Environmental Regulation promotes Green Technological Diversification: Evidence from Chinese Cities

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Papers in Evolutionary Economic Geography

# 22.26

Human Geography and Planning
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Abstract: Accelerating the development of green technologies is essential to achieve a green transition, but green technologies tend to be more radical and complex. It means that they require significant efforts to scale and we need to understand all possible levers of green technological change. In this paper, we investigate whether environmental regulation can provide opportunities for path-breakthrough and complex technology diversification during the green transition process. The analysis is based on patenting activities in Chinese cities from 2003 to 2016. Our results show that cities with tighter environmental regulations are more likely to branch into new green technology spaces. In addition, environmental regulations help cities enter less related and more complex green domains. This study provides significant policy implications for the green transition literature.

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

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1. Introduction

The urgency to mitigate environmental degradation and climate change is often considered the most pressing challenge of our times. To deal with these issues, governments, research institutes, and firms are all making considerable efforts by issuing environmental and climate policies, investing in green technologies, and upgrading industrial structures. Green technologies, which hold the promises of having few or zero adverse effects on the environment (Oltra & Sain Jean, 2009; Driessen & Hillebrand, 2002), 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 significant economic benefits, and broader potential applications across various technological areas than non-green innovations (Dechezleprêtre et al., 2014; Popp & Newell, 2012; Nemet, 2012), the process of diversifying into green tech domains is challenging and risky due to the nature of green innovations. Helping regions jump the technological trajectories and create new and more complex green technology development paths is vital to sustainable development.¹

In the regional diversification literature, whether a region can develop and diversify a new technology depends on its own preexisting knowledge and capabilities related to this specific technology. Hidalgo et al. (2018) coined the principle of relatedness to express the idea that cities gradually diversify by leveraging related, preexisting economic activities, which are known to be path-dependent and are supported by numerous empirical research (Balland & Rigby, 2017; Boschma & Capone, 2015; 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 (Asheim & Gertler, 2005; Kogut & Zander, 1992) and accelerates economic development in the long-term (Hidalgo & Hausmann, 2009; Balland & Rigby, 2017).

Considering the important role of green innovation, the regional diversification literature has made numerous recent contributions to our understanding of the green innovation space (Montresor & Quatraro, 2020; Santoalha et al., 2021; Li et al., 2020; Moreno & Ocampo-Corrales, 2022; Barbieri et al., 2020; Cecere et al., 2014; Perruchas et al., 2020). However, the majority of previous studies only address the characteristics of the innovation itself. During processes of sustainable/green transition, path-breaking and complex technology is more common and contains more risks. Therefore, branching into green technology spaces requires a broader range of external sources

¹ Regional diversification is a branching process that creates new activities within regions (Frenken and Boschma, 2007).
and knowledge inputs to prevent the initial resources (De Marchi, 2012; Barbieri et al., 2020; Rennings & Rammer, 2009; Cainelli et al., 2015; Santoalha & Boschma, 2021; Smith & Raven, 2012). In addition, green innovations suffer from environmental and knowledge externalities (Popp, 2019; Aghion et al., 2016), which causes market participants not to have enough incentives to invest (Popp, 2019; Aghion et al., 2016; Dechezleprêtre et al., 2014). Without external sources, market participants are reluctant to develop this kind of innovation, and the technology development process tends to be a self-lock-in.

Therefore, academics have become more interested in how policies impact green innovation and move the city’s technological frontier forward. Nevertheless, the conclusion is mixed. On the one hand, the proponents of the "Porter Hypothesis" consider that environmental regulations encourage firms to develop more technological innovations, aiming to enhance their long-term competitiveness (Aghion et al., 2016; Popp, 2019; Porter & Van der Linde, 1995). On the other hand, other scholars contend that environmental regulations squeeze out the resources and investment in research and development, further leading to a decline in new technology (Shen et al., 2019; Popp & Newell, 2012; Noailly & Smeets, 2015). While this strand of research deepens our understanding of how external factors affect the innovation process, they mainly explore the number of green technologies and tend to ignore the embedded knowledge and technological structure.

With this in mind, this study connects the environmental policy and diversification literature and investigates whether environmental policies can help cities embrace a more complex and less related green technology. Using China's annual patent data at the city level from 2003 to 2016, we find: First, environmental regulations foster cities' expansion into new green technology spaces in general. Second, environmental regulations stimulate cities to create less related and more complex green technologies. Third, there is significant regional heterogeneity in the consequences of environmental regulations.

In doing so, we bridge the knowledge gap in environmental policy and diversification literature. First, the porter hypothesis supporters have suggested that the effect of environmental regulations on innovation depends on the existing technology and path-dependence, while most just use the lagged innovation as an indicator of the existing technology structure. They tend to ignore the relatedness of a specific technology with other technology and city-specific green technological characteristics (e.g., comparative technological advantage, technological maturity). However, such cross-technology relatedness is vital for cities to spur more innovations. Therefore, we introduce the cross-technology relatedness from the diversification literature into our framework and delve into city-specific knowledge structures embedded in different technology.

Second, the recent technology diversification literature has started to notice green innovation space, while they mainly focus on the characteristics of the innovation itself.
rather than exploring the policy's effect. Since green innovation diversification is more challenging and market forces do not have enough incentives to innovate in a green way, whether and how external policy shock can alter the path-dependent innovation process is important but is under-explored. Recent studies started to focus on how external factors affect the green diversification process (Smith & Raven, 2012; Santoalha & Boschma, 2021), but this stream of literature is mainly about supporting policies that provide subsidies and reduce costs. In addition, they rarely pay attention to the technological complexity to be explored. We differ from them by focusing on environmental regulations, which frequently result in cost increases, and considering the technological complexity as well.

2. Hypothesis development

Regional development is constrained by pre-existing knowledge bases, which generates a strong path-dependent process (Boschma and 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, that as a result tends to strongly concentrate in large cities (Balland et al., 2020). Regions are not isolated from each other and to a certain extent, the lack of related knowledge can be compensated by extra-regional linkages. These links can facilitate the diversification process by providing missing knowledge pieces (Aghion et al., 2016; Chatterjee & Wernerfelt, 1991; Mazzucato, 2016; Neffke et al., 2011; Dong et al., 2022).

A big question, however, concerns environmental regulations. They are fundamental to fighting climate change, but understanding whether they create or hinder economic opportunities is essential to receive societal support at large. In his 1991 essay, Michael Porter argued that environmental regulations might have a positive effect on the performance of domestic firms by stimulating innovation. This is known as the Porter hypothesis and we test it at the city level:

\[ H1: \text{Cities that have tighter environmental regulations are more likely to diversify into new technologies.} \]

Though environmental regulation plays a vital role in the diversification of both non-green and green technology spaces, it will undoubtedly have a more substantial effect on green diversification. Next, we, therefore, argue that environmental regulations provide specific incentives for public and private investments into green technology (Aghion et al., 2016; Popp, 2019; Porter & Van der Linde, 1995). The idea is that it leads firms to develop new and less costly technologies that reduce emissions and provide clear alternatives to fossil fuels. Environmental regulations somehow push local firms to become early inventors, foster green diversification, and will later create the possibility to export products in which this technology is embedded.

This is for two reasons. First, the nature of green innovation suffers from both knowledge externalities and environmental externalities, which leads to insufficient
incentives for green technology by market forces (Popp, 2019; Aghion et al., 2016; Dechezleprêtre et al., 2014). The environmental policy could deal with this market failure and incentivize the market to invest in green innovations (Klemetsen et al., 2018; Rogge & Schleich, 2018; Popp, 2019).

Second, green technologies are usually more radical at the initial stage of the life cycle (Consoli et al., 2016). Being an expert in green technology and understanding their knowledge base is more complicated and entails more significant uncertainties (Braungart et al., 2007). Therefore, diversifying into green technology space need more external sources (Braungart et al., 2007; Barbieri et al., 2020). The environmental policy intervention could provide such sources and reduce uncertainties by altering consumer preference, improving public awareness, and regulating the firm's production process (Barwick et al., 2019). Therefore, we develop our last hypothesis as below:

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

The technology diversification process is path-dependent. In addition, cities are more likely to enter economic activities whose complexity level is similar to the current existing knowledge and capacity base (Dong et al., 2020). If regions want to jump the technological trajectories and gain a path-breaking and more complex innovation, the role of niches is essential. In the transition literature, niches are the temporary "protective space" in the processes of path-breaking innovation (Kemp et al., 1998; Rip & Kemp, 1998; Schot et al., 1994). The initial protection of niches is vital and prevents selection pressure since path-breaking and complex innovation is more risky and easy to fail (Rip & Kemp, 1998; Raven et al., 2016; Smith & Raven, 2012).

During processes of sustainable/green transition, path-breaking and complex technology are more common (Barbieri et al., 2020; Rennings & Rammer, 2009; De Marchi, 2012; Santoalha & Boschma, 2021). Such innovations have the following characteristics (i) they are typically at the beginning of the life cycle, which carries greater risk and uncertainty (Consoli et al., 2016; Barbieri et al., 2020); (ii) they are more complicated and unrelated that require diverse and distant knowledge inputs (Cainelli et al., 2015; Dong et al., 2020; Horbach et al., 2012; Li et al., 2020; Barbieri et al., 2020; Rennings & Rammer, 2009). Therefore, outside sources and knowledge inputs are needed for these path-breaking and green technologies (De Marchi, 2012; Barbieri et al., 2020). Without external sources, firms and institutions have inertia and resistance towards this kind of innovation, and the technology development process tends to be a self-lock-in.

As a kind of external source, policy interventions can provide "niches" for the diversification process into path-breaking and complex technology space. First, the environmental policy requires replacing the pollution-intensive equipment and jeopardizes the region's existing "dirty" specialties (Acemoglu et al., 2016). In order to meet the requirement, firms need to search for other technologies unrelated to the existing 'dirty' specializations. Second, the policy enhances public awareness of environmental issues and alters the customer preference for products from the demand
side (Barwick et al., 2019), which further affects the supply-side decisions in the production and innovation process. Third, the environmental policy provides guidance and support for clean and green technology, reducing the risks and costs of regions searching in complex and distant technology spaces. Therefore, the environmental policy could provide a safe area with less risk and need fewer resources to cultivate path-breaking and more complex innovations.

To sum up, environmental policy enables regions to reduce the dependency on the existing knowledge base and move the city’s technological frontier forward. Thereafter, we propose our third and fourth hypotheses:

\[ H3: \text{Environmental regulations enable unrelated green diversification of cities.} \]

\[ H4: \text{Environmental regulations foster cities to develop more complex green technologies.} \]

3. Data and Methodology

3.1 Data and variable definition

There are three main sources of data in this study. The first one is patent data from the IncoPat Global patent database to calculate the technology diversification and the related index from 2003 to 2016. The second one is China's environmental statistical yearbook which provides information to construct the environmental regulation index at the city level. The third one is the China city statistical yearbook, which provides information about the control variables in the empirical analysis.

3.1.1 Technology-related variables

We constructed the technology-related indexes using the patent data, following Hidalgo et al. (2007) and Hidalgo & Hausmann (2009). We got access to information on Chinese patents from a commercial patent database called IncoPat. IncoPat contains data on patents from 102 countries and territories. All Chinese inventions applied from September 1985, including the patent title, abstract, application date, and grant date are contained in IncoPat. We compile the application number, name of applicants, address of applicants, and main 4-digit IPC class of invention patents of firm applicants. 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. We observed the patent applications of firm applicants to measure cities' activities and outcomes in terms of technological innovation in a particular year. Based on raw data, the number of patent applications at the city-IPC-year level was calculated. Since the grants of patent rights attest to the validity of the applicants’ technological innovation efforts, we only counted patent applications that are ultimately authorized. We excluded patent applications that were denied official grants because they cannot reflect a city's success in entering technical fields.

(1) Revealed comparative advantage (RCA)
To determine whether a city has an advantage in a certain technology, we employed the revealed comparative advantage (RCA). RCA was 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:

\[
RCA_{i,c,t} = \begin{cases} 
1, & \frac{\sum_i T_{\text{Technology}_{i,c,t}}}{\sum_i \Sigma_i T_{\text{Technology}_{i,c,t}}} \geq 1 \\
0, & \frac{\sum_i T_{\text{Technology}_{i,c,t}}}{\sum_i \Sigma_i T_{\text{Technology}_{i,c,t}}} < 1 
\end{cases}
\] (1)

Here, \(i, c\) and \(t\) stand for technology, city and year, respectively. \(T_{\text{Technology}_{i,c,t}}\) 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's is higher than that of the national average level, and equals zero otherwise.

(2) Relatedness (\(\varphi_{i,j,t}\)) and relatedness density (\(\text{Density}_{i,c,t}\))

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:

\[
\varphi_{i,j,t} = \min \{ P(RCA_{i,c,t} = 1 | RCA_{j,c,t} = 1), \ P(RCA_{j,c,t} = 1 | RCA_{i,c,t} = 1) \} 
\] (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 (\(\text{Density}_{i,c,t}\)) is measured as the weighted average RCA of all other technologies in a certain city weighted by their relatedness with this particular technology and is calculated as follows:

\[
\text{Density}_{i,c,t} = \frac{\Sigma_j RCA_{j,c,t} \varphi_{i,j,t}}{\Sigma_j \varphi_{i,j,t}} 
\] (3)

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

(3) 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 and Haussmann (2009) create 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 product 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 that have 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:

\[
\text{Diversity}_c = K_{c,0} = \sum_c M_{i,c,t} \tag{4}
\]

\[
\text{Ubiquity}_i = K_{i,0} = \sum_i M_{i,c,t} \tag{5}
\]

Where \( M \) is a city-technology adjacency matrix \( M_{i,c,t} \). \( M_{i,c,t} \) equals 1 if \( \text{RCA}_{i,c,t} \) 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:

\[
\text{KCI}_{c,t} = K_{c,n,t} = \frac{1}{k_{c,0}} \sum_i M_{i,c,t} \text{TCI}_{i,n-1,t} \tag{6}
\]

\[
\text{TCI}_{i,t} = K_{i,n,t} = \frac{1}{k_{i,0}} \sum_c M_{i,c,t} \text{KCI}_{c,n-1,t} \tag{7}
\]

Higher value of \( \text{KCI}_{c,t} \) suggests a city is more complex in its technology portfolio and higher value of \( \text{TCI}_{i,t} \) indicates knowledge intensity of a technology is higher.

Then, we made the difference between \( \text{TCI}_{i} \) and \( \text{KCI}_{c} \) to quantify the relative complexity of industry \( i \) to city \( c \)'s specialization basket. A positive \( \text{GCI}_{i,c} \) represents that industry \( i \) has a higher level of complexity than city \( c \)'s average.

\[
\text{GCI}_{i,c} = \text{TCI}_{i} - \text{KCI}_{c} \tag{8}
\]

### 3.1.2 Environmental regulation

The key independent variable is Environmental Regulation (ER) stringency. In the literature, there are several prevailing measurements for the stringency of environmental policy. The first one is usually based on a single indicator method, such as energy prices (Dechezleprêtre & Sato, 2020), inspections and violations of polluting companies (Brunnermerier & Cohen, 2003), pollutant emissions or emission intensity...
(Ren et al., 2018), etc. The second one is to construct evaluation standards to score the level of environmental regulations from different perspectives. For example, the Public and Environmental Research Center (IPE) and the Natural Resources Conservation Association (NRDC) develop the pollution source regulatory information disclosure. The third one usually constructs a comprehensive index based on the result variables of various pollutant emissions using different indicator construction methods, which can reflect the intensity of environmental regulations more objectively (Dechezlepretre & Sato, 2020; Liu et al., 2021).

Considering the availability of city-level data and the challenges the single indicator and objective score, this study uses the third method and follows Wang and 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 that are related to the stringency of environmental regulation (Zhao & Sun, 2016; Ren et al., 2018; Liu et al., 2021), including garbage harmless treatment rate, smoke and dust removal rate, industrial solid waste utilization rate, SO2 removal rate, and sewage treatment rate. The raw data is from China's environmental statistical yearbook. The concept of the entropy weight method is the greater the degree of dispersion and differentiation of a sub indication can contain more information, and then the higher the weight it will get (Huang et al., 2018; Liu et al., 2019; Yuan et al., 2019). The calculation process is as below:

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

$$x_{jct}^* = \frac{x_{jct} - \min(x_{jct})}{\max(x_{jct}) - \min(x_{jct})}$$  \hspace{1cm} (9)

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

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

$$e_{jt} = -\frac{1}{\log(n)} \sum_{c=1}^{n} y_{jct} \log(y_{jct})$$  \hspace{1cm} (10)

The divergence coefficient $d_{jt}$ will be:

$$d_{jt} = 1 - e_{jt}$$  \hspace{1cm} (11)

The larger $d_{jt}$, the more important the indicator. The weight of indicator $j$ at time $t$ is:
The environmental regulation stringency index will be the weighted sum of the selected sub-indicators:

$$w_{jt} = \frac{d_{jt}}{\sum_{j=1}^{m} d_{jt}}$$  \hspace{1cm} (12)$$

$$ER_{ct} = \sum_{j=1}^{m} w_{j} x_{jt}^{*}$$  \hspace{1cm} (13)$$

Figure 1 shows the geographical distribution of the mean environmental regulation and city-level index 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 midwest, southern 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), and Jiuquan\(^3\) in northwest China.

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\(^3\) Jiuquan is known for modern spaceflight and nuclear industry in China.
Figure 2. The geographical distribution of knowledge complexity across cities (2003-2016)

3.1.3 Control variables

We followed Dong et al. (2020) and used population density (\textit{Pop\_Den}), total population (\textit{Pop}), foreign direct investment (\textit{FDI}), and gross domestic product (\textit{GDP}) as control variables. The China City Statistic Yearbooks were used to collect all of the control variables at the city level. These factors could capture the differences in size, economic development, openness, and agglomeration economies between cities.

Table 1. Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
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<td>\textit{Entry}</td>
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<td>0.055</td>
<td>0.228</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>\textit{Density}</td>
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<td>7.245</td>
<td>7.895</td>
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<td>100</td>
</tr>
<tr>
<td>\textit{GCI}</td>
<td>1715860</td>
<td>0.055</td>
<td>0.151</td>
<td>0.169</td>
<td>0.978</td>
</tr>
<tr>
<td>\textit{ER}</td>
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<td>1</td>
</tr>
<tr>
<td>\textit{Pop}</td>
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<td>453.71</td>
<td>409.499</td>
<td>16.37</td>
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<tr>
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<td>438.777</td>
<td>327.429</td>
<td>4.7</td>
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</tr>
<tr>
<td>\textit{FDI}</td>
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<tr>
<td>\textit{GDP}</td>
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<td>16091150</td>
<td>23735765</td>
<td>317731</td>
<td>2.818e+08</td>
</tr>
</tbody>
</table>

3.2 Model specification

By employing a linear probability model with fixed effects, we estimated the likelihood that a city will specialize in a new specific technology (Balland et al., 2019;
Dong et al., 2022).

The basic model specification is as below:

\[
\text{Prob(Entry}_{i,ct} = 1) = \alpha_0 + \alpha_1 * ER_{c,t-1} + \alpha_2 * \text{Density}_{i,ct-1} + \alpha_3 * \n\]
\[
GCI_{i,ct-1} + \alpha_4 * GCI_{s,i,ct-1} + \beta * X_{c,t-1} + \delta_i + \delta_c + \mu_t + \epsilon_{i,ct} \quad (14)
\]

The dummy variable \text{Entry}_{i,ct} takes 1 if city \(c\) does not have RCA in year \(t-1\) and then develops RCA in year \(t\) in the technology domain \(i\). \(\alpha_1\) estimates how ER relates to the probability of entering in a new specific technology. \text{Density}_{i,ct-1} refers to the technological relatedness density, measuring how technology \(i\) is closely connected to city \(c\)’s other existing technologies at \(t-1\). \text{GCI}_{i,ct-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., 2021), we include its quadratic term \text{GCI}_{s,i,ct-1}, and \(\alpha_4\) is expected to be negative to indicate the inverse U-shape relationship between GCI and entry probability \(X_{c,t-1}\) are city-specific control variables, including GDP, foreign direct investment, total population, and population density. We controlled for city and technology-fixed effects to absorb some technology-specific heterogeneities \((\delta_i, \delta_c)\) that might not be able to be observed in our controls. We also included year-fixed effects 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:

\[
\text{Prob(Entry}_{i,ct} = 1) = \alpha_0 + \alpha_1 * ER_{c,t-1} + \alpha_3 * ER_{c,t-1} * Green_i + \alpha_2 * \n\]
\[
\text{Density}_{i,ct-1} + \alpha_3 * GCI_{i,ct-1} + \alpha_4 * GCI_{s,i,ct-1} + \beta * X_{c,t-1} + \delta_i + \delta_c + \mu_t + \epsilon_{i,ct} \quad (15)
\]

Where \text{Green}_i is a dummy indicating whether a technology belongs to green technology or not \((\text{Green}_i=1\) if is a green technology and \(=0\) otherwise). The green and non-green technologies are classified based on the 4-digit code of International Patent Classification (IPC) of each patent and the green innovation classification of Intellectual Property Organization (WIPO). All variables are defined in the same way as in Equation (14).

To test hypotheses \(H3\) and \(H4\), we included the cross term of \(\text{Density}*ER\) and \(GCI*ER\) based on the subset of green technologies, estimating whether ER could lead to a technology breakthrough and help the city enter more complex green technology domains.

\[
\text{Prob(Entry}_{i,ct} = 1) = \alpha_0 + \alpha_1 * ER_{c,t-1} + \alpha_3 * ER_{c,t-1} * \text{Density}_{i,ct-1} + \n\]
\[
\alpha_2 * \text{Density}_{i,ct-1} + \alpha_4 * \text{Density}_{i,ct-1} + \alpha_5 * GCI_{i,ct-1} + \alpha_6 * GCI_{s,i,ct-1} + \beta * X_{c,t-1} + \delta_i + \delta_c + \mu_t + \epsilon_{i,ct} \quad (16)
\]

\(\alpha_2\) is expected to be negative and \(\alpha_3\) is expected to be positive in Equation (16). All variables are defined in the same way as in Equation (14).
4 Results and discussions

4.1 Baseline result

Table 2 shows the overall effect of environmental regulation. In the most baseline model (Column (1)), 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 own existing technological infrastructure. This result is consistent with the previous relevant studies on diversification (Boschma & Capone, 2015; Balland et al., 2019). The coefficients of the square term of GCI ($GCI_{sq}$) in both columns are negative, indicating that there exists 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).

Column (2) exhibits the estimated result based on Equation (15). The coefficient on environmental regulation ($ER$) is positive, suggesting that stricter environmental regulation ($ER$) improves the possibility of diversifying into new technology spaces. $H1$ – the Porter hypothesis - is supported. Column (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, suggesting that environmental regulation’s effect is larger for green innovation than for non-green innovation. At a 5% significant level, the coefficient on $ER$ loses its significance after considering $ER*Green$. 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 innovation space than non-green innovation space. The environmental policy intervention could provide such sources, reduce uncertainties, deal with this market failure, and incentivize the market to invest in green innovations. Such a result supports our hypothesis $H2$. 
Table 2 Baseline result

<table>
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<th>VARIABLES</th>
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<th>(3)</th>
</tr>
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<td>All</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>ER</td>
<td>0.0095***</td>
<td>0.0038*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0019)</td>
<td>(0.0020)</td>
<td></td>
</tr>
<tr>
<td>Density</td>
<td>0.0063***</td>
<td>0.0063***</td>
<td>0.0063***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>ER*Green</td>
<td></td>
<td></td>
<td>0.0346***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0035)</td>
</tr>
<tr>
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<td>0.0121***</td>
<td>0.0123***</td>
<td>0.0128***</td>
</tr>
<tr>
<td></td>
<td>(0.0016)</td>
<td>(0.0016)</td>
<td>(0.0016)</td>
</tr>
<tr>
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<td>-0.0439***</td>
<td>-0.0449***</td>
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<td>(0.0027)</td>
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<td>1,641,719</td>
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<tr>
<td>City FE</td>
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<td>YES</td>
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<tr>
<td>Adjusted R-squared</td>
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<td>0.0930</td>
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</table>

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

4.2 Heterogeneity in knowledge structure

Table 3 exhibits the result regarding how the technology structure, namely, density and complexity, affects the role of environmental policy based on Equation (16). Column (1) shows the estimated result about whether environmental policy helps cities to gain path-breaking green innovation. We can see that the cross-term Density*ER is significantly negative, which means that environmental regulation helps cities generate a path breakthrough and develop less related green technology, which proves that environmental regulation could compensate for the weak capabilities to develop less related technology in a region. Column (2) shows the estimated result about how complexity matters in terms of the role of environmental policy on technology. The significant and positive coefficient on GCI*ER indicates that environmental regulation helps cities diversify into more complex green technology spaces. We consider both Density*ER and GCI*ER in Column (3). The result is still robust.

To sum up, the above results prove our hypotheses **H3** and **H4**: environmental regulations enable unrelated and complex green diversification. Environmental regulations, an external source, can provide "niches" for green innovations and alter the transition into path-breaking and complex green technology space.
Table 3 Heterogeneity analysis in density and complexity

<table>
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<tr>
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<th></th>
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<td>0.0094***</td>
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<td>Density*ER</td>
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<td>-0.0039***</td>
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<td>GCI*ER</td>
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<td>0.1206***</td>
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<td>0.0728***</td>
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</table>

Controls  YES | YES | YES
Observations 266,309 | 266,309 | 266,309
Year FE | YES | YES | YES
City FE | YES | YES | YES
Industry FE | YES | YES | YES
Adjusted R-squared 0.0894 | 0.0893 | 0.0894

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

4.3 Heterogeneity in regions

Considering there is a huge regional difference in China and the technology diversification depends a lot on the regional capabilities (Boschma & Capone, 2015; Boschma et al., 2017), the impact of the environmental policy is expected to be varied across regions. This section 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 4.

For the result of the overall impact of the environmental policy, the coefficient of ER is significantly positive in columns (1) and (5), and significantly negative in column (3) at 10% significance level. In the East area of China, the porter hypothesis effect dominates, and the environmental policy helps regions specialize in new technology. In the Middle area, the crowding-out effect dominates, and the environmental policy deters regions from entering new technology space. In the West area, the stimulating effect of the environmental policy on diversifying to new technology spaces is significant but weaker than that in the East area.

The rationale behind such different impacts is related to the regional capability and institutional background. As we can see in Appendix 1, the environmental regulation stringency decreases from East to West. East area is relatively developed with higher innovation ability. The residents here usually have more demand for a better environment, and the government here can provide support to invest in new and risky technology. Therefore, firms here can more easily invent new technology that has less harmful effects on the environment. The middle region usually relies on polluted and energy-intensive industries a lot, so it need to pay more in the transition to a green economy. In addition, cities in this region do not have enough capacity to invest in new
technology. Thus, the middle region suffers from the crowding-out effect the most. The west region is less developed and suffers less from pollution. The lowest regulation level makes cities there less likely to be affected by the crowding-out effect.

Columns (2), (4), and (6) examine the effect of environmental policy across different regions in terms of branching into green technology. In general, the positive coefficient on \( ER*Green \) demonstrates that environmental policy helps cities enter the green technology spaces in all regions. To be more specific, in the East region of China, the probability of entering green and non-green technology space experience an increase when the environmental regulation is higher, while the effect on green technology is stronger. In the West region, environmental regulation deters cities from entering non-green technology space but encourages cities to enter green technology space. Such a result indicates that the relative strength of the “Porter” effect and crowding out effect is different between green and non-green technology. Environmental regulation could help cities specialize in green domains but squeeze out the investment in non-green domains. In the West areas, environmental regulation does not significantly affect the probability of entering non-green technology space but improves the likelihood of diversification into green technology space.

**Table 4** Heterogeneity in regions

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>East (1)</th>
<th>East (2)</th>
<th>Middle (3)</th>
<th>Middle (4)</th>
<th>West (5)</th>
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<td>0.0061***</td>
<td>*</td>
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<td>(0.0001)</td>
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<td>(0.0002)</td>
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Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
5 Conclusion

This study probes whether environmental policy can help cities branch into a less related and more complex technology. Using China's annual patent data at the city level from 2003 to 2016, our results show that (i) environmental policy fosters cities to branch into new green technology spaces in general; (ii) environmental policy fosters cities to develop less related and more complex technology; (iii) the effects of environmental policy have a regional heterogeneity. For example, the environmental policy may harm the probability of entering new technology domains in the middle area.

In doing so, this study fills the research gap from the following perspectives. First, by quantifying cross-technology relatedness from the regional diversification literature, we differ from the previous environmental policy literature, which only uses the lagged innovation to measure the path-dependent process. In addition, we delve into city-specific knowledge structures embedded in different technology and explore the effectiveness of the environmental policy, which sheds light on the environmental policy literature. Second, compared with the existing regional diversification literature mainly discussing green diversification within the nature of the technology itself, we focus on how environmental policy affects the branch into different technology domains. As a different external shock compared with the other supporting policies, exploring the environmental policy’s effect during the diversification process complements the regional diversification literature.

The result of this study has some practical implications. At the broader level, environmental regulations are fundamental to fighting climate change. However, citizens, firms, and cities will be less likely to support new environmental regulations if they hinder economic opportunities. Unpacking this tension and showing that environmental regulation promotes green diversification means that such green policy are economically and politically viable.

At the regional level, path dependence means that less developed regions have difficulties in branching into more complex and green spaces. They are more likely to be confined in high-carbon and high-pollution regimes. This is particularly problematic as the urgency to deal with environmental degradation and climate change is more vital in less developed regions. Therefore, proper interventions, such as providing niches for these technologies with environmental policies, can help regions jump the technological trajectories and create new and more complex green technology development paths. This is vital to environmental justice and sustainable development across cities.

In addition, our results identify that the environmental policy helps regions gain a path-breakthrough, but cities may differ in capacities and willingness to respond to the policy. Therefore, how to coordinate different regions and provide necessary support to less developed areas is significant to sustainable development and environmental justice as well.
Reference


Cainelli, G., De Marchi, V., & Grandinetti, R. (2015). Does the development of environmental


Horbach, J., Rammer, C., & Rennings, K. (2012). Determinants of eco-innovations by type of


Wang, Z., & Feng, C. (2014). The impact and economic cost of environmental regulation on

**Appendix**

Appendix 1. Environmental regulation stringency across regions

<table>
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<th>Variable</th>
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<th>Std. Dev.</th>
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<th>Max</th>
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<td>.14</td>
<td>.178</td>
<td>.978</td>
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<td>.148</td>
<td>.211</td>
<td>.971</td>
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<tr>
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<td>.613</td>
<td>.149</td>
<td>.169</td>
<td>.951</td>
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