Does green foreign investment contribute to air pollution abatement? Evidence from China

Abstract: To better balance economic growth and environmental protection, the Chinese government is encouraging green foreign direct investment. However, few studies have discussed its environmental impact. Combing a unique dataset on green FDI and fine-scale air pollution data, we empirically investigate the environmental impact of green FDI at small spatial scales. To address the endogeneity, an instrumental variable is constructed following Bartik (1991). Results shows that green FDI could significantly alleviate local air pollution. Specifically, a 10% increase in the number of green FDI enterprises in a region leads to a decline in air quality index (AQI) by 0.6%. This effect is more pronounced in the vicinity of green FDI enterprises' sites, and decays as the distance increases. Also, it is more salient in areas where local governments highlight environmental protection. Heterogeneous analysis finds that the effect is remarkably more significant when enterprises are small-scale and sole-venture, or in manufacturing industries.

Keywords: Green FDI enterprises; Air pollution; Small spatial scale; Bartik instrument; China

1. Introduction

Since the reform and opening-up, China has gradually become a major investment destination country, enjoying a continuous influx of foreign investment (Zhao et al., 2022). The large amount of foreign direct investment (FDI) significantly triggers the economic growth, and makes China the world's second largest economy. According to the Ministry of Commerce of PR China, the total amount of FDI in China has reached 1,139.36 billion yuan in 2021. However, the rapid growth of FDI towards China has also led to serious environmental problems because of the desperate pursuit of economic development as well as the slack environmental regulation over the past few decades. The excessive environmental pollution in China has been a growing threat to the economy. Taking air pollution as an example, people's exposure to the high concentration of particulate materials may cause health problems, which could further lead to loss in human capital and productivity (Lan et al., 2012). The average value of welfare loss from air pollution in China was estimated to account for 5.765% of GDP during 1990-2017 (IPCC, 2014). Thus, if the problem of environmental pollution is not solved, it will eventually backfire China's economic growth (Ali & Oliveira, 2018).

To better achieve a balance between attracting foreign investment and protecting the environmental, the Chinese government is currently committed to improving the quality of FDI with a preference for the green and low-carbon foreign investment (Zhao et al., 2022; Wang et al., 2019). The National Development and Reform Commission issued "*Several Policy Measures on Promoting Foreign Investment to Expand Increases and Stabilize Stocks and Improve Quality with a Focus on Manufacturing*". It clearly puts forward that foreign investment in new-energy, low-carbon, and green-production will be encouraged. The National Bureau of Statistics released the standard "*Statistical Classification of Energy Conservation and Environmental Protection Clean Industry*", which delineates the scope of green industries. According to the industrial classification, there has already been more than 70,000 green FDI enterprises entering China during 2008-2017. However, it is uncertain whether green FDI has played an important role in improving China's environmental quality. First it is difficult to accurately identify a green enterprises (Inderst et al., 2012). Secondly, even though an enterprise is classified as a green one when it establishes, it cannot ensure that it produce green products and services. Also, if not well regulated, green enterprises may lower their environmental standards and discharge pollutants covertly.

Perhaps due to a lack of relevant data, few scholars have explored the impact of green FDI on the environment. Numerous literatures have explored the effect of FDI on environmental quality, but the research conclusions are controversial. Some scholars consider the foreign-invested enterprises in developing countries as the destroyers of the environment (Bao et al., 2011; Baek &Choi, 2017; Zugravu-Soilita, 2017). The relatively weak environmental regulations in these countries make them become the "pollution heaven", absorbing a large number of high-polluting enterprises from developed countries. High-polluting enterprises could bring about the rapid accumulation of capital and economic boom in the short run. However, such development at the cost of the environmental is not sustainable in the long term (Wheeler, 2001; Yang et al., 2018). Nevertheless, some scholars hold the opposite view, claiming that FDI inflow could exert a positive effect on the environment of developing countries, as new technology and knowledge will be spread along with foreign enterprises' entry, namely the "pollution halo" (Balsalobre-Lorente et al, 2019; Zugravu-Soilita, 2017). The spillover effect, demonstration effect, and the competitive effect caused by foreign investment would improve the resource efficiency, which could indirectly contribute to improving environmental quality (Jeon et al., 2013; Luo et al., 2021).

To narrow the aforementioned research gaps, this paper estimates the environmental effect of green FDI in China's context by employing a unique dataset from the Foreign Investment Management Platform of the Ministry of Commerce of P.

R. China and the monitoring data of air pollution. To ensure the accuracy, the estimation is based on a small spatial unit that takes each air pollution monitoring station as the center and its surrounding area within a certain radius following Li et al., 2019, because it can fit well with the locality of enterprises' impact on the environment. To address the potential endogeneity problem, we construct an instrumental variable following Bartik (1991) and perform a two-stage least squares (2SLS) estimation. The results show that if the number of green FDI enterprises increases by 10%, it will cause a decline in air quality index (AQI) by 0.6%, indicating that green FDI could improve the environmental quality. In addition, this effect is more salient in heavily polluted areas and areas whose governments highlight environmental protection. The effect of green FDI on improving air quality would decay with the distance increasing.

Our study may contribute to the existing literature from the following three aspects. First, to our knowledge, , we are the first to construct the dataset of green FDI in China, and pioneer estimating the environmental effects of green FDI, which is frequently mentioned in previous studies but lacking empirical evidence. Second, in terms of the spatial scale, previous studies usually take administrative regions as observation units, making the causal relationship between foreign investment and environmental quality easily interfered by unobservable regional characteristics (Wang & Liu, 2019). In this paper, we establish a small spatial unit to overcome the limitation of using administrative regions, which helps accurately identify the causal relationship. Third, our findings extend the literature on the environmental impacts of FDI in developing countries. Findings of previous studies are mixed on whether foreign investment inflowing to developing countries can devastate or improve the environmental quality (Lee et al., 2009; Li & Ramanathan, 2021). That is mainly because they usually studied the effect of foreign investment based on aggregate data and rarely probed into FDI of specific characteristics. We demonstrate a positive effect of green FDI on the environmental quality of host countries, which could serve as new evidence for the "pollution halo" hypothesis (Castellani et al., 2022).

This paper also bears some policy implications. Policymakers in transitional economies often consider the trade-offs between maintaining economic growth and enhancing environmental protection. Some have sought to protect the environment by enacting strict environmental regulation or directly restricting the entry of foreign investment, often causing high economic cost. Our findings suggest that improving the quality and structure of foreign investment could help governments to achieve a balance among multiple goals. Under the pressure of facilitating sustainability of development, enhancing the proportion of green FDI, which is characterized by energy-efficient, low-carbon, and environmentally-friendly, will benefit both the economy and environment. This is enlightening for many developing countries facing the challenge of green transformation.

The remainder of the paper is structured as follows. Section 2 construct the hypotheses based on the existing theory and literature. Section 3 gives the empirical research design. Section 4 reports the empirical results, and Section 5 carries out further discussion. The final section concludes.

2. Literature and hypothesis

2.1 Concept and definition of green FDI

Although frequently mentioned, there is no unified definition of green FDI. In reality, defining or measuring the green FDI are quite challenging. A common practice is to classify FDI by enterprises' products, depending on whether their products are green or not (Eyraud et al., 2013). However, a certain kind of goods or service usually has multiple usages, which makes it difficult to delineate between green and non-green product. Also, enterprises' green activity may be associated not just with a particular product or service but a green technology or process. Even some non-green products may be used as intermediate products in the production of green products, and vice versa. That is to say, it appears easier to clearly define an activity as green or not, but more difficult to certify a foreign-invested enterprise as green. Only the OECD tried to give the definition of green FDI. In 2011, the OECD pioneers defining and measuring green FDI in an attempt to construct a statistical basis to support governments' evaluation of green foreign investment flows and their performance (Inderst et al., 2012). They claimed that green FDI covers: (1) FDI in environmental goods and services (EGS) sectors, and (2) FDI in environmental-damage mitigation processes, i.e. use of cleaner and/or more energy-efficient technologies.

A similar concept is the green investment (GI). Heinkel et al. (2001) explain green investment from the perspective of investors' ethical standards. Investors will choose to invest in enterprises with pollution-treating technologies and enterprises that meet environmental standards, which are defined as green investments, according to their own ethical standards constraints. Eyraud et al. (2013) define green investments as investment projects aimed at reducing greenhouse gas emissions and air pollutant emissions, specifically in sectors such as low-emission energy supply, energy efficiency technology development, and carbon sequestration. Its funding sources include both private investment and financing, as well as financial investment. Martin & Moser (2012) consider green investment as a production activity or socially responsible behavior undertaken by enterprises aimed at reducing carbon emissions. This definition is more similar to Doval & Negulescu, (2014) and Voica et al. (2015). Ren et al. (2022) defines green investment as the internal investment of government and enterprises in equipment, technology, materials, energy and purchased services to improve the companies' environmental performance, develop green management and reduce environmental risks.

In general, there is still some controversy and uncertainty about the measurement of green FDI. Till now, both GI and green FDI are relatively vague concepts. In recent years, the Chinese government has paid more attention to environmental protection and formulated many policies or laws for clean production. The National Bureau of Statistics of China issued the "*Classification of Clean, Environmental and Energy-saving Industries*" in 2021. It uses industry classification to define clean, environmental and energy-saving industries, which provides us with a reference for identifying green FDI. Green FDI enterprises have green production technology, produce green, energy-saving products, and provide clean services, which are highly consistent with the classification standards of the National Bureau of Statistics. Therefore, it is reasonable to use the industry standards for Clean, Environmental and Energy-saving Industries to identify green FDI enterprises.

2.2 Foreign investment and environmental quality

Over the past decades, international investment flows and industrial shifts have led to the transfer of pollution among countries and regions. Governments in developing countries, such as China, Vietnam, and India, have long been valuing foreign investment as a practical and effective measure to accelerate domestic economic growth (Chen et al., 2020). However, the inflow of foreign investment has also caused serious environmental problems, such as severe air pollution. At the same time, a growing number of researchers have tried to sort out the nexus between foreign investment and environmental pollution. The environmental Kuznets curve (EKC) explains why many developing countries face more severe environmental pollution than developed countries, and reveals that economic development through attracting foreign investment would inevitably lead to environmental degradation at the initial stages of economic growth (He, 2006). The hypothesis of "pollution haven" argues that trade and investment liberalization lead to easier relocation of foreign-invested polluting enterprises to countries with relatively lax environmental regulations, exacerbating air pollution in these less developed countries (Levinson & Taylor, 2008).

In recent years, many studies have estimated the impact of foreign direct investment on environmental degradation by considering other control variables, including: economic growth, trade openness, R&D level, energy consumption, urbanization, etc. (Yin et al., 2008, Cole et al., 2011, Mutafoglu, 2012, Wang et al., 2017a). For example, Omri et al. (2014) estimated the relationship between foreign direct investment, economic growth and carbon dioxide emissions, and found a bidirectional causality between foreign direct investment and environmental pollution, indicating that foreign direct investment inflows aggravated environmental pollution.

Their results showed that there was a causal relationship between foreign direct investment and carbon dioxide emissions, indicating that foreign direct investment led to higher carbon dioxide emissions.

However, some studies unveil different findings. The Porter hypothesis holds the opposite view, claiming that introducing foreign investment could help developing countries to mitigate air pollution through technological progress and diffusion, bringing about the so-called "pollution halo" effect (Porter & Van Der Linde, 1995). Studies in this focus have shown that green technological progress accompanying FDI inflows can rapidly increase energy efficiency, thereby reducing carbon dioxide emissions (Dincer and Rosen, 2011, Lee, 2009). Also, foreign-owned enterprises usually implement uniform and strict environmental standards, and therefore FDI may reduce local pollution emission levels (Chudnovsky et al., 2005). In addition, the international environmental standards implemented by FDI enterprises can promote the development of environmental technologies in the host country, further verifying the existence of the pollution halo hypothesis (Eskeland and Harrison, 2003).

To summary, although previous literature has intensively discussed the relationship between foreign investment and environmental quality. However, due to limited accessibility of data, few of them probe into the effects of FDI with different types or characteristics. In practice, different types of FDI are diverse in their motivations, scales, or technology levels, and thus possibly making their environmental impacts heterogeneous. For example, if FDI enterprises themselves belong to clean, energy-saving and environmentally friendly types of enterprises, they are more likely to have less impact on environmental pollution, or even contribute to improving the environment. What’s more, the existing literature mainly tests the effect of aggregated FDI at the regional level, and estimates the overall effect. However, the impact of a single or a few enterprises on the overall environmental quality of a region may be minimal, while the impact on the neighboring areas surrounding the enterprise may be more salient, which implies the potential underestimates in previous studies. To address this problem, a fine-grained enterprise-level dataset is used in this paper to provide secure evidence at a small spatial scale.

2.3 How could green FDI affect local air pollution?

Beneficial from the extensive literature research, we propose our main hypothesis to test the impact of green FDI on air quality. Different from the influence channels of general FDI, the impact of green FDI on the environment can be summarized into two channels. The direct impact channel is that green FDI directly reduces the amount of pollutants emitted by enterprises to the environment. The indirect impact channel is reflected in the spillover effect of green technology.

We first demonstrate the direct channel. Green foreign-invested enterprises are usually energy-efficient, environmentally friendly and adopting clean production process, which could largely reduce energy consumption and pollution emissions, compared with heavy-pollution or high-energy-consumption enterprises (Wang et al., 2019). In addition, with the strengthening of environmental regulations in many developing countries, the green processes and technologies adopted by green FDI enterprises can reduce the pressure from emission fees or environmental taxes, thus giving them advantages in the market competition (Greenstone et al., 2012).This advantage could allow green FDI to exert a crowding-out effect on the high-pollution and high-energy-consumption enterprises in the long run, which could improve local environmental quality (Ouyang et al., 2020).

The indirect channel relates to the spillover effect of green FDI. Existing studies shows that foreign investment is not only capital flow across countries, but also a process of technology and knowledge diffusion (Narula & Dunning, 2010). Analogously, the entry of green FDI provides opportunities for domestic enterprises to access foreign advanced knowledge and technology for cleaner production. Through learning or imitating green production process or technology, domestic enterprises could improve their energy-efficiency, reduce emission, and finally turn to be green producers. In fact, owing to the increasingly stricter environmental regulations, domestic enterprises may have strong motivation to take up green technology to reduce environmental cost. Compared with increasing R&D input in researching green technology on their own, it may be less costly to learn or imitate those from green FDI enterprises, which may stimulate the rapid diffusion of green technology in host countries (Tabrizian, 2019). In addition, the spillover effect of green FDI is also reflected in the "inter-industry correlation effect". Green FDI not only refers to enterprises that produce green products, but also includes enterprises providing clean and environmental services for other enterprises. Therefore, green FDI could facilitate clean production and improve local environmental quality through inter-industry interaction with domestic enterprises. Based on the above analysis, we propose our main hypothesis for empirical test:

H1: Controlling other factors, green FDI enterprises can have a negative effect on local environmental pollution.

3. Research design

3.1 Identification strategy and model setting

The most direct impact of production on air quality is usually confined to the vicinity of the enterprise’s site, which makes it less accurate to estimate the effect of green FDI on whole cities' air quality. In addition, many factors could influence cities' air quality, such as the wind velocity, water areas, and some other geological features. Furthermore, these factors may be of great diversity even among regions from a single city, making it difficult to control their influence in an estimation model. For a reliable and precise estimation of the impact of green FDI on air quality, we follow Li et al. (2019) and use small areas within a certain distance from the sites of air pollution monitoring station to artificially delineate the observation unit (seen in Fig. 1).

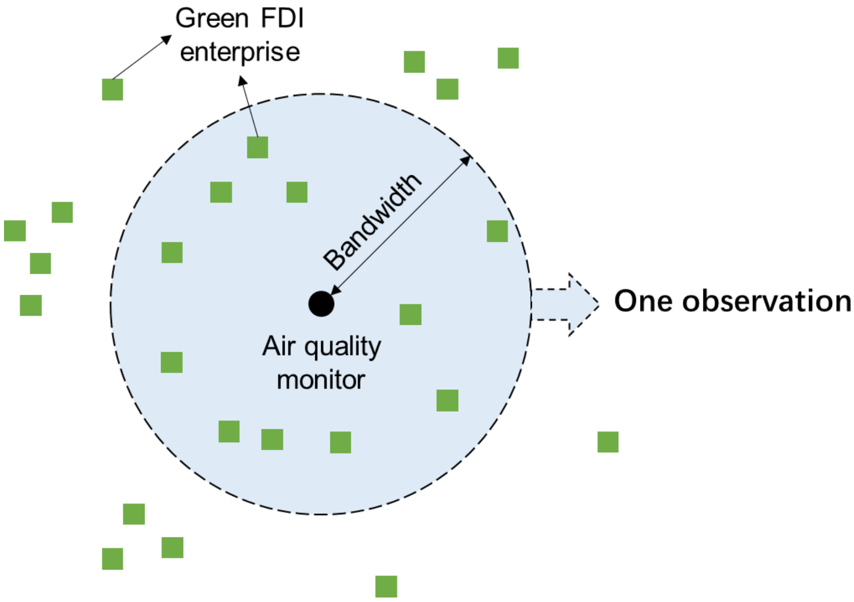

Figure 1. Diagram illustrating the setting of the an observation unit.

Note: The large dark dot in the center represents an air quality monitoring station, and the blue circle is the surrounding areas within a certain distance from the monitoring station, which is the observation unit in our study. Each green square denotes a green FDI enterprise. They may locate both in and out of the observation unit (blue circle). We count the number of green FDI enterprises in the blue circle and match it with the air pollution index obtained from the monitoring station to build our baseline dataset.

The Chinese government has set up a large number of air quality monitoring stations across the country since 2012, enabling us to estimate the effect of green FDI at fine-grained scales (seen in Fig. 2). Notably, there are several or even dozens of air quality monitoring stations even within a single city. So several observation units may belong to a same city.

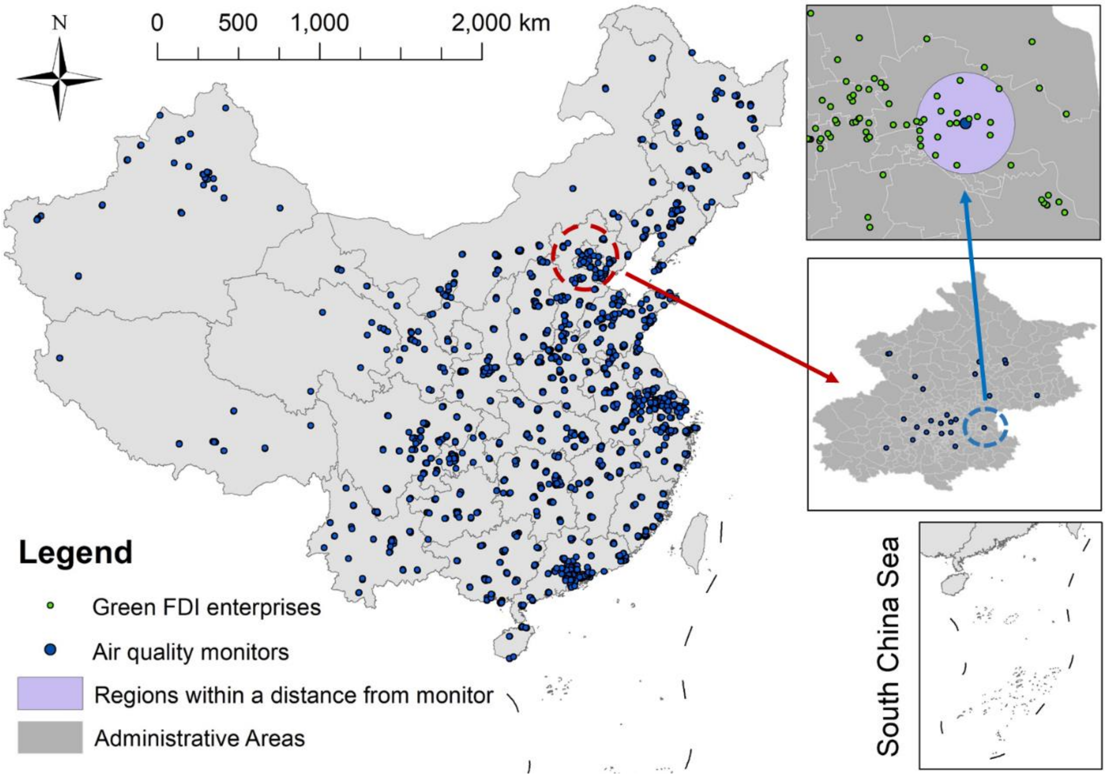

Figure 2. The distribution of air quality monitoring stations.

Note: The blue dots represent air pollution monitors all over the country, and the green dots represent green FDI enterprises. They may locate both in and out of observation unit (purple circle). We count the number of green FDI enterprises in the circle and match it with the air pollution index obtained from the monitoring station to build our baseline dataset.

The small spatial scale of the observation unit can bear two advantages. First, once the distance is refined to a small value, vast majority of the threatening factors that potentially confound our estimations may be eliminated, because climatic or geological features are very similar or stable within a small region. Second, the small spatial scale helps to improve the accuracy of air pollution measurement. Many researchers measure air pollution using satellite data. However, the remote sensing data based on the aerosol optical depth (AOD) have low spatial resolution and cannot distinguish between different pollutants (Chen et al., 2013; Jung, 2022). More importantly, it does not precisely reflect the concentration of pollutants near the ground, where human economic activities can have a direct impact. Instead, data from air quality monitoring stations can provide a rich variety of near-surface pollutant concentration levels, enhancing the accuracy of our measurements. Based on the above analysis, we construct the following equation to estimate the effect of green FDI on air quality at the small spatial scale:

$$ln(Pollution_{ict}) = \alpha \cdot GreenFDI_{ict} + \boldsymbol{X}'_{\boldsymbol{ct}} \cdot \boldsymbol{\beta} + Monitor_i + City_c + Year_t + \varepsilon_{ict} \quad (1)$$

Where the subscript i, c, and t represent monitor station, city, and year, respectively. $ln(Pollution_{ict})$ is the logarithm of air pollution indicator at each monitor station. $GreenFDI_{ict}$ reflects the number of green FDI enterprises within the 3 kilometers from each monitor station. $\boldsymbol{X}$ is a series of city-level control variables. In addition, we include the monitoring station fixed effect ($Monitor_i$), city fixed effect ($City_c$), and the year fixed effect ($Year_t$) to control the unobservable inherent interference.

3.2 Monitor-based air pollution

In 2012, the Chinese government launched a nationwide air quality monitoring and disclosure program, intending to stimulate the air pollution abatement. This program is rolled out to cities in three waves. By the end of 2014, over 367 cities in China have built up air quality monitoring station and started publicly disclosing the air pollution level in real-time. There are 1,160 air-quality monitoring stations established. Around 60% of them locate in urban areas, while 40% of them locate in suburbs or rural areas. The data on air quality monitoring stations is obtained from the Qingyue platform [1] This platform records the detailed location information of air quality monitoring stations, including it's the latitude and longitude, which enable us to map their spatial distribution.

The origin source of the air pollution monitoring data is compiled from the website of Ministry of Ecology and Environmental of the PR China, which publishes the air pollution index hourly and daily. Then we calculate the yearly averaged AQI and the concentrations of various pollutants at individual station, including PM2.5, PM10, SO2, NO2, CO, and O3. All these indicators are logarithmized. The AQI is a comprehensive indicator measuring the air quality. As robustness checks, we also use the other indicators for concentration of specific pollutants to measure air quality.

3.3 Measurement for green FDI

The key explanatory variable we use is green FDI. Although the OECD has given a definition and measurement for green FDI in 2010, the existing literature rarely discussed the issues of green FDI, mainly due to the lack of data.

In this study, we take advantage of a unique dataset gleaned from the website of the Foreign Investment Management Platform of the Ministry of Commerce of P. R. China to calculate green FDI , which records the detailed registration information of all the newly-established foreign-invested enterprises over the last few years, including enterprise's name, registering capital, ownership, 4-digit industrial code, address, latitude, longitude, host country, and the scope of products. The most important issue is how to extract the green FDI enterprises from the full sample. The OECD did not

[1] It is a well-known open data platform in China, mainly focusing on offering free and solid data source for environmental researchers (http://data.epmap.org).

classify green FDI by industry, and we could hardly identify green FDI in our dataset. Instead, we use the *Statistical Classification of Energy Conservation, Environmental Protection, and Clean Industry* issued by the National Bureau of Statistics (NBS). It gives 4-digit code of the classification of energy-saving, environmental-friendly, and clean industries. FDI enterprises with these characteristics are likely to be “green”. Similar method is also used in Cui et al. (2021). The full sample size of our dataset is 332,131, of which 73,531 enterprises are classified as green FDI according to the criterion of NBS. Then, we match each green FDI enterprise together with the air monitoring station according to their latitude and longitude. Thus, we can construct an indicator to depict the green FDI at such a small spatial scale -- the number of green FDI enterprises, by counting the number of green FDI enterprises located within 3 km from each air monitoring station. Noticeably, due to the availability of air pollution monitoring data, the sample period is from 2014 to 2017. However, the calculation of green FDI is based on accumulated values from 2008. It is based on an assumption that there were almost no green FDI before 2008 (the beginning year of green FDI dataset). Actually, this assumption is too strict, so we further discuss this issue in the robustness test.

3.4 Endogeneity issues and Bartik IV

Noticeably, using OLS method to estimate the effect of green FDI on local air pollution may suffer from serious endogeneity problems, such as omitted variables and simultaneity. For example, foreign-invested enterprises usually prefer to locate nearby other foreign enterprises, resulting in a geographical agglomeration effect, which may increase the number of FDI enterprises and devastate local environmental quality at the same time. Meanwhile, the distribution of green FDI is also endogenous, because FDI usually forms agglomeration. Due to the limited data, we cannot precisely figure out the original number of FDI enterprises in a region, which makes it impossible control the potential bias caused by these omitted factors.

The simultaneity problem may also mislead our estimation result, because the locational choices of green FDI enterprises may be largely affected by local air quality. On one hand, if air pollution is much severer in a region, there may be stricter environmental regulations, filtering out non-green FDI enterprises. On the other hand, the core business of some green FDI enterprises is to provide pollution treatment services to those heavy-polluting enterprises. Severe air pollution in a region can bear larger market demand for pollution treatment service, which could strongly attract the entry of green FDI enterprises. In addition, local governments may deliberately drive the green FDI enterprises to locate nearby monitoring stations to lower down the monitored air pollution level. This may lead to a larger concentration of green FDI enterprises near the monitoring stations. In summary, if the endogeneity problem is not addressed, our estimation result may not be reliable.

To address the estimation biases caused by potential endogeneity issues, we use instrumental variable (IV) regression. Following Zhao et al. (2021), we use the Bartik instrumental variable method to correct the estimated results. This method was first proposed and used by Bartik et al. (1994) in employment research and later widely applied in population mobility studies (Howard, 2020). The basic idea of constructing Bartik instrumental variables is to estimate the virtual values of analyzing units for subsequent periods based on the initial values of analyzing units and the overall growth rate, which are highly correlated with the actual values but not related to factors in the random error term, thus satisfying the basic conditions of instrumental variables.

The potential endogenous variable in this paper is the number of green FDI enterprises within those small regions around air quality monitoring stations, which is selected based on 4-digit industry codes delimited by the National Bureau of Statistics. We let j denote the 4-digit industrial code of a green industry, and J denotes the set of industrial codes of green industries. Then the following formula holds:

$$GreenFDI_{ict} \equiv \sum_{j \in J} GreenFDI_{ictj} \tag{2}$$

Then we denote the nationwide growth rate of green industry j from 2008 to year t as G_{jt}. The initial year is 2008, and the expected number of green FDI enterprises in the subsequent years could be calculated based on the initial value and growth rate, expressed as:

$$GreenFDI_{Bartik_{ict}} = \sum_{j \in J} GreenFDI_{icj,2008} \times \left(1 + G_{jt}\right)^{t-2008} \tag{3}$$

where $GreenFDI\_Bartik_{ict}$ is the Bartik instrumental variable of $GreenFDI_{ict}$.

3.5 Other variables and sources

In addition to foreign investment, the air quality is influenced by the features of prefectural-level cities. In line with previous studies (Ren et al., 2022), the following variables are controlled: local economic development represented by the GDP per capita ($ln(GDPper)$); local market scale measured by population density ($ln(Populdens)$); infrastructure level represented by the road length per kilometer square ($ln(Roaddens)$); environmental endowment measured by the percentage of green space in built-up areas ($Greenland$). Besides, we control for the fiscal intervention indexed by the percentage of fiscal expense to GDP ($Fiscal$), which may affect local governments' intension or strength for attracting FDI and further influence air quality.

The data is mainly collected from the China City Statistical Yearbook (2013-2016), the China Regional Economic Statistical Yearbook (2013-2016), and the China Urban Construction Statistical Yearbook (2013-2016). Some missing data has been supplemented through corresponding provincial and municipal statistical yearbooks, or filled in through interpolation methods. Table 1 reports the descriptive statistical results of the main variables used in our empirical analysis.

Table 1. The summary statistics of variables used

Variable	Definition or explanation	Num.	Mean	S.D.	Min.	Max.
Monitor level variables:						
AQI	Air Quality Index. (unit: 1)	5,800	74.51	22.66	23.96	240.95
PM2.5	Fine particle concentration. (unit: ug/m^3)	5,800	46.80	17.31	7.52	188.89
PM10	Inhalable particle concentration. (unit: ug/m^3)	5,800	83.62	33.17	18.55	461.23
SO2	Sulfur dioxide concentration. (unit: ug/m^3)	5,800	21.14	14.84	2.03	293.89
NO2	Nitrogen dioxide concentration. (unit: ug/m^3)	5,800	32.61	12.48	3.30	88.45
O3	Ozone concentration. (unit: ug/m^3)	5,800	58.99	12.81	9.80	125.71
CO	Carbon monoxide concentration. (unit: ug/m^3)	5,800	1.01	0.35	0.09	3.74
Observation unit level variables (depend on bandwidth):						
GreenFDI(5km)	The number of green FDI enterprises within 5 km from a monitoring station. (unit: 1)	5,800	16.89	73.74	0.00	1375
GreenFDI_IV(5km)	The Bartik IV for GreenFDI(5km)	5,800	16.57	71.47	0.00	1621.32
GreenFDI(7km)	The number of green FDI enterprises within 7 km from a monitoring station.	5,800	20.11	83.63	0.00	1444.00
GreenFDI_IV(7km)	The Bartik IV for GreenFDI(7km).	5,800	19.64	80.16	0.00	1669.08
GreenFDI_nonstar	The number of green FDI enterprises (industries symbolled * removed) within 7 km from a monitoring station. (unit: 1)	5,800	18.45	72.91	0.00	1643.42
GreenFDI_sum	The total registered capital of green FDI within 7 km from a monitoring station. (unit: million yuan)	5,800	858.54	2825.31	0.00	72080.08
City level variables:						
GDPper	Regional economic development, measured by GDP per capita. (unit: 100)	5,800	665.97	370.01	186.12	2601.33
Populdens	Regional market scale, measured by population per km^2. (unit: 100/km^2)	5,800	4.97	3.97	0.00	26.48
Roaddens	Regional infrastructure, measured by length of road per km^2. (unit: km/km^2)	5,658	0.22	0.40	0.00	3.69
Greenland	Urban environment, measured by the percentage of green land to urban areas. (%)	5,463	2.02	5.69	0.00	49.02
Fiscal	Government intervention, measured by the ratio of fiscal expense to local GDP. (%)	5,784	0.20	0.14	0.00	1.94
Institution	Institutional quality, measured by the marketization index (Fan Gang Index). (unit: 1)	5,800	12.39	1.83	7.27	18.26
Energyuse	Total energy use, measured by consumption of	5,709	19.97	18.38	1.71	114.54

coal equivalent. (unit: 10^6 tce)

4. Baseline result and discussion

4.1 Preliminary estimation

In the preliminary estimation, we set a 5 km radius distance from the air quality monitoring station to construct the small spatial observation unit. Then we estimate model (1) with OLS and 2SLS respectively. Table 2 presents the results. In column (1), we simply regress the number of green FDI enterprises to the air pollution level (*Ln(AQI)*). We add the monitor fixed effect, city fixed effect, and the year fixed effect in the regression. The coefficient of *GreenFDI* is negative but statistically insignificant. Column (2) include a series of city-level time-variant control variables, and the estimated coefficient is -0.0077, but still insignificant. These results show a possibly negative correlation between green FDI and air pollution, though it is not statistically significant.

Columns (3)-(6) report the results of the two stage least square (2SLS) regression with the Bartik instrumental variable. In the first-stage regression, we find a significant positive correlation between the Bartik instrument variable and endogenous explanatory variable, regardless of whether control variables are included or not, which is in line with our expectations. Columns (5) and (6) show the results of the second-stage regression, the coefficients of the key explanatory variable, *GreenFDI*, are significantly negative (-0.0617 and -0.0584). It basically shows that green FDI could improve the air quality nearby, especially when the potential endogeneity issues are solved. Specifically, if the number of green FDI enterprises increases by 10% in the areas surrounding monitoring stations, the AQI will decrease by approximately 0.584%.

Table 2. Estimating the impact of green FDI on air pollution using OLS and 2SLS approach

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Ln(AQI)	Ln(AQI)	Ln(GreenFDI)	Ln(GreenFDI)	Ln(AQI)	Ln(AQI)
Ln(GreenFDI)	-0.0043	-0.0032			-0.0617^{***}	-0.0584^{***}
	(0.0079)	(0.0073)			(0.0162)	(0.0165)
Ln(GreenFDI_Bartik)			0.6479^{***}	0.6489^{***}		
			(0.0191)	(0.0201)		
Ln(GDPper)		0.0201^{***}		0.0053		0.0208^{***}
		(0.0026)		(0.0050)		(0.0021)
Ln(Populdens)		-0.0726^{*}		0.1640^{**}		-0.0454
		(0.0432)		(0.0816)		(0.0619)
Ln(Roaddens)		0.0008		0.0382^{**}		0.0031
		(0.0096)		(0.0181)		(0.0109)

Greenland		-0.0031		0.0079^{**}		-0.0022
		(0.0019)		(0.0035)		(0.0016)
Fiscal		-0.2976^{***}		0.1175		-0.3033^{***}
		(0.0685)		(0.1292)		(0.0913)
Ln(Energyuse)		0.0733^{***}		0.0459		0.0760^{***}
		(0.0167)		(0.0314)		(0.0230)
Institution		-0.0089^{*}		-0.0257^{***}		-0.0103
		(0.0050)		(0.0094)		(0.0063)
Monitor fixed effect	Y	Y	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y
adj. R^2	0.9327	0.908	0.988	0.988		
F	0.2371	11.5108	1070.9803	134.4472	14.4536	15.8726
Kleibergen-Paap rk Wald F					1150.216	1038.696
N	5777	5439	5777	5439	5777	5439

Note: Standard errors clustered to monitor level are placed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For simplicity, we do not report the constant terms. Columns (1) and (2) perform OLS, while columns (3) – (4) are results of 2SLS. We perform a Hausman test for whether the IV should be used. The chi^2 is estimated to be 11.93 (Prob > chi^2 = 0.0006), supporting the validity of our IV.

4.2 Discussion on bandwidth selection

Different from traditional empirical strategy that using observation unit based on administrative boundaries, our study constructs observation units based on the location of air pollution monitoring stations at a small spatial scale. This type of method usually faces the so-called "Modifiable Areal Unit Problem". In the preliminary estimation, we subjectively determine 5 km as the bandwidth of the spatial units, which may lead to the estimation results being accidental or non-robust.

Given the fact that the air pollution monitoring stations may only monitor the air quality within a certain distance around their location, if a too small bandwidth is used, many green FDI firms around the monitoring stations will not be included in the estimation, but they are likely to be important contributors to the improvement of the local air quality. Otherwise, if a too large bandwidth is used, it will include firms that are far away from the monitoring stations, and these firms can hardly have an impact on the air quality around the monitoring stations. Therefore, to accurately estimate the impact of green FDI on air quality, we must determine an appropriate bandwidth.

Specifically, we set a bandwidth every 0.1 km within the range of 1 km to 10 km. Based on these different bandwidths, we generate a series of observation units with diverse scale. Then accordingly, we calculate the number of green FDI enterprises and generate the Bartik instrumental variable under different observation units. We perform

2SLS estimation one by one (a total of 90 estimations) and present the estimated coefficients of the key explanatory variable (*GreenFDI*) and their 95% confidence intervals in Figure 4. It is easy to find that as the bandwidth increases gradually from 1 km to 10 km, the magnitudes of coefficients grow, and the statistical significance also increases. Using observation units with larger bandwidth will include more green FDI firms in the estimation, and the effects of green FDI on improving air quality are increasingly significant.

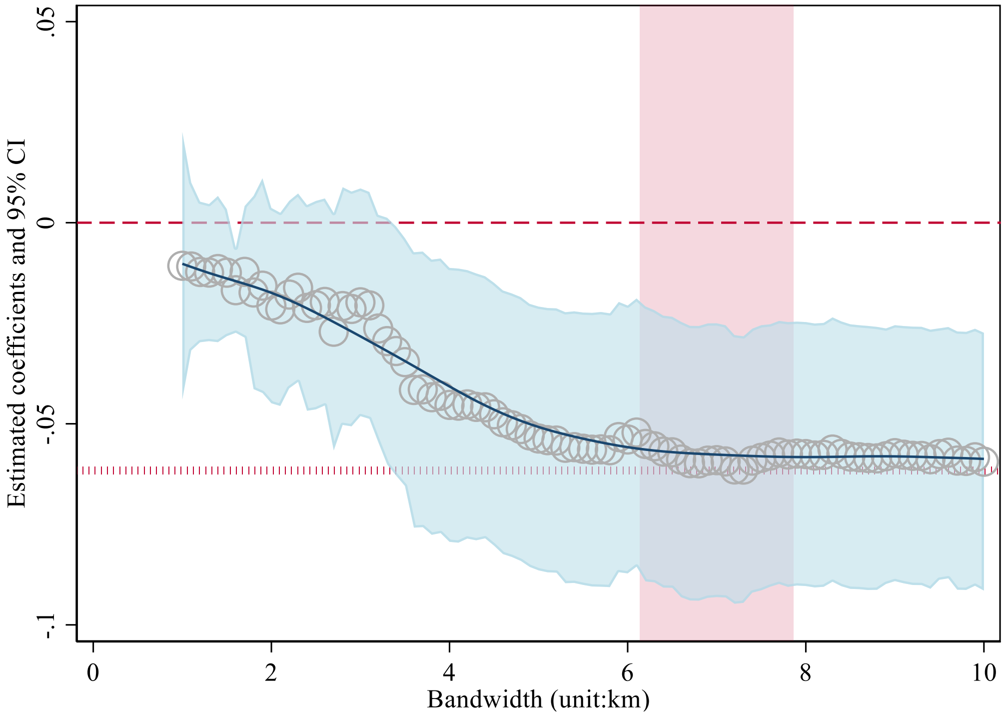

Figure 3. Estimation results of using different radius distance to construct the key explanatory variable.
Note: above figure shows the estimation results of using observation units that constructed with different bandwidths. The grey hollow dots represent the coefficients of Ln(GreenFDI) and the light blue areas denote the 95% confidence intervals. All the coefficients are below the zero-line (the red dash line). In the red colored areas around 7 km bandwidth, the coefficients tend to remain stable.

However, when the bandwidth is close to 7 km, the magnitudes of the coefficients do not increases any more. In other words, the continued increase in the number of green FDI enterprises included in each observation unit does not account for air pollution abatement to a larger extent. It seems that 7 km is likely to be the farthest distance that the monitoring station can monitor the impact of green FDI firms on air quality. Thus, using a larger bandwidth may be unnecessary, and using a smaller bandwidth may lead to bias as well. Therefore, we consider 7 km as an appropriate bandwidth.

4.3 Ruling out the spatial spillover effect

Another factor that may interference the causal relationship between green FDI and air quality is the spatial agglomeration and spillover effect of green FDI enterprises. Previous studies have demonstrated that FDI usually form spatial agglomeration to overcome potential risks in the host country or enjoy the external benefits of agglomeration effect (Crozet et al., 2004). Given the spatial agglomeration of FDI, green FDI enterprises outside but close to the border of the observation unit are not randomly distributed. Namely, when there are many green FDI firms inside the circle, there may also be many outside. For an observation unit, the green FDI firms outside but close to the boundary may still have an impact on the air quality around the monitor station.

To eliminate the interference of spillover effect, we need to control for the green FDI in the surrounding areas outside the observation unit (seen in Figure 4). According to the previous section, we use 7 km as the optimal bandwidth to construct the observation unit. The spillover effect is likely to come from areas beyond 7 km from the monitoring station. One possible solution is to calculate the exact number of green FDI enterprises located in the circular area surrounding each observation unit and use it as a control variable. We calculate the number of green FDI enterprises located between 7-8 km from the monitoring station, and add it into model (1). Accordingly, we modify the baseline model as:

$$ln(Pollution_{ict}) = \alpha \cdot GreenFDI_{ict} + \tau \cdot Spillover_{ict} + \boldsymbol{X}'_{\boldsymbol{ct}} \cdot \boldsymbol{\beta} + Monitor_i + City_c + Year_t + \varepsilon_{ict} \quad (4)$$

We expect the coefficient of this control variable to be not statistically significant so as to ensure that all green FDI enterprises that may have an impact on the air quality near the monitoring station are included in the key explanatory variable (*GreenFDI*). Table 5 reports the estimation results of model (4).

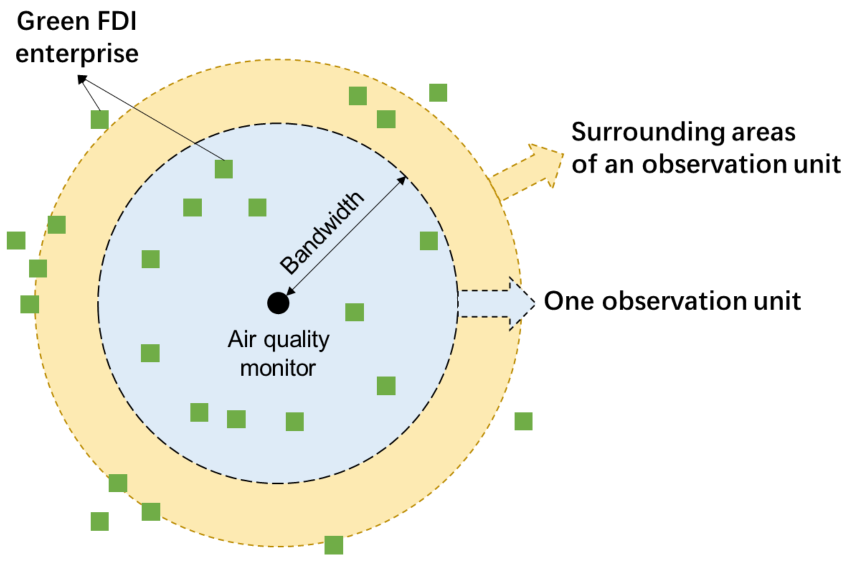

Figure 4. Construction the variable to control the spillover effect from outside areas.

Note: The large dark dot in the center represents an air quality monitoring station, and the blue circle is *the surrounding areas within a certain distance from the monitoring station, which is the observation unit in our study. Each green square denotes a green FDI enterprise. They may locate both in and out of the observation unit (blue circle). We count the number of green FDI enterprises in the blue circle as the key explanatory variable. Meanwhile, we count the number of green FDI enterprises in the yellow circle to build the variable that could help control the spatial spillover effect.*

Table 3. Estimating the impact of green FDI on air pollution using 2SLS approach

	(1)	(2)	(3)	(4)
Dep. Var.:	Ln(GreenFDI)	Ln(GreenFDI)	Ln(AQI)	Ln(AQI)
Ln(GreenFDI)			-0.0588***	-0.0564**
			(0.0212)	(0.0219)
Ln(GreenFDI_Bartik)	0.5753***	0.5827***		
	(0.0584)	(0.0642)		
Ln(Spillover)	0.1824***	0.1746***	-0.0126	-0.0110
	(0.0405)	(0.0407)	(0.0148)	(0.0145)
Other control variables		Y		Y
Monitor fixed effect	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
adj. R^2	0.988	0.988		
F	78.0931	19.6845	7.7078	14.2413
Kleibergen-Paap rk Wald F			1052.852	1000.381
N	5777	5439	5777	5439

Note: Standard errors clustered to prefecture-city level are placed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For simplicity, we do not report the constant term. Columns (1) and (2) are the first stage regression, and columns (3) and (4) are the second stage regression.

4.4 Robustness test

4.4.1 Using alternative measures for green FDI

In this part, we use two alternative measures for green FDI. First of all, we excluded some industries when measuring green FDI. Although the "*Statistical Classification of Energy Conservation, Environmental Protection, and Clean Industry*" specifies industry codes, it also marks certain industry codes with the symbol "*", which means only some enterprises in these industries can be recognized as green ones. For example, some manufacturing enterprises can only be considered as green if they produce green products. To ensure the robustness of our finding, we exclude these asterisk-marked industries from the green FDI sample and re-estimated model (4).

Columns (1) and (2) of Table 5 report the estimation results, where column (1) is the regression result of the first stage and column (2) is the regression result of the second stage. We find that even after excluding these special industries and re-calculate the number of green FDI enterprises, the coefficient of $GreenFDI\_nonstar$ in column (2) is still significantly negative, and the magnitudes are significantly enlarged compared to those in Table 2. In fact, industries strictly classified as green mainly cover industries such as energy-saving engineering, environmental technology services, waste recycling and treatment, new energy, and new materials. Green FDI enterprises from these industries can offer green service for other enterprises, such as pollution treatment. Through inter-industry interaction, they could amplify the positive impact of green FDI on the environmental quality.

Second, we use the registered capital of green FDI enterprises to measure *GreenFDI*. In the baseline regression, we use the number of green FDI enterprises to measure *GreenFDI*. In fact, our dataset also provides the registered capital of each enterprise, which enables us to construct an alternative measure for *GreenFDI* by summing up the registered capital. However, the estimated coefficient of green FDI measured by registered capital is negative but insignificant (column 4). A possible explanation is that the total registered capital is easily affected by the size of individual enterprise's capital and may not accurately reflect the level of green FDI agglomeration in a region. To overcome the possible bias from size effect, we generate a variable *Mean_scale* to denote the average size of each green FDI enterprise within each observation unit, and use it as a control variable. Columns (5) and (6) show the results. We find the coefficient of *GreenFDI_amount* turn to be statistically significant.

Table 4. Results of 2SLS estimation using alternative measures for green FDI.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Ln(GreenFDI_nonstar)	Ln(AQI)	Ln(GreenFDI_amount)	Ln(AQI)	Ln(GreenFDI_amount)	Ln(AQI)
Ln(GreenFDI_nonstar_bartik)	0.2648***					
	(0.0182)					
Ln(GreenFDI_nonstar)		-0.1432				
		(0.0407)				
Ln(GreenFDI_amount_bartik)			0.6062***		0.2766***	
			(0.0760)		(0.0285)	
Ln(GreenFDI_amount)				-0.0046		-0.0157*
				(0.0031)		(0.0081)
Ln(Spillover)	-0.0014	-0.0001	0.0517	-0.0002	0.0360***	0.0001
	(0.0022)	(0.0013)	(0.0317)	(0.0017)	(0.0098)	(0.0017)
Ln(Mean_scale)					4.7988***	0.0978**
					(0.0785)	(0.0433)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Monitor fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.665		0.944		0.993	
F	33.78	11.44	8.0850	13.4123	453.9495	11.6769
Kleibergen-Paap rk Wald F		210.053		445.908		717.679
N	5,439	5,439	5,439	5,439	5,439	5,439

Note: Standard errors clustered to prefecture-city level are placed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For simplicity, we do not report the constant term. Columns (1), (3), and (5) are the first stage regression, and columns (2), (4), and (6) are the second stage regression.

4.4.2 Using alternative measures for air pollution

Then, we replace the dependent variable Ln(AQI) with other air pollution indexes. The dataset also provides concentration levels for other specific pollutants, including fine particulate matter (PM2.5), inhalable particulate matter (PM10), sulfur dioxide (SO2), nitrogen dioxide (NO2), ozone (Ozone), and carbon monoxide (CO). We regress model (4) with 2SLS method, using the annual average values of various specific pollutants as the dependent variables. Columns (1) to (6) in Table 5 report the regression results using different pollutants as the dependent variable, respectively. The results show that *GreenFDI* still has a significant negative impact on the concentration of different pollutants, which supports the robustness of our findings.

Table 5. Results of 2SLS estimation using alternative measures for air pollution.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Ln(PM2.5)	Ln(PM10)	Ln(SO2)	Ln(NO2)	Ln(Ozone)	Ln(CO)
Ln(GreenFDI)	-0.0786^{***}	-0.0745^{***}	-0.0235^{***}	-0.0408^{**}	-0.0593^{**}	-0.0028
	(0.0241)	(0.0219)	(0.0104)	(0.0203)	(0.0301)	(0.0153)
Ln(Spillover)	0.0007	0.0022	-0.0016	0.0031^{*}	-0.0021	0.0031
	(0.0019)	(0.0018)	(0.0035)	(0.0018)	(0.0024)	(0.0022)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Monitor fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
F	9.2530	9.8187	3.5754	6.7828	5.6350	3.8659
Kleibergen-Paap rk Wald F	916.781	916.781	916.781	916.781	916.781	916.781
N	5439	5439	5439	5439	5439	5439

Note: Standard errors clustered to prefecture-city level are placed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For simplicity, we do not report the constant term. All the columns report the results of the second stage regression of 2SLS.

4.3.3 Removing special observations

We also removed special observations in the regression. In order to eliminate the potential bias from some special cities, we deleted the monitoring stations located in the four municipalities[2] from the samples and re-regress model (4) with 2SLS method. Columns (1) and (2) in Table 6 report the regression results, where column (1) is the first-stage regression result and column (2) is the second-stage regression result. The result in column (2) shows that the coefficient of *GreenFDI* is still significantly negative, which means that our main conclusion still holds even after removing observations from special cities.

Secondly, as mentioned earlier, the number of green FDI enterprises is calculated based on the cumulative number of newly-established green FDI enterprises since 2008. However, in practice, we cannot ensure that there were few green FDI enterprises in China before 2008, which may lead to an overestimation of the impact of green FDI on air quality. To check the impact of this issue, we excluded the top 10% of regions with the highest number of newly-established green FDI enterprises in 2008 from the sample. That is because these regions were more likely to have already had a large number of green FDI enterprises before the year 2008. Columns (3) and (4) in Table 6 present the regression results, with column (3) showing the first-stage result and column (4) showing the second-stage result. The estimated coefficient of *GreenFDI* remains negative and significant at the 1% level, indicating that our findings is robust, though the estimated coefficient has slightly decreased in comparison to the baseline results.

In addition, we also need to discuss the issue of "zero values". Our observation units are constructed based on the location of the air pollution monitoring stations, and a bandwidth of 7 km is imposed. Within such a small area, the number of green FDI enterprises may be small. In particular, some observation units may have zero green FDI enterprises throughout the sample period. For them, the Bartik instrument variable generated is also zero. If a large proportion of the observations takes the value of zero, it may cause bias in our estimation. According to our dataset, under the 7 km bandwidth, about 17% of the observation units are all zeros in the sample period. We are not sure whether this proportion causes serious bias. Therefore, we simply remove them from the sample and re-estimate. Columns (5) and (6) report the regression results. It shows that after removing the "all-zeros" observation units, the estimated coefficient is still significantly negative.

Table 6. Results of 2SLS regression after deleting some special observations.

	(1)	(2)	(3)	(4)	(5)	(6)
	Removing municipality cities		Removing observations with large number of green FDI enterprises in 2008		Removing zero green FDI throughout the entire sample period	
Dep. Var.:	Ln(GreenFDI)	Ln(AQI)	Ln(GreenFDI)	Ln(AQI)	Ln(GreenFDI)	Ln(AQI)
GreenFDI_Bartik	0.6074***		0.6089***		0.5195***	

2 Four municipalities are Beijing, Tianjin, Chongqing and Shanghai, which is more developed than other cities.

	(0.0201)		(0.0203)		(0.0229)	
Ln(GreenFDI)		-0.0624***		-0.0538***		-0.0527**
		(0.0177)		(0.0178)		(0.0217)
Ln(Spillover)	0.0165***	0.0011	0.0165***	0.0007	0.0195***	0.0001
	(0.0025)	(0.0014)	(0.0025)	(0.0014)	(0.0029)	(0.0015)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Monitor fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.988		0.987		0.985	
F	125.5375	11.4775	123.5497	10.8900	76.2924	9.2065
Kleibergen-Paap rk Wald F		916.781		901.065		514.413
N	5439	5439	5381	5381	4475	4475

Note: Standard errors clustered to prefecture-city level are placed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For simplicity, we do not report the constant term. Columns (1), (3), and (5) are the first stage regression, and columns (2), (4), and (6) are the second stage regression.

4.3.4 Potential bias from monitoring stations' locations

Another identification threat comes from the non-random distribution of the air pollution monitoring stations. If the site decision of monitors depends on some local features, it may cause bias. In particular, most of monitors are likely to be located in urban areas, because it makes more sense to monitor the air quality in densely populated cities. However, green FDI may be more prevalent in the peripheral areas away from urban areas, because factories tend to relocate to the suburbs as the economy develops.

To test whether the endogenous site decision of monitors misleads our main conclusions, we conduct grouped estimation based on the characteristics of the areas where the monitors are located. Specifically, we group by the types of township-level administrative divisions where the monitors are located. China's township-level administrative divisions mainly include Streets (街道, Jiedao), Towns (镇, Zhen) and Townships (乡, Xiang). Streets are usually areas with high urbanization rate and no rural areas. Villages are areas with low urbanization rate, usually far away from cities, and almost entirely rural. Towns are between the two types.

According to our dataset, among all the monitors, about 60% are located in urban areas, and the remaining 40% are located in towns and villages. Table 6 reports the results of grouped estimation with 2SLS. We find that green FDI can significantly reduce the level of air pollution in any type of area. Although the distribution of the monitors is not completely random, it does not exert a serious impact on our main findings.

Figure 5. Grouped estimation by different administrative divisions.

Dep. Var.: Ln(AQI)	(1) Streets	(2) Towns	(3) Townships
Ln(GreenFDI)	-0.0804***	-0.1813***	-0.0771**
	(0.0252)	(0.0823)	(0.0380)
Ln(Spillover)	0.0032	0.0005	-0.0033
	(0.0021)	(0.0041)	(0.0047)
Other control variables	Y	Y	Y
Monitor fixed effect	Y	Y	Y
City fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
F	12.5765	3.8100	1.0303
Kleibergen-Paap rk Wald F	62.936	42.269	17.687
N	3354	1089	996

Note: Standard errors clustered to prefecture-city level are placed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For simplicity, we do not report the constant term. All the columns report the results of the second stage regression of 2SLS.

5. Further discussion

5.1 Decay effect with distance increasing

We have confirmed that the more the green FDI enterprises in a certain area, the stronger their effect on air pollution abatement. Considering that the impact of a single enterprise is limited to the vicinity of its location, the environmental improvement effect of green FDI enterprises may diminish as distance increases. To test whether the diminishing effect exists, we propose an identification method following Li et al. (2019). First, we calculate the geographic distance between green FDI enterprise and its nearest air quality monitoring station. Then, we group them based on the calculated distances. By setting a cutoff point every 1 km, we calculate the number of green FDI enterprises within 1-2 km, 2-3 km, ..., 9-10 km, and beyond 10 km from each monitoring station, and generate several explanatory variables to denote them. Moreover, considering that the areas of different annular regions differ, we normalize the number of green FDI enterprises by each circular region's area (unit: km^2). The model is set as follows:

$$ln(Pollution_{ict}) = \sum_{l=0}^{9} \alpha_l \cdot \frac{1}{S_l} \cdot GreenFDI(l \le d < l+1)_{ict} + \alpha_{10} \cdot \frac{1}{S_{10}} \cdot GreenFDI(d > 10)_{ict} + \boldsymbol{X}'_{ct} \cdot \boldsymbol{\beta} + Monitor_i + City_c + Year_t + \varepsilon_{ict} \quad (5)$$

We include all the explanatory variable indicating different circular areas

$GreenFDI(l \leq d < l+1)_{ict}$ into the model. α_l is the estimated coefficient of our interest. S_l is the area of each annulus. Control variables and fixed effects are the same with model (4).

To save space, we plot the regression coefficients and their 95% confidence intervals in Figure 4. All the coefficients are significantly negative, indicating that increasing the number of green FDI enterprises could significantly reduce the air pollution. More importantly, when the distance is greater than 4 km, the estimated coefficients gradually approach 0 and become insignificant. It suggests that the improvement effect of green FDI on air quality will diminish as the distance increases, which supports the existence of a decay effect.

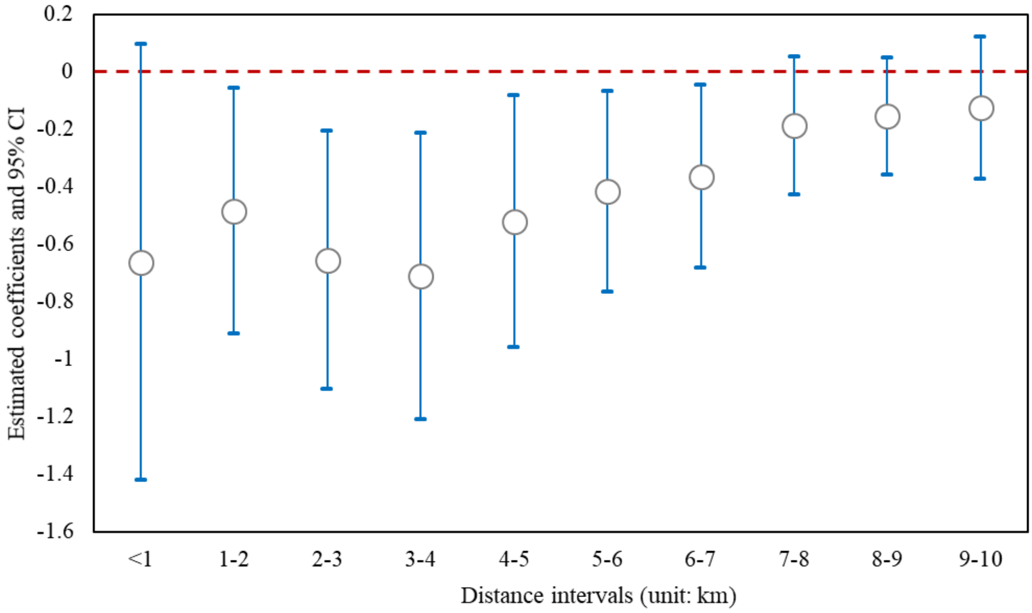

Figure 6. Results of distance decay effect estimation using circular areas around air monitoring stations

Note: Above figure shows effects of green FDI located in circular areas of different distance from air-quality monitors. The grey hollow dots represent the coefficients of $GreenFDI(l \leq d < l+1)$*, and the blue lines with caps at their tops and bottoms are the confidence intervals (CI) at 5% significance level. We draw a dash red line to denote the zero value, and find all the coefficients are negative. However, as the distance grows, the magnitudes of coefficients diminish and their significance also decreases.*

5.2 Local governments' environmental governance

The improvement effect of green FDI on environmental quality may be correlated with the stringency of local environmental governance. In China, local governments can exert a significant impact on economic activities, which could also influence the location choice of foreign-invested enterprises. With the strengthening emphasis of the central government's on ecological protection, local governments are increasingly paying more efforts into environmental governance, seeking to achieve a balance between economic growth and environmental protection. Under this circumstance, local government may not desperately pursue the expansion of foreign investment, and focus on adjusting the structure of FDI simultaneously to align with sustainable development goals. In recent years, green FDI enterprises are becoming more preferable due to its dual attributes of investment expansion and ecological protection. Governments in regions with more stringent environmental regulations are more likely to carry out preferential policies to support green FDI enterprises, thereby enhancing its impact on local environmental quality.

To empirically examine whether local environmental governance could moderate the effects of green FDI on air pollution, we refer to Chen & Chen (2018) and use the frequency of environmental-related vocabulary in the annual reports of prefecture-level city governments (ER) to measure the environmental governance. Then, the variable *ER* and its interaction term with *GreenFDI* are incorporated in model (4) for estimation. Columns 1 and 2 in Table 7 report the results of the regression, where the column 2 include all the control variables. The results show that the coefficients of *GreenFDI* and the interaction term *GreenFDI* × *ER* both are significantly negative. The negative coefficient of interaction term indicates that when the local government carries out more stringent environmental governance, the green FDI can have a larger effect on improving local air quality.

Table 7. Moderating effects of local government environmental governance and the subsample estimation among regions with different level of air pollution.

	(1)	(2)	(3)	(4)
Dep. Var.: Ln(AQI)	Moderating effect of environmental governance		Cities with heavy pollution	Cities with light pollution
Ln(GreenFDI)	-0.0687***	-0.0761***	-0.1054***	-0.1460
	(0.0242)	(0.0244)	(0.0335)	(0.1098)
Ln(GreenFDI) ×ER	-0.0082*	-0.0090**		
	(0.0045)	(0.0045)		
ER	0.0315***	0.0288***		
	(0.0088)	(0.0087)		
Control variables		Y	Y	Y
Monitor fixed effect	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
F	19.3679	12.2632	24.7632	3.4397
Kleibergen-Paap rk Wald F	41.997	40.237		
N	5,367	5,367	2,763	2,675

Note: Standard errors clustered to prefecture-city level are placed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For simplicity, we do not report the constant term and coefficients of *Spillover*. All the columns report the results of the second stage regression of 2SLS. Column (1) does not include any other control variable except *Spillover*.

5.3 Local severity of air pollution

The impact of green FDI may also vary in regions with different levels of air pollution. We calculated the average air pollution level for each region during the sample period based on prefecture-level cities, and divided the sample into heavily polluted and lightly polluted regions according to the median value of the average air pollution level. The regression results are shown in Columns (3) and (4) of Table 7. We found that the estimated coefficients of the core explanatory variables were significantly negative, indicating that regardless of the severity of air pollution, the green FDI could bring about an improvement in air quality. It is worth noting that the impact of green FDI on regions with severe air pollution is greater, which indicates that heavily polluted areas should focus more on introducing green FDI to achieve coordination between economic development and environmental protection.

5.4 Heterogeneity concerning enterprises' characteristics

In this part, we try to analyze the heterogeneity effects caused by the different characteristics of green FDI enterprises, including industries, investment scales and types of ownership.

Firstly, we analyze the heterogeneous effects of green FDI enterprises in different industries. We divide green FDI enterprises into two sub-samples: manufacturing enterprises and service enterprises. We then calculate the number of these two types of green FDI enterprises within 7 km radius of air quality monitoring stations and use them as dependent variables for model (4). Columns (1) and (2) of Table 8 report the regression results. We find that the coefficients of *GreenFDI* are both negative and significant at the 5% significance level, indicating that both manufacturing and service industries' green FDI can help reduce local air pollution. The magnitude of manufacturing green FDI on air pollution is stronger, which might be due to its adoption of green and efficient production technology, directly reducing the impact of economic activity on the surrounding environment. Service industry enterprises mainly achieve indirect pollution reduction through inter-industrial interaction, especially by providing green technology services.

Secondly, we detect the heterogeneity effect caused by the different investment scale of green FDI enterprises. In columns (3) and (4), we divide green FDI enterprises into large-scale and small-scale groups based on the median of registered capital. Then, we use the number of large-scale and small-scale green FDI enterprises as explanatory variables for subsample estimation. The results show that both large- and small-scale green FDI enterprises can significantly reduce local air pollution. The effect of small-scale green FDI enterprises on improving air quality is much larger, which might be because the environmental impact of small-scale enterprises is limited, while that of large enterprises' might still be significant even if they adopt environmental-friendly production process.

Thirdly, we analyze the heterogeneous effects of green FDI enterprises with different ownership. Columns (5) and (6) present the results of subsample estimation using joint-venture and sole-venture green FDI enterprises. We find that both of them can significantly reduce air pollution. Meanwhile, an increase in the number of sole-venture green FDI enterprises brings about a greater reduction in air pollution. One possible explanation is that sole-venture green FDI enterprises execute their production process without disturbs from domestic owners, and could do better in product quality control.

Table 8. 2SLS estimation results of subsample divided by enterprises' industries, investment scales, and ownerships.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: Ln(AQI)	Manufacturer	Service	Large-scale	Small-scale	Sole-venture	Joint-venture
Ln(GreenFDI)	-0.0772***	-0.0692***	-0.2018***	-0.2440***	-0.2623**	-0.1626***
	(0.0375)	(0.0329)	(0.0748)	(0.0802)	(0.1303)	(0.0641)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Monitor fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
F	12.33	14.68	12.77	15.51	13.44	3.4397
Kleibergen-Paap rk Wald F	68.342	53.145	12.935	16.670	16.386	11.194
N	5439	5439	5439	5439	5439	5439

Note: Standard errors clustered to prefecture-city level are placed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For simplicity, we do not report the constant term and coefficients of *Spillover*. All the columns report the results of the second stage regression of 2SLS. Column (1) does not include any other control variable except *Spillover*.

6. Conclusion and policy implication

Foreign investment has played an important role in driving China's economic growth, but it has also brought about serious environmental problems. To address the dilemma, the Chinese government has placed great emphasis on shifting from merely focusing on the expansion of foreign investment to greenization of FDI. However, due to limitations in data, existing studies have not yet assessed the environmental impact of green FDI. Based on a unique dataset, our study empirically identify the causal effects of green FDI on air pollution at a small spatial scale. Our results show that green FDI can significantly reduce local air pollution levels. Further exploration shows that local governments' greater attention paid to environmental governance can amplify the impact of green FDI on air pollution abatement. Also, in areas with severe pollution, the impact of green FDI is much more pronounced. In addition, green FDI enterprises that are in manufacturing industries, small-scale and sole-venture have larger effect on pollution reduction.

Our findings could bear implications for developing countries to better achieve a balance between economic development and environmental protection. Through evaluate the filter FDI projects, governments can facilitate the greenization of FDI, and finally contribute to the improvement of environmental quality. Also, our finding can offer suggestions for air-quality monitoring program itself to improve its efficiency. One the one hand, governments should increase the number of air-quality monitoring stations so as to ensure the impact of economic activities on the environment can be effectively captured and monitored. This is conducive to a reasonable assessment of the impact of various economic activities on the overall welfare from the perspective of environmental quality. On the other hand, more attention should also be paid to the location choice of air-quality monitoring stations to ensure the quality of air-quality monitoring data. Some local governments may deliberately establish the monitoring stations in the blocks or suburbs with better air quality for the purpose of concealing pollution to prettify their political performance, which reduces the credibility of the air pollution data. Following a uniform distribution to set up the monitoring stations rather than artificially selecting locations should be advocated in the future.

Our study has some limitations. Existing data lacks the information of regional FDI stock, and cannot construct indicators such as the proportion of green FDI enterprises. Also, our sample period is short, and we do not test and discuss the long-term impact of green FDI. Future research should pay more attention to the impact of FDI structure change on the economy, society, and environment of developing countries, and provide evidence to support for achieving more fair, effective, and sustainable international investment.

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.

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