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Innovation incentives and urban carbon dioxide emissions: A quasi-natural experiment based on fast-tracking green patent applications in China

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ABSTRACT

Carbon dioxide (CO_2) emissions reduction has become a core task with the goal of “emission peak and carbon neutrality”, in which green innovation plays an important role. This paper takes the fast-tracking green patent applications (FGPA) system in China as a quasi-natural experiment to empirically study the impact of green innovation incentive-based policies (GIIPs) on CO_2 emissions in Chinese cities by applying a continuous difference-in-difference approach. The results show that the CO_2 emissions of cities in the treatment group are significantly reduced by about 1.6% after the implementation of FGPA relative to that in the control group. After a series of robustness tests, the conclusion is still valid. Furthermore, the significant negative impact on CO_2 emissions is more reflected in cities located in eastern China, cities with lower financial pressure, and cities with more universities. Overall, this study fills up the gap in the empirical research on the impact of FGPA, and casts a new light on the significant environmental performance of GIIPs. The findings obtained through this study are conducive to strengthening and optimizing the implementation of FGPA, and offering policy-makers with a scientific basis of GIIPs to approach the task of reducing CO_2 emissions.

1. Introduction

The issue of climate change caused by environmental degradation has raised widespread concerns. Since the end of the nineteenth century, the global surface temperature has increased by 0.4–0.8 °C (Qiao et al., 2020), which is mainly caused by excessive greenhouse gas emissions (Cox et al., 2000; Kasman and Duman, 2015), especially carbon dioxide (CO_2) (EPA, 2021). The continuous rise of global temperature requires countries around the world to actively cooperate (Khan et al., 2021). As one of the countries with the most CO_2 emissions in the world (Z.G Li et al., 2021), China is facing tremendous pressure from environmental pollution (Liao, 2018; Hang et al., 2019; Zhang et al., 2019). In 2020, China announced at the United Nations General Assembly the goal of achieving “emission peak” by 2030 and “carbon neutrality” by 2060, where innovation is an increasingly important way to accelerate the comprehensive green transformation of economy and society in China.

What role do the green innovation incentive-based policies (GIIPs) play under such background? Green innovation is an important way to reduce CO_2 emissions. The number of green patents has become a measure of green innovation output (Kwon et al., 2017; Su and Moaniba, 2017). At the same time, intellectual property policies have a profound impact on innovation output. It is worth exploring whether public administrators can achieve the goal of reducing CO_2 emissions by formulating targeted patent policies. In 2012, the China National Intellectual Property Administration (CNIPA) formally implemented the fast-tracking patent applications system, which mainly focuses on patent applications related to green innovation (hereinafter referred to as the fast-tracking green patent applications, FGPA). FGPA shortens the examination period for qualified green patent applications and extends theoretical maximum protection period, thus stimulating green innovation. In this paper, we construct a set of panel data on the CO_2 emissions and green patent applications at the city-year level in China from 2007 to 2016. Using a continuous difference-in-difference (DID) approach, we explore whether FGPA reduces CO_2 emissions in Chinese cities by encouraging green innovation. We further discuss the heterogeneity of the impact from the perspectives of urban regional location, financial pressure and university quantity.

The key findings of this research include: (1) compared to cities in the control group, the CO_2 emissions of cities in the treatment group are significantly reduced by about 1.6% after the implementation of FGPA,

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providing empirical evidence for the environmental performance of GIIPs; (2) the conclusions still hold after a series of robustness tests, which include using standard DID models, replacing core indicators, changing model settings, and excluding the effects of other policies over the same period; (3) according to the results of heterogeneity analysis, the significant impact of FGPA on reducing urban CO_2 emissions is mainly reflected in cities located in the eastern region, cities with lower financial pressure, and cities with more universities.

The contributions of this paper are mainly manifested in the following three aspects. First, different from the existing research on the evaluation of environmental regulation-based policies (ERPs), this paper focuses on the patent policy closely related to green innovation, and sets up a continuous DID model to explore whether GIIPs are effective under environmental protection goals. It clarifies and enriches the instrumental connotation of patent policies, and provides public administrators with an alternative path except for ERPs to reduce CO_2 emissions. Second, we comprehensively consider the role of city's regional location, financial pressure, and university quantity in determining the environmental performance of GIIPs. It illustrates the basis for the realization of innovation incentive effects, and sheds light on the way of effective policy implementation. Finally, there are many theoretical discussions but few empirical studies on the policy effectiveness of FGPA. Meanwhile, most existing research focus on its impact on patent quality or innovation performance without taking environmental performance into account. This paper fills up the gap in the empirical research on the environmental performance of FGPA.

The rest of the paper proceeds as follows. Section 2 provides a brief review of the existing literature. Section 3 presents the policy background and research hypotheses. Section 4 introduces the identification strategy, including the methodology, the econometric model and data description. Section 5 reports the results and analysis of a series of empirical tests. Moreover, the final section concludes by providing policy recommendations corresponding to the major findings.

2. Literature review

In recent years, the studies on the factors of CO_2 emissions have become a focus of academic discussion (Lean and Smyth, 2010; Liu et al., 2017; Leal and Marques, 2020; Cheikh et al., 2021). Relevant studies can be categorized into four aspects. (1) Urbanization. Zhang and Lin (2012) find an increase of CO_2 emissions brought by urbanization in China. Martínez-Zarzoso and Maruotti (2011) find an inverted U-shaped relationship between urbanization and CO_2 emissions in developing countries, but Zhu et al. (2012) disagree with that. (2) Economic development. Kasman and Duman (2015) find an inverted U-shaped relationship between economic development and environmental performance in European countries. Xu and Lin (2016) discover that economic growth plays an important role in China's CO_2 emissions. (3) Fossil fuels. More than 40% of human CO_2 emissions come from the use of fossil fuels (Zhang et al., 2013). Hanif et al. (2019) point out that the use of fossil fuels is not only an important factor in promoting economic development but also a major source of CO_2 emissions. (4) Other factors. In addition, researchers show that secondary industry (Zhu et al., 2017; Liu and Bae, 2018), tertiary industry (Samargandi, 2017), and foreign direct investment (Zhang and Zhang, 2018) have an impact on CO_2 emissions.

Since air resources are non-competitive and non-exclusive public goods, the government needs to take a series of measures to prevent an environment-styled tragedy of the commons. There are many studies on the CO_2 reduction effect of policy tools recently, most of which are based on ERPs. (1) Carbon Emissions Trading Scheme (CETS). Z.Z Li et al. (2021) quantify the CO_2 reduction effect of CETS pilots with the PSM-DID method, and they find it reduces the CO_2 emissions of the treatment group by about 0.027% from 2013 to 2016 in China. The carbon reduction effect of CETS is also verified in other studies (Dong et al., 2020; Hu et al., 2020). (2) Low-carbon City Pilot Policy (LCCP). Liu (2022) uses a panel data of 272 Chinese cities from 2000 to 2018 to evaluate the effectiveness of LCCP based on a multi-period DID model, and finds that the policy reduces CO_2 emissions in pilot cities by about 6.92%. The study of Ren et al. (2022) also supports the CO_2 reduction effect of LCCP. (3) Environmental Protection Tax Policy. Taxation is regarded as an effective way to increase pollution costs and reduce CO_2 emissions (Gao et al., 2022). Lin and Jia (2019) suggest that levying taxes helps reduce CO_2 emissions in China. In addition, the effect is also verified in OECD countries (Hashmi and Alam, 2019) and G7 economies (Hao et al., 2021). Overall, relevant studies tend to confirm the environmental performance of ERPs. However, there are also some inherent shortcomings in ERPs (Guo et al., 2020). For example, CETS does reduce CO_2 emissions, but the effect is very short-lived, which gradually decreases and becomes insignificant two years after the policy's implementation (Ouyang et al., 2020; Shen et al., 2020). Zhang and Duan (2020) even point out that China's CETS policy has a negative impact on the gross industrial output, and production reduction is the main way for its reducing CO_2 emissions.

Except for EPRs, innovation is another effective way to cope with the scarcity of natural resources. Before crossing the turning point of the environmental Kuznets curve (Grossman and Krueger, 1991), green innovation is expected to bring a win-win situation for environmental protection and economic development. According to existing research, innovation contributes to CO_2 emissions reduction (Lin and Wang, 2015). Manoli et al. (2016) indicate that the rebound in global CO_2 emissions is due to an intrinsic delay in the diffusion of innovation, and it is necessary to strengthen the promotion of technological progress and transformation on a global scale. Shahbaz et al. (2020) show that technological development promotes economic development while avoiding the ignorance of environmental protection. In addition, compared with general innovation, Tobelmann and Wendler (2020) point out that environment-related green innovation reduces CO_2 emissions to a great extent, which is verified in China (Weina et al., 2015), OECD countries (Hashmi and Alam, 2019), and G7 economies (Khan et al., 2020). However, high-cost and strong positive externality are two issues that hinder the development of green innovation by making enterprises, which aim to maximize profits, lack of incentives to operate green innovation. Specifically, the high-cost is manifested in the following two aspects. Firstly, green innovation may impede industrial productivity and profitability by squeezing out other profitable innovation (Marin, 2014) and bringing technology transformation costs (Porter and van der Linde, 1995). Secondly, green innovation requires more heterogeneous sources of knowledge (Horbach et al., 2013; Ghisetti et al., 2015), which is reflected in the fact that green innovators collaborate with external partners to a greater extent than other innovators (Cainelli et al., 2015). These imply that green innovation requires more R&D investment. In addition, the positive externality of green innovation makes its private profits less than social benefits, which also discourages enterprises from undertaking green innovation. Therefore, public administrators are obliged to actively implement related policies like GIIPs, encouraging green innovation and promoting sustainable development.

As mentioned above, existing research focuses on exploring the sources of CO_2 emissions and different solutions to achieve CO_2 emissions reduction. Among them, ERPs are the focus of Chinese policy practice and existing research. While few studies are conducted on the effectiveness of GIIPs, which internalize green innovation's positive externality by reducing costs and increasing profits. It is worth noting that, compared to ERPs, the advantage of GIIPs is not its environmental performance in a short term. But rather, a long-term effect of GIIPs is expected. To fill up these research gaps, in this study, we take FGPA as an example of GIIPs, exploring the impact of which on CO_2 emissions in Chinese cities. This study contributes empirical evidence for the environmental performance of GIIPs, offering policy-makers an attractive path to sustainable development.

3. Policy background and research hypotheses

3.1. Policy background

In order to promote a sustainable development of social economy, an effective patent system can facilitate a desired increase in green innovation (Taylor, 2011). On June 19th, 2012, the CNIPA promulgated the Administrative Measures for the Fast-tacking Patent Applications, which became completely effective on August 1st, 2012. This policy is set to promote the optimization and upgrading of the industrial structure, giving priority review to patent applications in specific technical fields, especially low-carbon and resource conservation technologies. For patent applications that meet the FGPA requirements, CNIPA will give the first notice within thirty days, and the case should be settled within one year. This policy shortens the examination period for qualified green patent applications, and extends theoretical maximum protection period.

In addition, it is worth mentioning that FGPA is not only practiced in China. Other countries implementing FGPA include the United Kingdom (May 12, 2009), Australia (September 15, 2009), South Korea (October 1, 2009), Japan (November 1, 2009), the United States (December 8, 2009), Israel (December 27, 2009), Canada (March 3, 2011) and Brazil (April 17, 2012).[1] And FGPA has different system designs in terms of review standards and thresholds in different countries. For example, the low-standard FGPA represented by the United Kingdom Intellectual Property Office (UKIPO) requires green patent applicants to submit technical description documents to "make a reasonable assertion that the invention has some environmental benefit", and the UKIPO does not "conduct any detailed investigation into these assertions" (UKIPO, 2014). The high-standard FGPA represented by the Korean Intellectual Property Office (KIPO) puts forward requirements for specific green innovation scopes, official search reports, online applications, and written description documents (KIPO, 2016). Besides, FGPA in China sets an appropriate standard and threshold between the above two, with a requirement of self-application and moderate review.

There is some theoretical research on FGPA system (Patton, 2012; Lu, 2013), which mainly focus on the justification of the policy. Besides, Antoine (2013) conducts an empirical study by counting the number of green patent applicants requesting for accelerated examination globally and the corresponding shortened time for specific review. He finds that FGPA can indeed help green technology spread earlier. But this study does not further discuss FGPA's possible environmental performance. To fill up the gap, we take FGPA as an exogenous policy shock to investigate its environmental performance in this study.

3.2. Research hypotheses

Due to the contradiction between the blowout of patent applications and the limitation of patent examination resources, the complicated and time-consuming examination process often results in a long- and uncertain-time lag between a patent's disclosure and authorization. As one of GIIPs, FGPA shortens the examination time of green patent applications, allowing them to be quickly granted when meeting authorization conditions, thereby achieving the purpose of stimulating green innovation and expanding green technology spillover. The objective of this paper is to understand the impact of the implementation of FGPA on urban CO_2 emissions, and explore the logic behind the policy effects. Although FGPA was implemented simultaneously across the country in 2012, different cities had different degrees of green technology development at that time, which we consider a suitable proxy variable to measure the degree of policy shock. Therefore, the continuous DID method can be employed to investigate the impact of FGPA on urban CO_2 emissions in China. To investigate the policy effect of FGPA, the research framework is presented in Fig. 1.

3.2.1. The innovation incentive effect of FGPA

As one of GIIPs, FGPA may encourage green innovation in two ways. Firstly, the maximum life cycle for patents is twenty years from the date of application, and the time lag between application and authorization is mainly determined by the examination process. Therefore, the examination process directly affects the maximum protection time, which is closely related to patent profits (Qiao and Liu, 2021). FGPA shortens examination time and extends theoretical maximum protection time for green patents by pre-examining applications, thus encouraging green innovation. Secondly, the patent system provides a "provisional protection period" for patents filed but not yet granted. Because of the uncertainty of patent applications being granted, applicants are often unable to adequately protect disclosed technologies. Although Article 13 of the Patent Law of the People's Republic of China gives applicants the right to require appropriate payment from subjects who use the disclosed technology, the requirement is often refused due to the uncertainty in the status of patent applications. Even if applicants try to recover after being granted, they are still facing with a high cost of complex mediation or litigation proceedings. As a result, a long "provisional protection period" often compromises patent profits, reduces the effectiveness of patent application, and discourages technology diffusion. FGPA provides incentives for green innovation by extending the maximum protection duration, and shortening the "provisional protection period". Considering the contribution of green innovation to CO_2 emissions reduction (Tobelmann and Wendler, 2020) and the above two potential incentive paths for green innovation, we propose hypothesis 1a.

H1a. The implementation of FGPA significantly reduces CO_2 emissions in Chinese cities.

In practice, there may be a discrepancy between initial objectives and actual results of a policy. It is worth considering whether FGPA achieves the goal of stimulating green innovation. We think FGPA may form a crowding-out effect from two aspects to hinder green innovation. For one thing, the encouragement rather than compulsion of FGPA may lead to a weak incentive effect. The incentives of the policy may not yet be sufficient to bring potential innovators into the field but only stimulate existing green innovators. Besides, FGPA sets out a requirement for applicants to submit a compliant search report for the procedure. In practice, applicants are often required to submit a search fee of RMB 1,500, which may further reduce the actual incentive effect on green innovation. For another thing, all green patent applications have only one examination route before the implementation, without additional options for green innovators. Whereas after the implementation, green innovators have an additional faster examination route within rules. Considering the searching costs of FGPA, green innovators with greater capability are more likely to choose FGPA route. Besides, the system does tend to provide shortcuts for large and well-known companies in practice (Li and Zheng, 2014). These two aspects may increase the costs of green innovation for existing and potential innovators, thus creating a crowding-out effect, resulting in fewer green innovators and fewer green innovation, which in turn leads to unsatisfied environmental performance. Based on the above discussion, this paper proposes hypothesis 1b.

H1b. The implementation of FGPA does not decrease CO_2 emissions in Chinese cities.

3.2.2. The heterogeneity of FGPA's environmental performance

Then, we explore the heterogeneity of FGPA's environmental performance from three aspects: the intrinsic foundation, external support, and knowledge reserve of innovation. The economic logic of heterogeneity analysis is as follows. First, innovation is inseparable from

[1] Refer to https://www.wipo.int/wipo_magazine/en/2013/03/article_0002.html, last accessed on September 21, 2022.

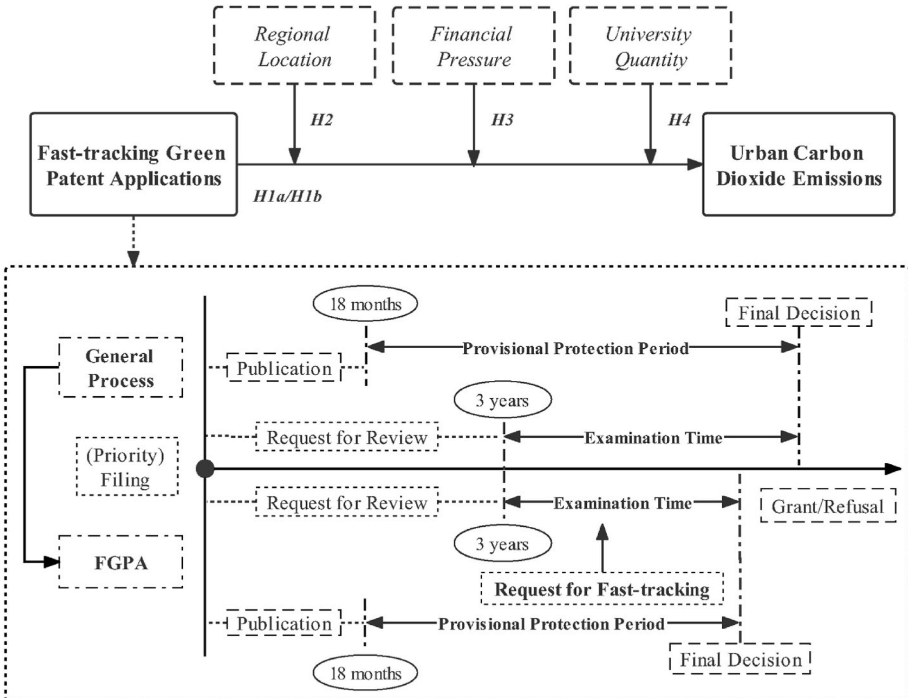

Fig. 1. Research framework.

economic support. Therefore, the economic development of cities is taken as an intrinsic basis for innovation. Allowing for the regional differences in the economic development of Chinese cities, this paper explores the heterogeneity of FGPA's environmental performance based on city's regional location. Second, as knowledge is public good, innovation is closely related to the external support provided by governments. Governments with fiscal imbalance are under high financial pressure, which may lead to investment choices that emphasize production over innovation and revenue-based innovation over green innovation. Thus, we explore the heterogeneity of FGPA's environmental performance in terms of municipal financial pressure. Finally, universities, as places with intensive R&D resources, are the knowledge reserves of innovation. On the one hand, universities, as one of the important innovation subjects, produce a large number of patents and transform the technologies through the system of industry-university-research cooperation, and give play to the technical function of patents in production and manufacturing. On the other hand, universities are more engaged in basic and general innovation, and some discipline-specific important discoveries often effectively promote technological innovation and industry development. This paper explores the heterogeneity of FGPA's environmental performance based on university quantity.

3.2.2.1. FGPA and region location. While green innovation theoretically helps reduce CO_2 emissions, some studies suggest that the heterogeneity of the impact exists depending on the applied context. For example, Wang et al. (2012) find that carbon-free energy patents play a significant role in reducing CO_2 emissions in eastern China, but not in central or western China. Yan et al. (2016) argue that green innovation contributes to CO_2 emissions reduction by promoting a low-carbon industrial structure, but this effect may be offset by the economic interventions of Chinese local governments. There is also significant regional heterogeneity in green technology spillovers, with Zhang (2017) finding that eastern China is the main area for green technology spillovers, while it is relatively weak in the central and western regions.

The above studies demonstrate that cities in different regions may differ in their responsiveness to GIIPs. As Popp (2012) point out, the application of green technologies often entails initial costs, which prevents poor economies from using advanced emission reduction technologies to achieve environmental goals. By studying the impact of green innovation on CO_2 emissions in 71 economies, Kerui et al. (2019) find that there is a threshold effect on the CO_2 emissions reduction of green innovation. Only economies with incomes per capita above a certain amount are able to reduce CO_2 emissions with green innovation. The threshold effect may lead to regional heterogeneity in the CO_2 emissions reduction effect of FGPA. Taking the differences in the economic development of China's geographic regions into account, we propose hypothesis 2.

H2. Compared with cities in central and western China, FGPA is more effective in reducing CO_2 emissions in eastern cities.

3.2.2.2. FGPA and financial pressure. Local governments in China are the main actors in the implementation of innovation-driven strategies, and the quantity and stability of their fiscal revenues and expenditures are crucial to the cultivation of regional innovation capabilities. The CO_2 emissions reduction effects of FGPA may also be heterogeneous depending on domestic governments' financial pressure. Innovation activities are not a priority for governments under high financial pressure because of the lag in economic output. Excessive financial pressure tends to lead local governments to favor productive investment choices that emphasize production over innovation, bringing direct taxation to alleviate fiscal pressure (Zheng and Lu, 2018). Besides, financial pressure may affect governments' innovation preferences. Zheng and Lu (2021) find that financial pressure significantly inhibits urban innovation, especially green innovation.

As discussed above, the high-cost of green innovation stems from its squeeze on other profitable innovation and the need for heterogeneous knowledge sources. For cities with higher financial pressure, local governments may provide less incentive and transformation funding for green innovation than cities with relatively lower financial pressure, which affects FGPA's environmental performance. Therefore, we propose hypothesis 3.

H3. Compared with cities with higher financial pressure, FGPA is more effective in reducing CO_2 emissions in cities with lower financial pressure.

3.2.2.3. FGPA and university quantity. As main undertakers of national science foundation projects and collaborators of innovative enterprises, universities possess intensive R&D resources, and are important knowledge reserves of innovation. The environmental performance of GIIPs may be heterogeneous depending on university quantity. Due to the function of providing public goods, universities are more likely to become the main source of knowledge spillover effects. The explicit knowledge spillover from universities is realized through non-embedded knowledge carriers such as academic publications and patents. Jaffe (1989) finds that university R&D investment significantly increases the number of patents and R&D investment of local enterprises in the United States. Yi and Long (2021) show that university research promotes the follow-on innovation and technology commercialization of enterprises through patent licensing and transfer. In addition, the implicit knowledge spillover from universities is realized through embedded knowledge carriers such as researchers and graduates. Ingo and Daniel (2008) suggest that the knowledge diffusion from university graduates significantly contributes to technological advancement in developing countries.

As mentioned above, green innovation has high costs and positive externalities, which hinders enterprise green innovation. Universities have an attribute of providing public goods, and the intensive R&D resources of universities meet the requirements of heterogeneous knowledge for green innovation. However, green innovation alone is not enough, there is still a process of technology transformation and application from green innovation to CO_2 emissions reduction, where knowledge spillover effect can effectively accelerate this process. Universities can help the transformation and application of green innovation through explicit means such as patent licensing and transfer, and implicit means such as talent flow, thus promoting the reduction of urban CO_2 emissions. Thus, we propose hypothesis 4.

H4. Compared with cities with fewer universities, FGPA is more effective in reducing CO_2 emissions in cities with more universities.

4. Methodology

4.1. Data collection

This paper uses 290 prefecture-level cities in mainland China as a sample to construct panel data on CO_2 emissions and green patent applications at the city-year level from 2007 to 2016.[2] Specifically, the identification of green patents is according to the "International Patent Classification (IPC) Green Inventory", a patent information search tool related to Environmentally Sound Technologies launched by the World Intellectual Property Organization (WIPO) in 2010. It classifies green patents into seven categories, including Transport, Waste management, Energy conservation, Alternative energy production, Administrative, regulatory or design aspects, Agriculture or forestry, and Nuclear power generation.[3] We search and compile the green patent applications in China based on the IPC provided by WIPO in the INNOJOY patent search engine of Dawei Computer Software Development Company (http://www.innojoy.com/search/home.html) to obtain information such as the year of applications and the location of applicants. The data on CO_2 emissions is obtained from J.D. Chen et al. (2020), and the data on control variables is obtained from the China City Statistical Yearbook.

4.2. Continuous difference-in-difference

The canonical DID research design compares outcomes between the treatment group and the control group (difference one) before and after that treatment begins (difference two) (Callaway et al., 2021). In the standard DID model, the policy grouping variable (treat) is a binary dummy variable, which reflects whether the individual receives the treatment of a policy. In some cases, different individuals are affected by the policy to different degrees, which can also be regarded as the difference among individuals. In other words, the variation in the individual dimension is not a 0 to 1 shift, but a continuous variation representing the degree to which the individual is affected by the policy. Based on this idea, we can actually replace the policy grouping dummy variable (treat) with a continuous variable (intensity) that captures the extent to which the individual is affected by the policy.

A continuous treatment may offer practical advantages over a binary treatment. Variation in treatment intensity makes it possible to evaluate treatments that lack untreated comparison units because all units are treated to some extent. Thus, the continuous DID method has been widely used to identify the causal effects of one-size-fits-all shocks, including legal revisions, WTO accessions, epidemics, famines, and so on. Due to the space constraints, three significant and highly cited papers are presented. Instead of using the binary dummy variable of whether the county is a tea-producing area or not, Qian (2008) uses the continuous variable of tea planting area of each county to capture the degree to which the sex-specific agricultural income of each county is affected by the post-Mao reform in China to estimate the effects of income on sex ratios of surviving children. Bai and Jia (2016) study the effect of the abolition of China's civil exam system on political stability. Since the abolition was implemented simultaneously in China, they use the ex-ante quotas on the entry level exam candidates in each prefecture to explore the variations caused by the abolition of China's civil exam system. Y. Chen et al. (2020) also use the continuous DID method to study the impact of the send-down movement on rural education in China. Since the send-down movement was nationwide during the Cultural Revolution, there is no direct treatment and control groups. They use the proportion of the send-down youth accepted by each county to reflect the extent to which each county is affected by the movement.

In summary, it can be found that when the policy is implemented nationwide at the same time, the degree of each individual being affected by the policy can be used to build up a continuous DID. To specify, in this case, the individuals that are more exposed to the policy are taken as the treatment group, and the individuals are less exposed to the policy are taken as the control group. Thus, the difference is from comparing outcomes between more affected individuals (treatment group) and less affected individuals (control group) (difference one) before and after the quasi-natural experiment (difference two).

4.3. Econometrical model

Using the continuous DID model, we regard the implementation of FGPA as an exogenous shock and divide the sample into the treatment group and the control group according to the degree to which cities are affected by FGPA. The causal effect of FGPA on CO_2 emissions in Chinese cities is explored by computing the difference in CO_2 emissions between the two groups before and after the implementation of FGPA. The benchmark regression model is set as follows.

$$CO2_{c,t} = \alpha + \beta_1 intensity_c \times post_t + \gamma controls_{c,t} + \delta_c + \lambda_t + \varepsilon_{c,t} \tag{1}$$

where the subscript c denotes a city and the subscript t denotes a year. The description of all the variables involved in the formulation is shown

[2] Since the CNIPA made major adjustments to FGPA in 2017, the sample data for this paper is as of 2016.

[3] Refer to https://www.wipo.int/classifications/ipc/green-inventory/home, last accessed on September 21, 2022.

Table 1
Variable descriptions and descriptive statistics.

Variable description (a)		
Variables	Definition	Description
$CO2_{c,t}$	CO_2 Emission	Carbon dioxide emission mass per unit of GDP in a specific city of a year
$intensity_c \times post_t$	Interaction Term	Interaction term of policy shock continuum variables and time dummy variables
Controlsc,t	Control variables	The matrix of control variables
lnpop	Population	The population of a city at the end of a year
Gdpct03	Secondary Industry	Proportion (%) of the secondary industry
Gdpct04	Tertiary Industry	Proportion (%) of the tertiary industry
lnprodu	Industry Product	The output value of industrial enterprises
lnfirm	Industrial Enterprise	The number of industrial enterprises
Eect03	Population Growth	The natural population growth rate
lnappli	Patent Application	The number of patent applications
lnsci	Innovation Expenditure	Government expenditure on innovation
lntrade	Foreign Direct Investment	The amount of foreign direct investment
lnedu	Schooling Years	The average years of schooling of the citizens
δ_c	City-fixed Effects	Dummy variable based on city setting
λ_t	Time-fixed Effects	Dummy variable based on year setting
$\varepsilon_{c,t}$	Random Error-term	Influence of other random factors outsides the model on the explained variable

Descriptive statistics (b)						
Variables	Count	Mean	S.D.	Min	Median	Max
CO2	2840	0.02	0.02	0.00	0.02	0.51
$intensity_c \times post_t$	2840	0.04	0.06	0.00	0.00	0.37
lnpop	2840	5.86	0.70	2.90	5.91	8.13
Gdpct03	2840	49.28	10.65	14.95	49.76	90.97
Gdpct04	2840	37.38	9.14	8.58	36.22	80.23
lnprodu	2840	16.43	1.29	0.43	16.47	19.60
lnfirm	2840	6.54	1.13	2.94	6.49	9.84
Eect03	2840	6.33	5.32	−8.90	5.70	40.78
lnappli	2840	6.50	1.69	1.61	6.34	11.66
lnsci	2840	9.83	1.37	6.15	9.69	15.21
lntrade	2840	13.51	2.41	0.00	13.55	19.62
lnedu	2840	2.15	0.08	1.44	2.16	2.52

in Table 1(a), and the descriptive statistics are shown in Table 1(b) .[4] We descale the explained variable to make it comparable across cities. $CO2_{c,t}$ refers to the CO_2 emission mass per unit of GDP corresponding to city c in year t. In the process of setting the interaction term, it is not possible to construct the control group and the treatment group simply by setting dummy variable, as FGPA is implemented simultaneously across the country in 2012. Following the ideas concluded in the above section, we use the ex-ante proportion of green patents to total patent filings to capture the extent to which each city is affected by FGPA. Specifically, we use $intensity_c$ to describe the degree of green innovation development in city c before the time of FGPA's implementation, i.e., $intensity_c = \frac{1}{3}\sum_{t=2009}^{2011}\frac{green\ patent\ applications_{c,t}}{patent\ applications_{c,t}}$. In other words, $intensity_c$ is the ratio of the average number of green patent applications[5] to the total number of patent applications in the last three years before the implementation (2009–2011). We consider that the greater the $intensity_c$, the greater the impact of FGPA on the city. It is worth noting that $intensity_c$ is not time-varying so that it is not spoiled by FGPA. In other words, this ratio is not the result of FGPA, but the basis for classifying the degree to which each city is affected by the policy. To specify, in this case, the cities that are more exposed to the policy are taken as the treatment group, and the cities are less exposed to the policy are taken as the control group. $post_t$ is a time dummy variable with a value of 0 for the year before FGPA's implementation (2007–2011) and 1 for the year after that (2012–2016). Thus, the difference is from comparing outcomes (CO_2 emissions) between more affected cities (treatment group) and less affected cities (control group) (difference one) before and after the implementation of FGPA (difference two).

$controls_{c,t}$ is the matrix of control variables of the model. Considering the availability of data and relevant research, the control variables are selected from two aspects: the level of economic development and innovation input factors. The control variables for the level of economic development include the share of secondary industry (*Gdpct03*), the share of tertiary industry (*Gdpct04*), the output value of industrial enterprises (*lnprodu*), the number of industrial enterprises (*lnfirm*), the amount of foreign direct investment (*lntrade*), the total population of a city at the end of a year (*lnpop*), and the natural population growth rate (*Eect03*). The control variables for innovation input factors include the number of patent applications (*lnappli*), government expenditure on innovation (*lnsci*), and the average years of schooling per capita (*lnedu*). Among them, all control variables, except for the three ratio variables *Gdpct03*, *Gdpct04* and *Eect03*, are treated by adding one and taking natural logarithm to eliminate potential heteroskedasticity problems. In addition, to control for unobservable and time-invariant factors from city level, such as city culture and city location, we include city-fixed effects (δ_c) in the model. To control for macro-level national influences such as the level of economic development and legal system, we include time-fixed effects (λ_t) in the model. The standard error is robust and clustered at province level.

The estimated coefficient β_1 of the interaction term $intensity_c \times post_t$ in the benchmark regression is the causal effect of FGPA that is the focus of this paper: $\beta_1 < 0$ indicates that the policy reduces urban CO_2 emissions, $\beta_1 > 0$ indicates that the policy increases urban CO_2 emissions, and $\beta_1 = 0$ indicates that the policy has no effect on urban CO_2 emissions.

5. Empirical results

5.1. Benchmark regression results

To examine the impact of FGPA on CO_2 emissions in Chinese cities, a panel of Chinese prefecture-level city data from 2007 to 2016 is included in the model with standard errors clustered at province level, and the results are shown in Table 2. In general, the model has a corrected coefficient of determination of 0.623 and a joint test result of $F = 12.87$ ($p < 0.01$), indicating that the model is meaningful and explains over 60% of the variation in urban CO_2 emissions.

First, the results in Table 2 show that FGPA significantly reduces CO_2 emissions in Chinese cities. The estimated coefficient of the interaction term is −0.0164, which is significant at the 5% level. In terms of economic significance, the CO_2 emissions of cities in the treatment group are significantly reduced by approximately 1.6% after the implementation of FGPA compared to those in the control group. In terms of statistical significance, the estimated coefficient of the interaction term has a 95% confidence interval from −0.0321 to −0.0006, which is significantly different from 0 at the 5% level. This result supports the *H1a* and rejects the *H1b*.

Second, this paper finds a significant positive effect of population size on CO_2 emissions (Coef. = 0.0045, 95% CI: 0.0002 to 0.0089, $p < 0.05$), while the natural population growth rate has no significant impact on that. It reflects that CO_2 emissions are closely related to population stock, while natural population growth rate has a lagging effect on population size and therefore does not lead to an increase in CO_2 emissions in a specific year. A higher share of tertiary industries

[4] Table 1 (b) in the paper presents descriptive statistics based on the sample used in the baseline regression. The observations are reduced from 2900 to 2840 due to the missing of control variables, including the total population of a city at the end of a year (*lnpop*) and the natural population growth rate (*Eect03*).

[5] Unless otherwise specified, the number of patent applications referred to the regression in this paper includes both invention patents and utility model patents.

Table 2
The result of benchmark regression.

Variables	Coef.	St. Err.	t value	p value	95% Confidence Interval	
					lower	upper
$intensity_c \times post_t$	−0.0164	0.0080	−2.0400	0.0410**	−0.0321	−0.0006
lnpop	0.0045	0.0022	2.0400	0.0420**	0.0002	0.0089
Gdpct03	0.0001	0.0001	1.1700	0.2420	−0.0001	0.0002
Gdpct04	0.0003	0.0001	3.5300	0.0000***	0.0001	0.0005
lnprodu	−0.0007	0.0006	−1.1700	0.2420	−0.0020	0.0005
lnfirm	−0.0050	0.0009	−5.6200	0.0000***	−0.0067	−0.0032
Eect03	0.0000	0.0000	−1.1300	0.2560	−0.0001	0.0000
lnappli	0.0018	0.0011	1.6300	0.1020*	−0.0004	0.0039
lnsci	−0.0004	0.0002	−1.6100	0.1080	−0.0008	0.0001
lntrade	−0.0003	0.0003	−0.9400	0.3470	−0.0009	0.0003
lnedu	−0.0305	0.0162	−1.8800	0.0600*	−0.0622	0.0013
Observations	2840	adj_R^2	0.623	Clustvar	"Clustvar": "Province"	
City-FE	Yes	Year-FE	Yes	N_cluster	"N_cluster": "31"	

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

significantly increases CO_2 emissions (Coef. = 0.0003, 95% CI: 0.0001 to 0.0005, $p < 0.001$), confirming the findings of Ma et al. (2021) that tertiary sector is an important source of CO_2 emissions in China. Finally, we find that the number of patent applications and the average years of citizens' education are significantly associated with CO_2 emissions at the 10% level, while government expenditure on innovation and foreign direct investment have no significant impact.

5.2. Dynamic effects

The benchmark regression results indicate that FGPA significantly reduces CO_2 emissions in Chinese cities. However, it does not reveal the trend of the treatment and the control group before and after the implementation of the policy. Thus, it cannot indicate whether the parallel trend assumption is satisfied, which is an important assumption of the DID method. The parallel trend assumption means without the implementation of FGPA, CO_2 emissions in the two groups should maintain the same trend. To further enhance the credibility of the results, we extend the benchmark regression model to the following dynamic model (2), in which the dummy variable $post_t$ in model (1) is replaced by the dummy variable representing several years before and after the implementation of FGPA, and other variables remain unchanged. The dynamic model is as follows, and the results are shown in Fig. 2.

$$CO2_{c,t} = \beta_k \sum_{k=-4}^{5} intensity_c \times post_{2011+k} + \gamma controls_{c,t} + \delta_c + \lambda_t + \varepsilon_{c,t} \qquad (2)$$

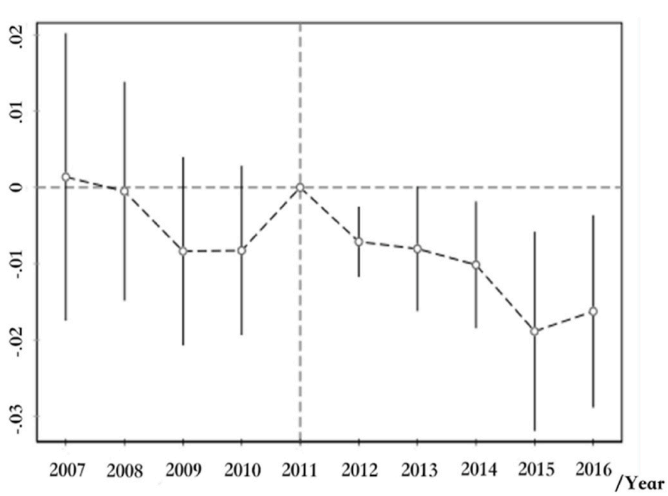

Fig. 2. Dynamic effects.

As can be seen from Fig. 2, the estimated coefficients of the interaction terms are all insignificant and around the value of zero in the ex-ante years. This indicates that, controlling for other factors, the trend in urban CO_2 emissions in the treatment and the control group are essentially the same before the implementation of FGPA, satisfying the assumption of parallel trends required by the DID model. In contrast, after the implementation of FGPA, the coefficients of the interaction terms are significantly negative, which indicates the CO_2 emissions of the two groups show different trends. It demonstrates a significant decrease in CO_2 emissions in the cities that are more affected by FGPA compared to the less affected ones.

5.3. Robustness checks

The benchmark regression results show that FGPA significantly reduces urban CO_2 emissions in China by approximately 1.6%, and this result is statistically significant at the 5% level. The dynamic effects test show that the model satisfies the parallel trend assumption. We further verify the robustness of the results in four ways, which include using standard DID models, replacing core indicators, changing model settings, and excluding the effects of other policies over the same period. The results are shown in Table 3.

5.3.1. Standard DID model

To further address this issue, we work out how to use the standard DID model, i.e., using binary dummy variables 0/1 to represent the control group and treatment group. The results are shown in column (2) to column (5) in Table 3(a). First, the groupings are divided based on the median of $intensity_c$ in column (2), Specifically, below the median is the control group, and above the median is the treatment group. Second, we use other quantiles as the basis of grouping, rather than the median. In column (3), the quartile of $intensity_c$ is used as a means of grouping. Below the 25% quantile (the first quartile) of $intensity_c$ is the control group, and above the 75% quantile (the last quartile) of $intensity_c$ is the treatment group. In column (4), cities with $intensity_c$ below the 20% quantile are the control group, and cities with $intensity_c$ above the 80% quantile are the treatment group. In column (5), below the 10% quantile of $intensity_c$ is the control group, and above the 90% quantile of $intensity_c$ is the treatment group. The coefficient of the interaction term in column (2) to column (5) remains about −0.017 at the 1% significant level, showing that the CO_2 emissions of the treatment group are significantly reduced by approximately 1.7% after the implementation of FGPA compared to the control group. The results are similar to the benchmark results (column 1), confirming the robustness of the results by the standard DID model with various grouping tools.

Table 3
Robustness checks.

Robustness checks (a)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CO2	CO2	CO2	CO2	CO2	CO2
$intensity_c \times post_t$	−0.016** (0.008)					
$treat_c \times post_t$		−0.017** (0.008)	−0.016*** (0.004)	−0.017*** (0.006)	−0.018*** (0.005)	
$intensity_{c\_2} \times post_t$						−0.011* (0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2840	2840	1399	526	1110	2840
City-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.623	0.624	0.940	0.962	0.931	0.623

Robustness checks (b)						
Variables	(1)	(7)	(8)	(9)	(10)	(11)
	CO2	*CO2*	*CO2*	*CO2*	*CO2*	*CO2*
$intensity_c \times post_t$	−0.016** (0.008)		−0.018** (0.009)	−0.010** (0.005)	−0.014* (0.008)	
$intensity_{c\_3} \times post_t$		−0.010** (0.005)				
$intensity_{2007\text{-}2011} \times post_t$						−0.019** (0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2840	2840	2842	954	2268	2836
City-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.623	0.623		0.941	0.540	0.623
Log likelihood			9114.6541			

Cluster standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

5.3.2. Alternative indicators

In the interaction term of the benchmark regression, the ratio of the average number of green patent applications to the overall number of patent applications in a specific city from 2009 to 2011 is used as a proxy indicator for the degree of ex-ante green innovation development to measure the degree of policy shock. In order to ensure the robustness of the results, we make two adjustments separately: (1) replace the average level of green innovation three years beforehand with the level of green innovation of one year beforehand, i.e., $intensity_{c\_2} = \frac{green\ patent\ applications_{c,2011}}{patent\ applicaions_{c,2011}}$; (2) replace patent applications with invention patent applications, i.e., $intensity_{c\_3} = \frac{1}{3}\sum_{t=2009}^{2011}\frac{green\ invention\ patent\ applications_{c,t}}{invention\ patent\ applicaions_{c,t}}$. Other settings remain consistent with the baseline regression. The results are shown in column (6) in Table 3(a) and column (7) in Table 3(b). Compared to the results of column (1), the significance of the interaction term coefficient in column (6) has slightly decreased, but is still significant at the 10% level. Moreover, the interaction term coefficient in column (7) still remains significant at the 5% level. The explanatory power of the model remains stable as evidenced by the corrected coefficient of determination. The alternative indicators test confirms the robustness of the results.

5.3.3. Non-linear model

The benchmark regression is based on two-way fixed effects estimation. As the explained variables take values between [0,1] after descaling, to further explore the robustness of the results, we consider instead using a panel Tobit regression model. The results are shown in column (8) in Table 3(b). As can be seen, the panel Tobit regression model is overall significant at the 1% level (Prob > chi2 = 0.0000). The result for the core explanatory variable remains largely consistent with column (1), showing that the implementation of FGPA significantly reduces CO_2 emissions in Chinese cities, which is significant at the 5% level. Replacing the estimation method further confirms the robustness of the benchmark results.

5.3.4. Exclusion of contemporaneous policy interference

In 2010, the National Development and Reform Commission of the People's Republic of China launched a pilot project on "Low-carbon Cities". In addition, the scope of the pilot project was expanded in 2012 and 2016, respectively. As the sample of this paper spans the period from 2007 to 2016, in order to prevent the bias in the results caused by the "Low-carbon Cities" pilot scheme, we exclude the cities involved in the two pilot schemes in 2010 and 2012 from the research sample.[6] The results are shown in column (9) in Table 3(b), which are generally consistent with the results of column (1), showing that FGPA's implementation significantly reduces urban CO_2 emissions in China, and the results are significant at the 5% level. The robustness of the benchmark results is confirmed by the exclusion of "Low-carbon Cities" pilot project.

One more thing to be aware of in the sample interval is that the third amendment to the Chinese Patent Law was implemented in 2009, making the invention patent applications not comparable before and after the amendment. Specifically, prior to 2009, only relative novelty was required for invention patent applications, while in 2009 and thereafter, the granting criteria for invention patent application were raised to require absolute novelty. Thereby, we think it is more reasonable to use the ratio of the average number of green patent applications to the total number of patent applications in the last three years before the implementation of FGPA (2009–2011).To further strengthen the reliability of the results, we perform two additional tests in the robustness check, including setting the sample interval to 2009–2016 and setting $intensity_c$ to the 2007–2011 ex-ante five-year ratio. The results are shown in column (10) and (11) in Table 3(b), which confirm the robustness.

[6] For the cities involved in the pilot, please refer to https://www.ndrc.gov.cn/xxgk/zcfb/tz, last accessed on September 21, 2022.

5.4. Heterogeneity analysis

The empirical study confirms the CO_2 emissions reduction effect of FGPA, and the findings remain valid after a series of robustness checks. To further investigate the impact of city-to-city differences on the environmental performance of FGPA, we discuss the heterogeneity in terms of city's regional location, financial pressure and university quantity. The results are illustrated in Table 4, and the corresponding visualization is shown in Fig. 3.

5.4.1. Region location

FGPA focuses on innovation incentives, and innovation often requires a certain economic foundation. Considering the regional differences in China's economic development, we divide cities into eastern, central and western cities according to their geographical locations, and investigate the impact of urban economic development on FGPA's environmental performance to capture the potential heterogeneous. The empirical results are shown in columns (2), (3) and (4) in Table 4. It can be seen that for cities in eastern China (column 2), which have a relatively higher level of economic development, the implementation of FGPA significantly reduces CO_2 emissions by approximately 4.1%, and this result is significant at the 5% level. However, FGPA's environmental performance is insignificant in central (column 3) and western China (column 4). This result supports hypothesis 2, which may be closely related to the intrinsic foundation of innovation. As concluded by Shahbaz et al. (2013), economic development plays an important role in reducing CO_2 emissions. In China, eastern cities, which are relatively more economically developed, have a better innovation base and are better equipped with human resources and hardware facilities. Therefore, they are more responsive to this policy than cities in the central or western region of the country, which are relatively less economically developed. Besides, considering the economic threshold effect of the CO_2 emission reduction effect of green innovation (Kerui et al., 2019), even if FGPA successfully stimulates green innovation in central and western cities, the subsequent effect of green innovation transformation and application is lower than that in eastern cities.

5.4.2. Financial pressure

Public finance is an important source of support for technological innovation and transformation, and also determines the direction of urban public policy. We use the ratio of local government fiscal expenditure to fiscal revenue as a measure of city's financial pressure to divide cities into two parts based on whether their financial pressure is higher than the median. Then we explore the impact of urban financial pressure on the environmental performance of FGPA. The empirical results are shown in columns (5) and (6) in Table 4. The results show that for cities with lower financial pressure (column 5), the implementation of FGPA significantly reduces CO_2 emissions by about 3.8%, which is significant at the 10% level, but the environmental performance in cities with higher financial pressure is not significant (column 6), which supports the hypothesis 3 of this study. Interestingly, ERPs such as CETS are more effective in reducing emissions in cities with poorer local fiscal positions (Chen et al., 2022). We believe that this may be related to the inherent logic of the reduction effects of the two types of policies. GIIPs are highly related to green innovation, which needs adequate public financial support. While ERPs tend to have more significant marginal utility for cities with higher financial pressure, which usually develop depend on resource consumption.

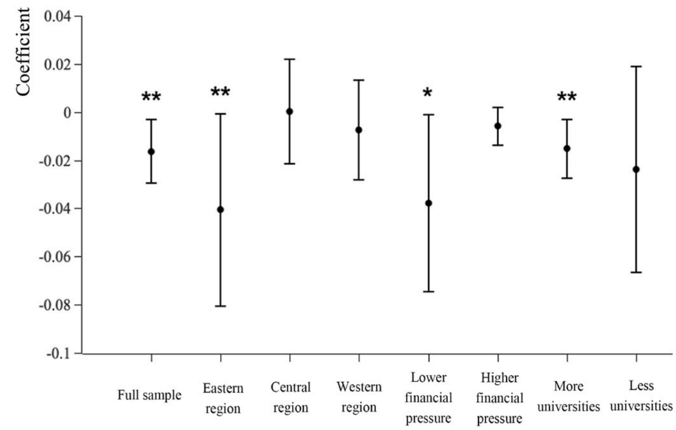

Fig. 3. Visualization of heterogeneity analysis results
Note: ***p < 0.01, **p < 0.05, *p < 0.1.

5.4.3. University quantity

Universities, possessing intensive R&D resources, are important knowledge reserves of innovation and knowledge spillover source. We divide cities into two parts based on whether their university quantity is greater than the median, and explore the impact on the environmental performance of the policy. The empirical results are shown in columns (7) and (8) in Table 4. The results show that the implementation of FGPA significantly reduces CO_2 emissions by about 1.5% for cities with more universities (column 7), and this result is significant at the 5% level. However, the environmental performance of cities with fewer universities is not significant (column 8). The hypothesis 4 of this study is verified. As concluded by Yu et al. (2015), technology can significantly reduce CO_2 emissions. This result reflects the important role of scientific research infrastructure in the environmental performance of GIIPs.

6. Conclusions and policy implications

With a sample of 290 prefecture-level cities in China from 2007 to 2016, we construct a set of panel data on CO_2 emissions and green patent applications at the city-year level. Then we conduct an empirical study using the continuous DID method to investigate the impact of FGPA on CO_2 emissions in Chinese cities. The findings show that the CO_2 emissions of cities in the treatment group are significantly reduced by about 1.6% after the implementation of FGPA relative to that in the control group. And the significant reduction effect of FGPA is mainly found in

Table 4
Heterogeneity analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CO2	CO2	CO2	CO2	CO2	CO2	CO2	CO2
$intensity_c \times post_t$	−0.016**	−0.041**	0.0002	−0.007	−0.038*	−0.006	−0.015**	−0.024
	(0.008)	(0.022)	(0.011)	(0.013)	(0.022)	(0.005)	(0.007)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2840	1001	981	858	1450	1369	1501	1339
City-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.623	0.217	0.939	0.934	0.368	0.947	0.935	0.365

Cluster standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

cities in the eastern region, cities with lower financial pressure, and cities with more universities.

The contributions of this paper are mainly manifested in the following three aspects. First, this paper fills up the gap in the empirical research on the environmental performance of FGPA. Second, we illustrate the basis for the realization of FGPA's environmental effects, and shed light on the way of effective policy implementation. Finally, we clarify and enrich the instrumental connotation of patent policies, and provide public administrators with an alternative path (GIIPs) except for ERPs to reduce CO_2 emissions.

Based on the above findings, the policy recommendations are as follows. Firstly, the role of FGPA in environmental protection should be emphasized. The implementation mechanism needs to be optimized, drawing the link between green innovation and environmental protection. Specifically, a technical expert consultation mechanism should be established to clarify the priority of green innovation based on technological development trends and realistic needs, so as to enhance the environmental performance of FGPA. Besides, an appropriate threshold for FGPA should be established to prevent ineligible patent applications from using the system to occupy examination resources, which leads to the alienation of the system, resulting in unfairness in patent granting process and a decline in patent quality. Secondly, greater emphasis should be placed on the development and implementation of GIIPs, deepening the parallel development of ERPs and GIIPs to jointly contribute to the achievement of the "emission peak and carbon neutrality" mission. Traditional ERPs such as environmental taxation, emissions trading, and environmental target responsibility system have played an important role in China's CO_2 emissions reduction process. Based on a new perspective, we empirically examine the CO_2 reduction effect of GIIPs. Therefore, while maintaining the instrumental use of ERPs, we should focus on the positive role of GIIPs in environmental protection. Finally, the subsequent formulation of GIIPs should focus on local conditions, and differentiated supporting measures should be set up for the policy implementation process. Specifically, (1) from the perspective of intrinsic foundation for innovation, we should increase incentives from green innovation to transformation in cities with poor economies, preventing the high-cost and transformation "threshold effect" of green innovation from reducing the environmental performance; (2) from the perspective of external support for innovation, governments should set institutional "red lines" in cities with fiscal imbalance, preventing the sacrifice of environment for the sake of economic development; (3) from the perspective of knowledge reserve for innovation, the active role of universities in knowledge spillover should be stimulated, realizing knowledge spillover from green innovation developed cities to others, steadily promoting the transformation from "local emission reduction" to "comprehensive emission reduction".

This study still has some limitations that warrant further attention in future research. Specifically, there is still a problem of selection bias in our research design, that is, the better the development of green innovation, the lower the carbon emissions. In order to alleviate this issue, we include a series of control variables in the model that may affect both the green innovation development and carbon emissions, including population, industry structure, education and so on. Meanwhile, city-fixed effects (δ_c) is also included in the model to control for unobservable and time-invariant factors from city level, such as city culture and city location. Although we have tried a series of measures to mitigate, the problem of selection bias still exists. As Imbens and Rubin (2015) concluded, any non-natural experiment research may more or less under the threat from the problem of sample selection, and how to overcome this problem is also a direction of future research in this field. We believe that future work will show a useful supplement in this aspect.

CRediT authorship contribution statement

Rui Liu: Conceptualization, Investigation, Writing – original draft. **Xuezhong Zhu:** Funding acquisition, Supervision. **Meiyang Zhang:** Methodology, Visualization, Writing – review & editing, Formal analysis. **Cheng Hu:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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