic Geography*, *16*(3), pp.611–635. https://doi.org/10.1093/jeg/lbv011

Tchorzewska, K. B., Garcia-Quevedo, J., & Martinez-Ros, E. (2022). The heterogeneous effects of environmental taxation on green technologies. *Research Policy*, *51*(7), p.104541. https://doi.org/10.1016/j.respol.2022.104541

Uhlbach, W. H., Balland, P. A., & Scherngell, T. (2022). Public R&D funding and new regional specialisations: The contingent role of technological relatedness. *Industry and Innovation*, *29*(4), pp.511–532. https://doi.org/10.1080/13662716.2022.2043147

van den Berge, M., Weterings, A., & Alkemade, F. (2020). Do existing regional specialisations stimulate or hinder diversification into cleantech? *Environmental Innovation and Societal Transitions*, *35*, pp.185–201. https://doi.org/10.1016/j.eist.2019.10.002

van Oort F.G. (2004). Urban Growth and Innovation. *Spatially bounded externalities in the Netherlands*. Ashgate, Aldershot. https://doi.org/10.4324/9781351143646

Verdolini, E., & Galeotti, M. (2011). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of Environmental Economics and Management*, *61*(2), pp.119–134. https://doi.org/10.1016/j.jeem.2010.08.004

Wang, Z., & Feng, C. (2014). The impact and economic cost of environmental regulation on energy utilization in China. *Applied Economics*, 46(27), pp.3362–3376. https://doi.org/10.1080/00036846.2014.929629

Yuan, J., Li, X., Xu, C., Zhao, C., & Liu, Y. (2019). Investment risk assessment of coal-fired power plants in countries along the Belt and Road initiative based on ANP-Entropy-TODIM method. *Energy*, *176*, pp.623–640. https://doi.org/10.1016/j.energy.2019.04.038

Zeppini, P., & van den Bergh, J. C. J. M. (2011). Competing Recombinant Technologies for Environmental Innovation: Extending Arthur's Model of Lock-In. *Industry and Innovation*, *18*(3), pp.317–334. https://doi.org/10.1080/13662716.2011.561031

Zhang, J., Kang, L., Li, H., Ballesteros-Pérez, P., Skitmore, M., & Zuo, J. (2020). The impact of environmental regulations on urban Green innovation efficiency: The case of Xi'an. *Sustainable Cities and Society*, *57*, p.102123. https://doi.org/10.1016/j.scs.2020.102123

Zhang, M., Yang, Y., Du, P., Wang, J., Wei, Y., Qin, J., & Yu, L. (2024). The effect of public environmental participation on pollution governance in China: The mediating role of local governments' environmental attention. *Environmental Impact Assessment Review*, *104*, p.107345. https://doi.org/10.1016/j.eiar.2023.107345

Zhu, J., Fan, Y., Deng, X., & Xue, L. (2019). Low-carbon innovation induced by emissions trading in China. *Nature Communications*, *10*(1), pp.1–8. https://doi.org/10.1038/s41467-019-12213-6

Appendix

Appendix A Indicator Description

Indicators	Description
Productivity per unit of smoke and dust produced by the secondary industry	(Industrial smoke and dust emission+Industrial smoke and dust removed)/Gross domestic product by secondary industry ①Industrial smoke and dust emission: The volume of soot in smoke emitted in process of fuel burning in premises of enterprises. ② Industrial smoke and dust removed: Volume of soot in smoke emitted in process of fuel burning in premises of enterprises.
Productivity per unit of wasted water produced by the secondary industry	(Industrial waste water discharged +Industrial waste water meeting discharge standards)/Gross domestic product by secondary industry ①Industrial waste water discharged: Volume of waste water discharged by industrial enterprises through all their outlets,including waste water from production process, directly cooled water,,ground water from mining wells which does not meet discharge standards and sewage from households mixed with waste water produced by industrial activities, but excluding indirectly cooled water discharged（it should be included if the discharge is not separated with waste water). ②Volume of industrial waste: Water discharge which, with or without treatment, reaches national or local standards.
Smoke and dust removal rate	Industrial smoke and dust removed/ (Industrial smoke and dust emission+Industrial smoke and dust removed)
Ratio of industrial solid wastes utilized	The percentage of industrial solid wastes utilized over industrial solid wastes produced (including stocks of the previous year).
Rate of urban domestic waste water treatment	The proportion of the quantity of domestic wastewater treated to the total quantity of domestic wastewater discharged at the end of reported period.
Rate of domestic garbage harmless treatment	The ratio of the volume of domestic garbage harmlessly treated to the volume of domestic garbage produced during the reference period. In practical statistics, as the volume of domestic garbage produced is difficult to obtain, it can be replaced by the volume of collected and transported.

Appendix B Baseline regression with *Green* dummy

	(1)	(2)	(3)
Variables	All	All	All
ER		0.0294***	0.0272***
		(0.0021)	(0.0022)
Density	0.0093***	0.0091***	0.0091***
	(0.0001)	(0.0001)	(0.0001)
*ER*Green*			0.0128***
			(0.0044)
Green		0.0236***	0.0158***
		(0.0007)	(0.0026)
Obs	1,484,406	1,137,802	1,137,802
Controls	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES
IPC4 FE	NO	NO	NO
Adj R^2	0.0602	0.0612	0.0613

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1