The Effect of Foreign Direct Investment on Air Pollution in China: Evidence from the Global Financial Crisis

Shenglong Liu (Tsinghua University)
Penglong Zhang[1] (Tsinghua University)

July 2019

Abstract: In recent decades, China has been notable both for its rapidly growing foreign direct investment (FDI) and its environmental degradation. Using the exogenous shock of the 2008 financial crisis as a natural experiment, we construct instrumental variables for FDI by distinguishing between the decrease in FDI in coastal and non-coastal cities. Based on panel data from China's prefecture-level cities during 2001–2015, we study the impact of FDI on air pollution in China. The results show that FDI has significantly worsened air quality in China, and that the effect is greater in big cities. FDI in China worsens air quality through increasing pollution emissions and resource depletion.

Keywords: air pollution, foreign direct investment, pollution haven.

JEL classification: Q53, Q56, F21.

1. Introduction

Since the reform and opening up, foreign direct investment (FDI) has been regarded as the fundamental driving factor behind China's economic growth. FDI has brought China capital, skills, technology transfer, market access, and export promotion. However, China's remarkable progress during the last 40 years has been accompanied by environmental pollution problems, and air quality in urban areas has rapidly deteriorated. In 2013, China experienced some of its highest concentrations of fine particulate matter (PM2.5) on record. In the country's capital city of Beijing, for example, average PM2.5 concentrations in 2013 were 91 μg/m^3, or nine times the amount the World Health Organization (WHO) considers safe. Although China's most populated areas have experienced improvements in air quality in recent years, only 121

[1] E-mail address: zhangpenglong@tsinghua.edu.cn.

of 338 cities that were monitored met the national standard for air quality in 2018.[2] Therefore, efforts to coordinate FDI and address regional environmental issues have become a serious challenge for local governments, and the relationship between FDI and environmental pollution has attracted wide attention.

One of the most significant statements regarding the impact of foreign direct investment on the environment in the existing literature is the "pollution haven" hypothesis. In the early stages of economic development, developing countries tend to relax their environmental regulation standards, accelerate the utilization of natural resources, and produce more pollution-intensive products to attract more foreign capital inflows. However, empirical studies have failed to provide conclusive results on the "pollution haven" hypothesis. Some have found significant effects,[3] while others have rejected the hypothesis and even found evidence that FDI has reduced regional environmental pollution.[4] Foreign firms are less polluting than their peers in developing countries, and thus foreign investors help improve the environment by using more energy-efficient technology as well as cleaner sources of energy.[5] As a result, the pollution haven hypothesis is considered by Kellenberg (2009) to be "one of the most contentious issues in the debate regarding international trade, foreign investment, and the environment".

One empirical challenge in testing the pollution haven hypothesis is the problem of potential endogeneity. Previous studies have mainly tackled the potential endogeneity of environmental regulations that affect both foreign direct investment and environmental pollution. Some studies have used instrumental variables that impact environmental regulations but do not directly impact firm location decisions or trade patterns, for example, lagged environmental regulation, location-specific attributes,[6] and geographic dispersion of industries.[7] Meanwhile, other studies have used the

[2] Based on an Environment Ministry survey.
[3] See Markusen (1999), List and Co (2000), and Keller and Levinson (2002).
[4] See Antweiler et al. (2001).
[5] See Letchumanan and Kodama (2000), Eskeland and Harrison (2003), and Frankel and Rose (2005).
[6] Examples range from economic variables such as the attributes of the agricultural sector, per capita income, and public expenditure to demographic variables such as the human development index, urbanization, infant mortality, population density, and schooling, and politico-economic variables such as corruption and proxies for industry lobby bargaining power.
[7] See Millimet and Roy (2016) for a survey.

difference-in-differences method, using factors such as domestic firms or pollution control areas as a control group.[8]

In contrast to studies that use environmental regulation as the instrument, this study deals with endogeneity by using a natural experiment design as the instrument. Specifically, using the exogenous shock of the 2008 financial crisis as a natural experiment, we construct instrumental variables for FDI by distinguishing between the decrease in FDI in coastal and non-coastal cities. FDI as a share of GDP fell following the financial crisis, and it fell more in coastal areas than in non-coastal areas. Thus, the interaction of a coastal city dummy and a post-crisis dummy is used as the instrument for FDI to analyze the effects of FDI on the environment. Using panel data for China's prefecture-level cities during 2001–2015,[9] we analyzed the impact of FDI as a share of GDP on China's PM2.5 concentrations. The results showed that FDI has significantly worsened air quality in China.

We also investigated the heterogeneous effect of foreign direct investment on air pollution across cities because there are huge differences among Chinese cities in terms of factors such as consumer behavior, population size, consumer sophistication, infrastructure, human resources, and business opportunities. Specifically, we examined whether FDI in big cities behaves differently to that in small cities in terms of air pollution. To this end, we categorize China's cities into two groups based on size. Interestingly, we find that the effect of FDI on PM2.5 emissions is statistically insignificant in small cities, but statistically significant in large cities.

To ensure that our baseline results did not solely depend on the particular measures used for the independent variable and the instrumental variable, we conducted three robustness checks. The financial crisis might have affected the environment not only through the production side, which is significantly affected by foreign direct investment, but also through the consumption side, such as changes in household consumption of energy and automobiles after the financial crisis. Therefore, we instrumented FDI using

[8] See List et al. (2003), List et al. (2004), Hanna (2011), Chung (2014), and Cai et al. (2016).
[9] Some papers use city-level PM2.5 data which focus on urban areas, e.g., Barwick et. al. (2018). Our paper uses prefecture-level data because FDI activities are located in both urban and rural areas.

the total area of economic development zones (EDZs) in each city. These are special areas in which encourage foreign direct investments, where trading, exports of manufacturing goods, became one of the main aspects of economic growth (see Section 4 for further details). Larger economic development zones make local areas to attract more FDI inflows, while have limited effect on local air quality. Compared with the baseline results, the effect of FDI activities on PM2.5 by instrument of EDZS is smaller, but still significant. The second robustness check is used in relation to the measure of the independent variable. In our baseline regression, we used FDI divided by GDP to measure FDI activity. We checked our baseline results by replacing the key independent variable with FDI per worker in each city. The results remained robust. The last robustness check is to use the shorter sample period 2004–2013 to replace 2001-2015 to kick out the effect from some other significant exogenous shocks that affected the Chinese economy, e.g., the event that China joined the WTO in 2001, The financial crisis shock is still a valid instrumental variable.

Finally, this study examines the channels by which foreign direct investment worsens air quality in China. First, we find that FDI significantly increases per capita industrial use of electricity and gas, which increase the pollution directly. Also, we use firm-level data to check the indirect effect of FDI on environment, i.e., the potential effect of foreign firms on the polluting behaviors of domestic firms. The results show that foreign firms are less likely than domestic firms to be polluters. The possible reason is either that domestic firms are forced to switch to more polluting industries in response to increased competition, or that domestic firms are incented to do more business in polluting industries due to the demonstration effect.

This study contributes to the literature on the impact of foreign direct investment on China's environment. Cole et al. (2011) analyzed data from 112 major cities between 2001 and 2004 and found that the entry of multinational companies was not responsible for increasing pollution in China because these firms used advanced technology, and thus were more efficient than domestic firms in most of the developing countries. Dean et al. (2009) analyzed provincial-level data from 1993–1996 and found that foreign

firms funded through Macao, Taiwan, and Hong Kong were attracted by China's relatively weak environmental regulations. In contrast, firms that were funded through non-ethnic sources were not drawn by China's lax environmental regulations. He (2006) analyzed panel data for China's 29 provinces and found that the overall impact of FDI on industrial SO_2 emissions was very small. Liang (2005) analyzed city-level data on air pollution, industry composition, FDI, and other socioeconomic factors and found a negative correlation between FDI and air pollution, suggesting that the overall effect of FDI may be beneficial to the environment. Cai et al. (2016) analyzed city-level data for 1992–2009 and found that tougher environmental regulations lead to less FDI. Multinationals from countries with better environmental protections than China were insensitive to toughened environmental regulations, while those from countries with worse environmental protections showed significant negative responses.

This study is related to environmental studies of China. Dean and Lovely (2010) analyzed China's official data on air and water pollution and found that China's increased trade has contributed to a decline in pollution intensity. In addition to studies on trade openness, there are numerous studies focused on the environment in China, e.g., economic growth and the environment (Lee and Oh, 2015), population growth and the environment (Wang et al., 2015), fiscal decentralization and the environment (He, 2015), and firm ownership and environment (Hering and Poncet, 2014).

More broadly, our study is related to the literature on the economic impact of foreign direct investment in China, including transfer of technology (Cheung and Lin, 2004; Fleisher et al., 2010), human capital (Su and Liu, 2016), economic growth (Gunby et al., 2017), and spillover effects (Lin et al., 2009; Havranek and Irsova, 2011; Xu and Sheng, 2012). It is also related to the literature on the non-economic impacts of FDI in China, e.g., local government competition (Cheng and Kwan, 2000).

The remainder of the paper is organized as follows. Section 2 describes the data, variables, and estimation strategy. Section 3 discusses the empirical findings. Section 4 reports the results of the robustness check. Section 5 discusses the channels by which FDI affects air pollution, and Section 6 concludes.

2. Data, variables, and estimation strategy

2.1 Data and variables

Our major data source is the China City Statistical Yearbook (various years) published by the National Bureau of Statistics of China. Our data sample consists of 279 prefecture-level cities, which accounted for 85 percent of the population and 80 percent of China's GDP in 2015. Four municipalities, Beijing, Shanghai, Tianjin, and Chongqing, are excluded because they are more similar to provinces in terms of their economic size and structure.[10] The sample period is 2001–2015.

The measure of air quality is the average annual concentration of PM2.5 in $\mu g/m^3$ in each prefecture.[11] The data source is the Socioeconomic Data and Applications Center. The data estimate ground-level PM2.5 by combining aerosol optical depth retrievals from NASA's MODIS, MISR, and SeaWiFS instruments using the GEOS-Chem chemical transport model, and are subsequently calibrated to global ground-based observations using geographically weighted regression (see van Donkelaar et al. (2016) for details). We calculated the average PM2.5 concentrations for 27 provinces (municipalities and autonomous regions), 333 prefecture (contain deputy provincial) administrative regions, and 2882 county-level administrative regions[12], and used the data for prefecture-level cities as our sample.

Figure 1 shows the annual average PM2.5 concentration in China. In general, the highest PM2.5 concentrations are in the most developed and high-populated city clusters such as the Yangtze River Delta (YRD) and Beijing–Tianjin–Hebei (BTH) regions, as well as the heavy-industry region in northeast China. The PM2.5 concentration rose in most cities from 2001 to 2015, particularly those in eastern and northeastern China. As shown in Figure 3, PM2.5 concentrations rose rapidly until 2007 and then remained high, except in 2012. The average PM2.5 concentration in non-

[10] We also checked our results by adding the four Chinese municipalities to our sample. The results were similar, and thus are not reported here.

[11] Fine particles (diameter < 2.5 mm) are more hazardous than larger particles (2.5 mm < diameter < 10 mm) in terms of mortality and cardiovascular and respiratory end points, and PM2.5 is considered to be the best indicator of the level of health risks from air pollution. For more background information, see Freeman et al. (2019).

[12] We excluded the municipalities of Beijing, Tianjin, Shanghai, and Chongqing, which are under the direct control of the central government, and Hong Kong, Macao, and Taiwan

coastal areas was significantly higher than that in coastal areas, although there was a common trend in both coastal and non-coastal areas during the sample period.

The measure of FDI is FDI divided by GDP in each year for each prefecture.[13] This captures the extent to which local economic development depends on foreign capital. The data source is the China City Statistical Yearbook published by the National Bureau of Statistics of China.[14] Figure 2 shows the geographic distribution of FDI divided by GDP. It can be seen that FDI is unevenly distributed in China. In 2001, dependence on FDI was higher in the most developed and highly populated city clusters such as the Pearl River Delta, YRD, and BTH regions, all of which are coastal areas. However, in 2015, dependence on FDI decreased in those regions. Cities in central and northeastern China have increased their FDI as a share of GDP and become the most dependent of all Chinese cities on foreign capital. One reason is that the global financial crisis in 2008 reduced foreign capital inflows to most coastal cities, where FDI is concentrated in export industries. As shown in Figure 4, FDI as a share of GDP declined overall during 2001–2015. Average dependence on FDI is significantly higher in coastal areas than in non-coastal areas. FDI dependence in the sample period showed a downward trend in both coastal and non-coastal areas, especially in coastal areas, and the decline was even more pronounced after 2008.

We also introduced other control variables that might affect air pollution. Table 1 shows their summary statistics. On average, the PM2.5 concentration in prefecture-level cities is 40.39 μg/m^3 with a standard deviation of 15.89 μg/m^3. Non-coastal regions had similar levels, while coastal regions had lower PM2.5 concentrations, implying that non-coastal cities suffer more air pollution than coastal cities. During the sample period, FDI accounted for 2.15% of GDP overall, divided into 3.89% in coastal areas and 1.77% in non-coastal areas. However, Figure 3 shows that FDI as a share of GDP was very similar in coastal cities and non-coastal cities in 2015, indicating that different regions of China have gradually become similar in terms of attracting FDI. In addition, we used real GDP per capita to control for the level of economic development

[13] Hansen and Rand (2006) also used this measure.
[14] FDI is adjusted by the US dollar/RMB exchange rate for each year.

in each city.[15] Coastal areas had significantly higher levels of income than non-coastal areas. Further, secondary industry valued added as a share of GDP was used to control for the industrial structure. Manufacturing as a share of GDP is higher in coastal areas than in non-coastal areas. We used population density to control for the impact of human consumption on air quality. Data for all variables were obtained from the China City Statistical Yearbook published by the National Bureau of Statistics of China. Finally, we also controlled for non-human activities by using the natural environmental condition variables annual potential evaporation (mm), average rainfall (mm), and average temperature (°C).

Table 1. Summary statistics

	All		Non-coastal		Coastal	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
PM 2.5 (μg/m^3)	40.39	15.89	40.85	15.96	38.21	15.38
FDI/GDP (%)	2.15	2.71	1.77	1.97	3.89	4.39
Per capita GDP (10 thousand Yuan)	2.20	2.11	1.93	1.86	3.50	2.68
Second industry/GDP (%)	43.47	14.02	42.27	13.35	49.24	15.60
Population density (people per square km)	411.6	352.6	369.7	266.7	611.0	574.3
Annual potential evaporation (mm)	2.72	0.33	2.69	0.34	2.89	0.24
Annual average rainfall (mm)	80.22	40.46	75.09	37.31	104.9	45.65
Annual average temperature (°C)	14.06	5.43	13.39	5.27	17.30	5.03

Data sources: China City Statistical Yearbook published by the National Bureau of Statistics of China, the Socioeconomic Data and Applications Center, and the Gridded Climate dataset.

[15] All city-level GDP per capita are adjusted by the province-level GDP deflators (2001=100).

Panel A. 2001 Panel B. 2015

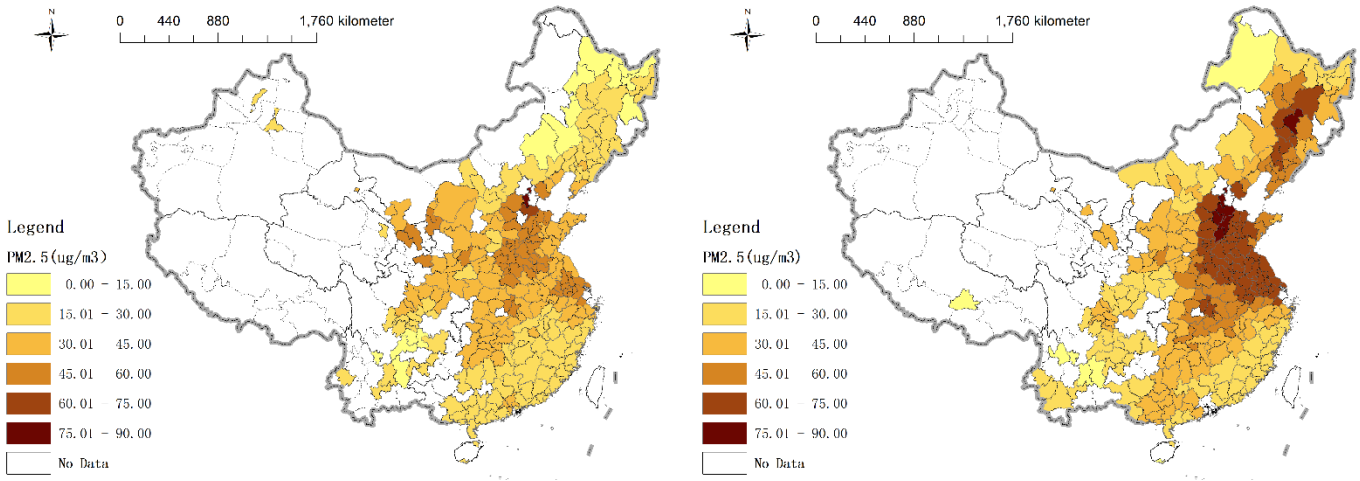


Figure 1. Average annual PM2.5 concentrations in China

Data source: Socioeconomic Data and Applications Center.

Panel A. 2001 Panel B. 2015

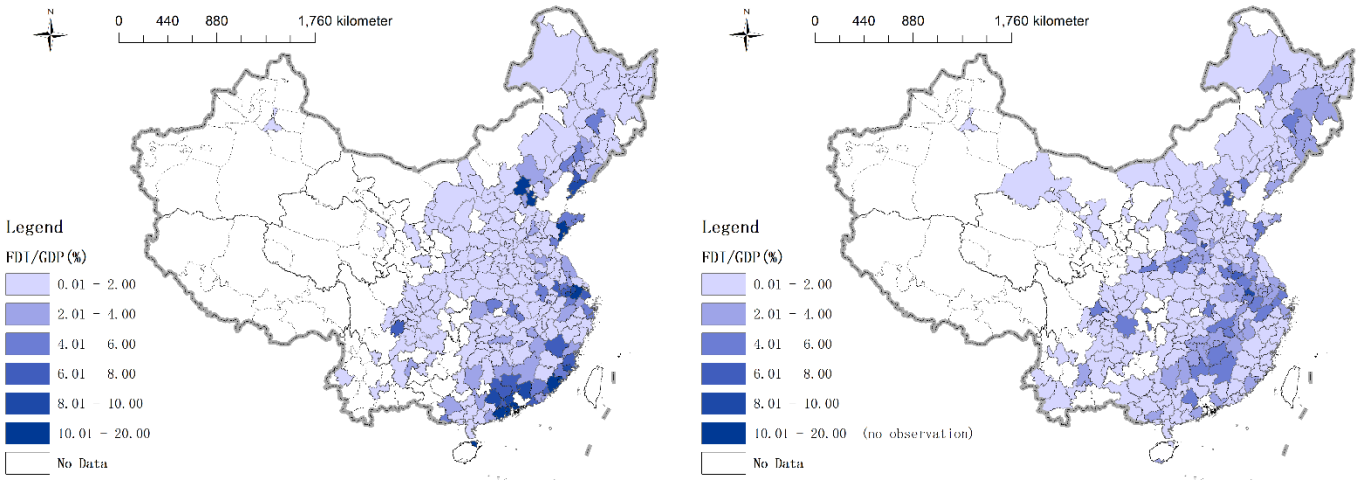


Figure 2. Geographic distribution of FDI divided by GDP in China

Data source: China City Statistical Yearbook published by the National Bureau of Statistics of China.

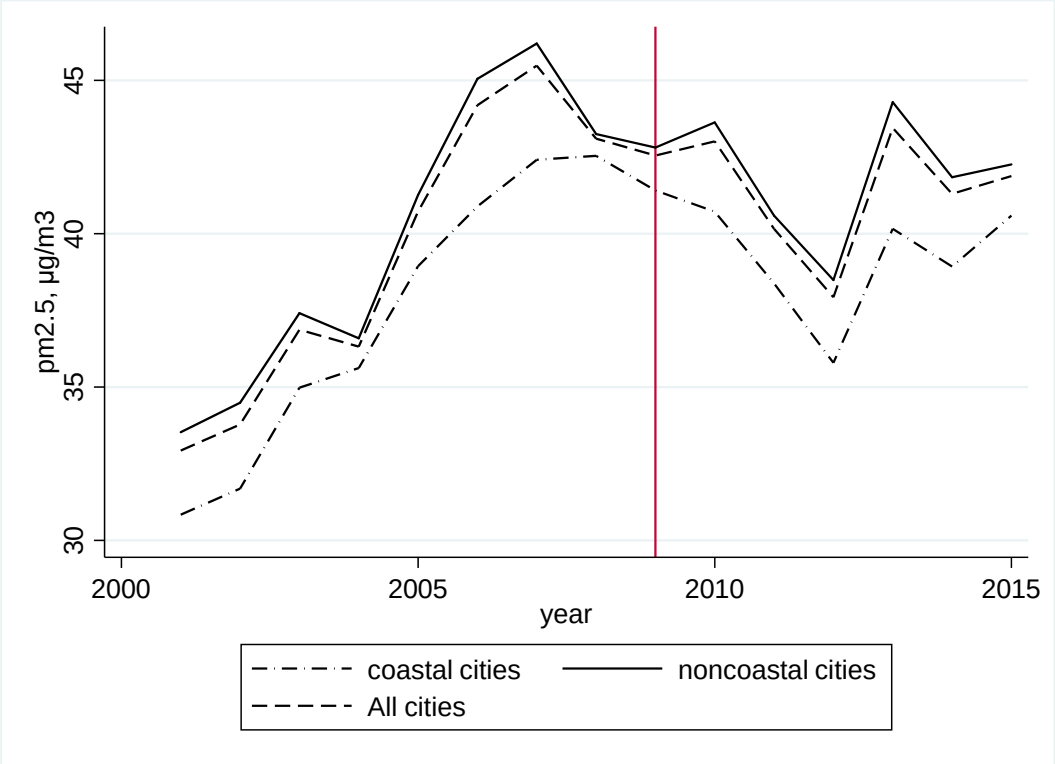


Figure 3. Average PM2.5 concentrations in China (2001–2015)

Data source: Socioeconomic Data and Applications Center.

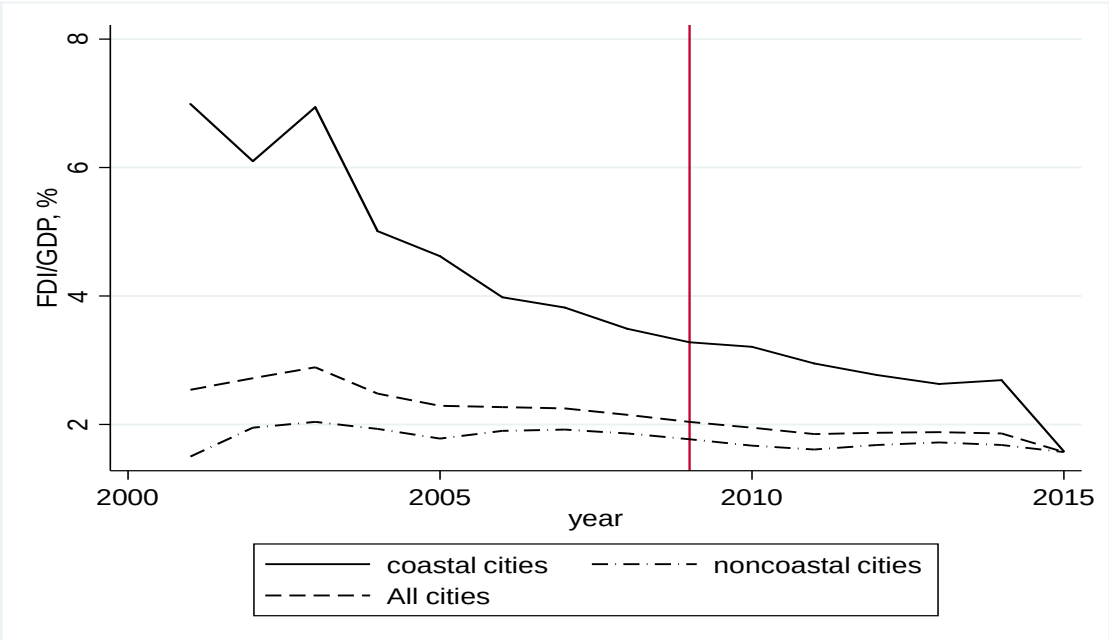


Figure 4. Average FDI divided by GDP in China (2001–2015)

Data source: China City Statistical Yearbook published by the National Bureau of Statistics of China.

2.2 Specification

To analyze whether FDI improves or worsens air quality, we test the equation:

$$PM2.5_{it} = \alpha FDI_{it-1} + \beta X_{it} + f_i + v_t + \varepsilon_{it}, \qquad (1)$$

where the dependent variable is PM2.5 concentration, the key independent variable is FDI as a share of GDP, X is a vector of all of the control variables, f_i and v_t are city- and year-specific fixed effects, and ε_{it} is the error term. The coefficient of FDI, α, is the parameter of interest.

However, neither OLS estimates nor panel data estimates are unbiased because of the endogeneity problem, despite controlling for prefecture-specific characteristics. One reason is reverse causality, whereby foreign firms choose to locate their factories where pollution is higher because of fewer regulations. Another reason is that FDI location choice may be determined simultaneously with environmental outcomes. The unobserved potential environment regulation of a prefecture may be correlated with FDI activities (see Millimet and Roy (2016)). Another example of omitted time-varying variables is the attributes of neighboring locations, which can influence the location choice for FDI (see, for example, Blonigen et al. (2007)). Because the endogeneity problem is obvious, the OLS estimate is likely to be biased, meaning that we must find the appropriate instrumental variable to estimate equation (1).

To obtain an unbiased estimate of coefficient α, we use the global financial crisis in 2008 as a natural experiment to estimate its impact on FDI inflows into China, and then identify the effect of FDI on air pollution. FDI as a share of GDP dropped more in coastal areas than in non-coastal areas after the crisis, although it decreased in both regions. Thus, we can use the different effects of the financial crisis on FDI in coastal and non-coastal areas to identify the effects of FDI on air pollution. Specifically, we use the following equation:

$$FDI_{it} = \delta d2009 * coast + \theta X_{it} + f_i + v_t + \varepsilon_{it}, \qquad (2)$$

where $d2009$ is a dummy variable that takes a value of 1 after 2008 and 0 otherwise, $coast$ is a dummy variable that takes a value of 1 for coastal cities and 0 otherwise, and δ is the coefficient of the interaction term $d2009 * coast$, which captures the effect of the financial crisis on FDI inflows in coastal cities. All of the other variables

in equation (2) are defined in the same way as in equation (1). Because the global financial crisis reduced FDI but did not directly affect air quality in China, its effect on FDI inflows into coastal cities could serve as a valid instrumental variable to identify the effects of FDI on air pollution. Our empirical strategy is similar to Blundell, Duncan, and Meghir (1998), who studied the effect of wage rates on labor supply. In their study, the endogenous wage rate is instrumented by the exogenous tax reform in the UK from 1978 to 1992, and identification is achieved because the wages of various groups of individuals are affected differently by the tax reform.

Because we also rely on the difference between coastal and non-coastal regions for identification, we need to take geographical effects on air pollution into account. For example, coastal regions tend to receive more precipitation and stronger winds, and thus have better air quality. However, these time-unvarying geographic characteristics could be absorbed by city fixed effects because they are time invariant. Therefore, the geographic effects of coastal regions on air pollution are not a concern in this study. City-specific fixed effects can also control for most time-invariant city characteristics, such as regional spillovers, corruption, and local political activism. Year fixed effects can capture most location-invariant changes, such as technology and national policy.

3. Empirical findings

3.1 OLS results

Before dealing with the endogeneity problem, we first check the OLS estimates from equation (1) to obtain the correlation pattern between FDI dependence and air pollution. Table 2 shows the OLS estimates for air pollution concentration and FDI. Column (1) shows the regression results with no control variables. The coefficient of FDI as a share of GDP is significantly positive, implying that FDI increases PM2.5 concentrations in China. Specifically, each percentage point increase in FDI as a share of GDP leads to a 0.19 $\mu g/m^3$ increase in PM2.5 concentrations. This effect becomes larger after controlling for GDP per capita and its square term, as shown in column (2). Adding more city economic characteristic variables, such as secondary industry share of GDP

and population density, makes the effect of FDI on PM2.5 concentrations even larger, as shown in column (3). The time-varying geographic characteristics produce the highest FDI coefficients, as shown in column (4). Thus, when controls remain constant, FDI is significantly positively correlated with air pollution.

The coefficients of GDP per capita and its square term are positive and negative, respectively. This implies that rising income levels first increase and then decrease air pollution. This inverted U-shaped relationship between economic development and the environment is known as the environmental Kuznets curve (EKC).[16] Possible explanations for the EKC include (i) the progress of economic development from a clean agrarian economy to a polluting industrial economy and then to a clean service economy, and (ii) the tendency of people with higher incomes to place greater importance on environmental quality.[17] Generally, any factor that promotes income growth has an indirect inverted U-shaped relationship with environmental quality. Thus, FDI improves air quality in the long term. However, the focus of this study is the short-term effect of FDI on air pollution. Thus, we did not include the square term of FDI in our main regression, leaving this for future studies.[18]

In addition, the secondary industry share of GDP is significantly positively correlated with PM2.5 concentration, as manufacturing generally causes more air pollution than the service sector. Population density is another important factor affecting PM2.5 concentration. For example, people living in areas with a high population density will have shorter distances to travel between their home and their place of employment, and will be more likely to switch from private vehicles to public transit or walking, thereby reducing vehicle emissions (Gaigné et al., 2012). Higher levels of evaporation and higher temperatures increase PM2.5 concentrations because they promote the photochemical reaction between precursors and clean the air. Meanwhile. Higher levels of rainfall reduce PM2.5 concentrations because raindrops attract tiny airborne particles to their surfaces before hitting the ground.

[16] The EKC concept emerged in the early 1990s with Grossman and Krueger's (1991) ground-breaking study of the potential impacts of NAFTA and the 1992 World Bank Development Report (IBRD, 1992).
[17] See Dinda (2004) for a survey.
[18] See Wang et al. (2015) for a discussion on the long-term effects of FDI on the environment in China.

Table 2. Air pollution concentration and FDI: OLS estimates

	(1)	(2)	(3)	(4)
Dependent variable：PM 2.5				
$(FDI/GDP)_{t-1}$	0.193***	0.203***	0.208***	0.244***
	(0.039)	(0.041)	(0.041)	(0.041)
Per capita GDP		0.605**	0.599**	0.853***
		(0.272)	(0.272)	(0.298)
Square of per capita GDP		-0.031**	-0.030**	-0.038**
		(0.015)	(0.015)	(0.016)
Second industry/GDP			0.029*	0.024
			(0.015)	(0.016)
Population density			-0.000	-0.001
			(0.001)	(0.001)
Annual potential evaporation				1.028
				(0.627)
Annual average rainfall				-0.001
				(0.004)
Annual average temperature				0.251
				(0.225)
City dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
_cons	42.422***	40.799***	39.535***	32.810***
	(0.473)	(0.837)	(1.177)	(3.951)
N	3721	3721	3720	3461
R^2	0.936	0.936	0.936	0.939

Table 2 shows the OLS estimates from equation (1). Standard errors are in parentheses, * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

3.2 Baseline results

Next we use the interaction term of the financial crisis and coastal cities as the instrumental variable for FDI dependence to conduct a two-stage least squares (2SLS) estimation using equation (1). Table 3 shows the 2SLS estimates for air pollution concentration and FDI. Column (1) shows the regression results with no control variables. The coefficient of FDI as a share of GDP is significantly positive, implying

that FDI increases PM2.5 concentrations in China. Specifically, each percentage point increase in FDI as a share of GDP leads to a 0.43 μg/m^3 increase in PM2.5 concentrations. This rises to 0.63 μg/m^3 after controlling for GDP per capita and its square term, as shown in column (2). Adding more city economic characteristic variables, such as secondary industry share of GDP and population density, increases the effect of FDI on PM2.5 concentrations to 0.68 μg/m^3, as shown in column (3). Time-varying geographic characteristics increase the FDI coefficient to 0.89 μg/m^3, as shown in column (4). Compared with the OLS estimates shown in Table 1, the PM2.5 concentrations are much greater for all specifications. This confirms that OLS estimates underestimate the true effect of FDI on the environment.

The first-stage results are also shown in Table 3. The coefficient for $d2009 * coast$ is significantly negative for each specification. The global financial crisis significantly reduced the coastal regions' dependence on FDI, implying that our instruments are powerful. The instruments are significant at the 1% level across all specifications, with all F-statistics well above the rule-of-thumb threshold.

Again, we observe an inverted U-shaped relationship between air pollution and GDP per capita, implying that rising income levels first increase and then reduce air pollution. The EKC effect is also significant in relation to the 2SLS results. In addition, a rising secondary industry share of GDP significantly increases PM2.5 concentrations, while increasing population density is another important factor that increases PM2.5 concentrations. Higher levels of evaporation increase PM2.5 concentrations, as do higher temperatures, while higher levels of rainfall reduce PM2.5 concentrations, but these effects are not significant.

The overall finding is that keeping all other necessary controls constant, FDI is significantly positively related to air pollution, and this relationship is stable. OLS estimates of the impact of FDI on PM2.5 concentrations are biased downwards. Although FDI can have both positive and negative effects on the environment, our study shows that the negative effects are dominant for Chinese cities during our sample period.

Table 3. Air pollution concentration and FDI: 2SLS estimates

	(1)	(2)	(3)	(4)
Dependent variable：PM 2.5				
$(FDI/GDP)_{t-1}$	0.425**	0.629**	0.682***	0.896***
	(0.169)	(0.244)	(0.253)	(0.332)
Per capita GDP		0.793**	0.809**	1.166***
		(0.312)	(0.315)	(0.368)
Square of per capita GDP		-0.027*	-0.025	-0.034*
		(0.016)	(0.016)	(0.018)
Second industry/GDP			0.038**	0.035*
			(0.016)	(0.018)
Population density			-0.000	-0.001
			(0.001)	(0.001)
Annual potential evaporation				1.000
				(0.642)
Annual average rainfall				0.001
				(0.005)
Annual average temperature				0.251
				(0.236)
City dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
First stage				
Coast*d2009	-1.883***	-1.405***	-1.375***	-1.098***
	(0.247)	(0.231)	(0.234)	(0.207)
Excluded F statistics	58.37	37.12	34.66	28.19
N	3719	3719	3717	3456
R^2	0.404	0.393	0.389	0.292

Table 3 shows the 2SLS estimates using equation (1). Standard errors are in parentheses, * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

3.3 Heterogeneous effects

Although all of the cities in our sample are at the prefecture level, there are significant differences among them in terms of consumer behavior, population size, consumer sophistication, infrastructure, human resources, and business opportunities. Previously, we estimated the average effect of FDI on air pollution for all locations. Using information on city characteristics, we can now investigate the possible heterogeneous effects across cities. We analyze whether FDI activities in big cities have a different effect to those in small cities in terms of air pollution. Thus, we divide the cities into two groups based on their population size. Based on a document published by the National Development and Reform Commission and National Bureau of Statistics in 2004, there are 70 large and medium-sized cities.

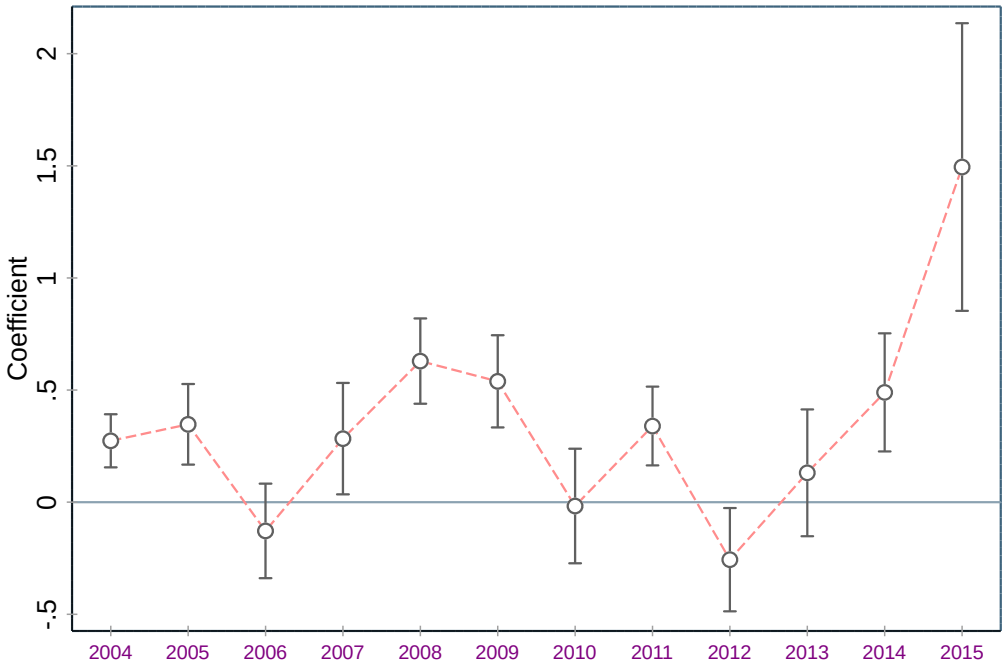
The regression results for the two groups of cities are shown in Table 4. Interestingly, we find that the effect of FDI on PM2.5 concentrations is statistically insignificant in small cities, but economically and statistically significant in big cities. The proportion of coastal cities is higher in the large and medium-sized cities group, and thus the treatment group and control group are more balanced. For example, in 2015, there were 63 large and medium-sized cities among the 279 prefecture-level cities, of which 18 (29%) were coastal cities, while of the 216 small cities in the treatment group, only 28 (13%) were coastal cities. For small cities, the treatment group is too small, so the estimation result is insignificant.

Another possible reason why FDI activities worsen air quality more in big cities is that environment regulation in big cities is usually less strict than that in small cities in China. Besides that, FDI in China occurred in large and medium-sized cities before the financial crisis. Taking the sample of 269 prefecture-level cities in 2007 as an example, 64 large and medium-sized cities received 53.72 billion US dollars in FDI, while the remaining 205 small cities received only 44.89 billion US dollars. Thus less than 25% of all cities received more than 50% of the FDI. The financial crisis had a much greater impact on large and medium-sized cities in terms of FDI, making the second phase of the estimation results more significant.

Table 4. Air pollution concentration and FDI by city size

	Big cities			Small cities		
	(1)	(2)	(3)	(2)	(3)	(4)
Dependent variable: PM 2.5						
FDI/GDP	0.589**	0.666**	0.934**	0.345	0.706+	0.844+
	(0.244)	(0.308)	(0.439)	(0.292)	(0.453)	(0.535)
Per capita GDP		1.199*	1.807**		0.581*	0.823**
		(0.720)	(0.895)		(0.329)	(0.356)
Square of p.c. GDP		-0.047	-0.069*		-0.013	-0.019
		(0.034)	(0.041)		(0.023)	(0.025)
Second ind./GDP		0.040	0.035		0.040*	0.035
		(0.036)	(0.040)		(0.021)	(0.024)
Population density		-0.001	-0.001		-0.000	-0.000
		(0.001)	(0.003)		(0.001)	(0.001)
Annual evap.			1.291			0.976
			(1.436)			(0.715)
Annual rainf.			0.011			-0.002
			(0.010)			(0.005)
Annual temp.			-0.536			0.490*
			(0.519)			(0.265)
City dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
First stage est.						
Coast*d2009	-2.40***	-2.06***	-1.51***	-1.378***	-0.949***	-0.837***
	(0.533)	(0.562)	(0.418)	(0.211)	(0.208)	(0.209)
Excluded F stat.	20.31	13.48	10.91	42.52	20.81	16.12
N	890	890	826	2829	2827	2630
R^2	0.342	0.327	0.214	0.417	0.411	0.322

Table 4 shows the 2SLS estimates using equation (1) by city size. Standard errors are in parentheses, $^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



Note：The vertical line represents the 95% confidence interval.

Figure 5. Effect of FDI on air pollution concentration (2004–2015)

We also investigate the heterogeneous effect of FDI on air quality over time. Figure 5 shows the coefficient for FDI on PM2.5 concentrations for each year during our sample period. First, it is significantly positive in most years, implying that FDI increases air pollution most of the time. Second, the coefficient displays large variations over time. Specifically, FDI had a significant polluting effect during 2008–2009, but no polluting effect in 2006 and 2010–2013. In other words, FDI had a more significant negative effect on air quality during the economic recession. One reason for this is that FDI was encouraged by local governments during the challenging economic times. Facing downward pressure on the economy, local governments in China tended to relax environmental regulations to attract more FDI and stimulate economic growth, which reduced the average quality of the FDI. The negative impact of FDI on air quality was reduced, often to an insignificant level, during 2010–2013. This might be because of the four trillion fiscal stimulus projects that make up the shortage of capital investment and the local government start to switch from quantity of FDI to quality.

4. Robustness

In this section, we conduct three separate robustness checks using different instrumental variables, measures of the key independent variable, or sample periods to make sure our baseline results are robust.

4.1 Alternative instrumental variables

In our baseline regression, we used the financial crisis in 2008 as the instrument measuring foreign direct investment to analyze the effect of FDI on air pollution. FDI as a share of GDP dropped more in coastal areas than in non-coastal areas after the crisis. However, the financial crisis might not necessarily be a completely clean instrumental variable because it might have a direct effect on the environment. For example, household consumption of energy and automobiles fell after the crisis as a result of the negative income shock, which reduced overall emissions in China. Therefore, we need to choose another instrumental variable to check whether our baseline results are robust.

The alternative instrument is the total area of EDZs in each city.[19] Since the reform and opening up, to attract more foreign capital to make up for the shortage of domestic capital, China has established a series of EDZs since 1984, starting with 14 cities along the coast and gradually extending to inland cities. By 2018, China had established 552 EDZs in various regions of the country. In the sample period from 2001 to 2015, some prefecture-level cities had no EDZs, some had them for the entire period, and others established EDZs in various years during the sample period. Thus, the EDZ variable has both cross-time and cross-sectional variations.

We use the total area of EDZs in each city adjusted for GDP as our instrumental variable. Larger EDZs attract more FDI. The area of EDZs in each city is relatively small and thus the economic activities inside have limited direct effects on air pollution. Thus, the total area of EDZs is a valid instrument for FDI activities. The data source is the China Development Zone Audit Announcement Catalogue published by the

[19] Economic development zones are special areas that encourage foreign direct investment, in which exports of manufactured goods are a main driver of economic growth. They are called "national economic and technological development zones" in some cities.

National Development and Reform Commission and the Ministry of Land and Resources in 2018. Within each cross-section, some cities have more than ten EDZs, while others have none. Numerous cities either started to establish or increased both the number and area of EDZs during the sample period.

Table 5 shows the results of robustness checks using an alternative instrumental variable, the area of EDZs divided by GDP. These results show the 2SLS estimates using equation (1), but with a different instrumental variable. City fixed effects and year fixed effects are included in all regressions. Column (1) shows the regression results with no control variables. The coefficient of FDI as a share of GDP is significantly positive, implying that FDI increases PM2.5 concentrations in China. Specifically, each percentage point increase in FDI as a share of GDP leads to a 0.22 $\mu g/m^3$ increase in PM2.5 concentrations. After controlling for GDP per capita and its square term, city economic characteristic variables, and time-varying geographic characteristics, the coefficient of FDI as a share of GDP is always stable, at around 0.2–0.3, as shown in columns (2)–(4). We also checked the results using both the financial crisis and EDZs as instruments, as shown in column (5). The results are very robust. Compared with the corresponding baseline results, the effect of FDI on PM2.5 concentrations is significant for each specification.

The first-stage results are also shown in Table 5. The coefficient for the total area of EDZs is significantly positive in each column. EDZs significantly raised dependence on FDI, implying that our instruments are powerful. Both the financial crisis and EDZs are significant in the first-stage estimation, implying that they are both valid instruments, as shown in column (5). The instruments are significant at the 1% level across the different specifications, with all F-statistics well above the rule-of-thumb threshold. Column (5), which shows the results with both the financial crisis and EDZs as instruments, also shows the results of the overidentification test (Hansen J test), which implies that the instruments are not jointly valid, as the p value is less than 0.05. Nonetheless, overall, the results are robust. FDI has significantly worsened air quality in China.

Table 5. Robustness checks using alternative instrumental variables

	(1)	(2)	(3)	(4)	(5)
Dependent variable：PM 2.5					
FDI/GDP	0.217***	0.255***	0.241***	0.206**	0.241***
	(0.057)	(0.063)	(0.061)	(0.085)	(0.089)
Per capita GDP		0.628**	0.614**	0.835***	0.851***
		(0.274)	(0.274)	(0.298)	(0.299)
Square of per capita GDP		-0.031**	-0.029**	-0.038**	-0.038**
		(0.015)	(0.015)	(0.016)	(0.016)
Second industry/GDP			0.030**	0.023	0.023
			(0.015)	(0.016)	(0.016)
Population density			-0.000	-0.001	-0.001
			(0.001)	(0.001)	(0.001)
Annual potential evaporation				1.029*	1.028*
				(0.624)	(0.624)
Annual average rainfall				-0.001	-0.001
				(0.004)	(0.004)
Annual average temperature				0.251	0.251
				(0.224)	(0.224)
City dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
First stage					
Area of EDZ/GDP	0.634***	0.602***	0.612***	0.566***	0.551***
	(0.063)	(0.071)	(0.070)	(0.104)	(0.108)
Coast*d2009					-0.572***
					(0.183)
Excluded F statistics	101.59	72.48	77.46	29.44	26.85
Hansen J statistic (p-value)					0.024
N	3719	3719	3717	3456	3456
R^2	0.410	0.411	0.412	0.332	0.332

Table 5 shows the 2SLS estimates using equation (1) with different instrumental variables. EDZ is economic development zone in each prefecture-level city. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Alternative measure for FDI activity

In our baseline regression, we used FDI as a share of GDP to measure FDI activity. The average share of GDP represented by FDI for cities in China is 2.15% with a standard deviation of 2.17%. However, it is possible that there is insufficient variation across regions, or that the relatively small share represented by FDI does not reflect the importance of FDI. Thus, we check the baseline results by replacing the key independent variable with FDI per worker in each city.[20] On average, cities receive 6,800 RMB of FDI per worker, with a standard deviation of 8,900 RMB.[21] This measure has a larger mean and larger variation across cities.

Table 6 shows the results of robustness checks using the alternative independent variable of FDI per worker. It shows the 2SLS estimates using equation (1), but with a different independent variable. City fixed effects and year fixed effects are included in all regressions. Column (1) shows the regression results with no control variables. The coefficient of FDI per worker is significantly positive, implying that FDI increases PM2.5 concentrations in China. Specifically, every 1 RMB increase in FDI per worker leads to a 0.05 μg/m^3 increase in PM2.5 concentrations. After controlling for GDP per capita and its square term, city economic characteristic variables, and time-varying geographic characteristics, the coefficient of FDI as a share of GDP is always stable at around 0.04–0.05, as shown in columns (2)–(4). The results are robust. Compared with the corresponding baseline results, the effect of FDI on PM2.5 concentrations is less significant, but remains valid at the 5% significance level.

The first-stage results are also shown in Table 6. The coefficient for $d2009 * coast$ is significantly negative in each column. The financial crisis significantly reduced the dependence of coastal regions on FDI, implying that our instruments are powerful. The instruments are all significant at the 1% level across the various specifications, with all F-statistics well above or closed to the rule-of-thumb threshold. The results are robust overall.

[20] Fleisher et al. (2010) also use this measure.

[21] FDI is adjusted using the US dollar/RMB exchange rate for each year.

Table 6. Robustness checks using an alternative measure for FDI activity

	(1)	(2)	(3)	(4)
Dependent variable：PM 2.5				
(Per worker FDI)$_{t-1}$	0.051**	0.044**	0.048**	0.058**
	(0.025)	(0.019)	(0.020)	(0.026)
Per capita GDP		-0.731	-0.882	-0.741
		(0.627)	(0.677)	(0.764)
Square of per capita GDP		0.041	0.052	0.052
		(0.038)	(0.042)	(0.049)
Second industry/GDP			0.048**	0.052**
			(0.019)	(0.024)
Population density			-0.001	-0.003*
			(0.001)	(0.001)
Annual potential evaporation				1.049
				(0.711)
Annual average rainfall				-0.001
				(0.005)
Annual average temperature				0.446*
				(0.268)
City dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
First stage				
Coast*d2009	-15.50***	-20.27***	-19.57***	-16.98***
	(5.412)	(5.558)	(5.588)	(5.605)
Excluded F statistics	8.31	13.30	12.27	9.17
N	3719	3719	3717	3456
R^2	0.308	0.345	0.328	0.183

Table 6 shows the 2SLS estimates using equation (1) with a different measure of FDI activity. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Alternative sample periods

In our baseline regression, we used the sample period 2001–2015. We used the exogenous shock of the 2008 financial crisis as a natural experiment and constructed instrumental variables for FDI by distinguishing between the decrease in FDI in coastal and non-coastal cities. To make as much use of the data as possible, we used the full sample. However, some other significant exogenous shocks also affected the Chinese economy during the sample period and might affect the results we obtained by using the financial crisis as our key natural experiment. For example, China joined the WTO in 2001, which stimulated the rapid growth of FDI in the following years. Furthermore, the global financial crisis and the European sovereign debt crisis that followed continued to affect China's economy until 2014. Thus, in this section we reduce our data window from 2001–2015 to 2004–2013 to check whether our baseline results are robust.

Table 7 shows the 2SLS estimates using equation (1) over the period 2004–2013. City fixed effects and year fixed effects are included in all regressions. Column (1) shows the regression results with no control variables. Although it is less significant,[22] the coefficient of FDI as a share of GDP is larger than that in our baseline results. Specifically, each percentage point increase in FDI as a share of GDP leads to a 0.73 $\mu g/m^3$ increase in PM2.5 concentrations. After controlling for the other variables, the coefficients of FDI as a share of GDP are even larger, as shown in columns (2)–(4). The results are robust.

The first-stage results are also shown in Table 7. The coefficient for $d2009 * coast$ is significantly negative in each column. The financial crisis significantly reduced the dependence of coastal regions on FDI, implying that our instruments are powerful. Compared with the baseline results, the first-stage estimation coefficient is smaller, implying that the change in FDI as a share of GDP in response to the financial shock is smaller over the shorter time frame. This seems more reasonable, because it eliminates the potential impact of joining the WTO.

[22] The coefficient is valid at the 15% significance level.

Table 7. Robustness test using a shorter time frame (2004–2013)

	(1)	(2)	(3)	(4)
Dependent variable：PM 2.5				
$(FDI/GDP)_{t-1}$	0.727^{+}	0.909**	0.942**	0.976**
	(0.534)	(0.400)	(0.413)	(0.422)
Per capita GDP		1.446***	1.447***	1.444***
		(0.405)	(0.415)	(0.431)
Square of per capita GDP		-0.066***	-0.065***	-0.064***
		(0.018)	(0.018)	(0.018)
Second industry/GDP			0.037*	0.038*
			(0.021)	(0.021)
Population density			-0.001	-0.001
			(0.001)	(0.001)
Annual potential evaporation				0.440
				(0.698)
Annual average rainfall				0.008
				(0.006)
Annual average temperature				0.004
				(0.277)
City dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
First stage				
Coast*d2009	-0.716***	-0.908***	-0.894***	-0.883***
	(0.175)	(0.204)	(0.207)	(0.202)
Excluded F statistics	16.85	19.75	18.64	19.12
N	2129	2673	2671	2671
R^2	0.276	0.339	0.337	0.334

Table 7 shows the 2SLS estimates using equation (1). Standard errors are in parentheses, $^{+}$ p <0.15, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Channel analysis

The previous results showed that the impact of FDI on air quality in China's prefecture-level cities is negative, and this conclusion is robust overall. Thus, the question is, how does FDI worsen the air quality in China? In this section, we provide evidence using both macro- and micro-level data. First, we check whether FDI increases resource depletion, and thus increases pollution emissions using prefecture-level data. Second, using firm-level data, we test whether domestic firms are pushed to emit more pollutants as a result of increased competition from foreign firms.

5.1 FDI and resource depletion

The existing literature shows that the effects of FDI on pollution are usually related to three economic characteristics: economic growth (scale effect), industrial composition (composition effect), and environmental regulation stringency (technique effect), which were identified by Grossman (1995) as the three economic determinants of emission from production activities. In the short run, FDI inflows generate both scale and composition effects. The scale effect refers to an increase in pollution emissions and resource depletion as a result of greater economic activity through FDI. The composition effect refers to the change in the amount of "dirty" goods as a share of GDP, which may come about because of a price change favoring their production. Income growth may also have a favorable effect on the environment in the long run by raising demand for relatively cleaner goods.

We now examine the scale effect whereby FDI increases pollution emissions and resource depletion by stimulating economic growth in the cities. The technique effect, which is related to environmental regulation stringency, will not be tested because there is already a large body of literature on this topic.[23] The composition effect is also avoided because there is neither a standard classification nor basic information about what constitutes "dirty" goods in China. In contrast to previous studies, we use prefecture-level city data to test the scale effect.

[23] See Millimet and Roy (2016) for a survey.

Table 8. Channels through which FDI affects air quality: macro-level evidence

	(1)	(2)	(3)
	electricity	coal	gas
$(FDI/GDP)_{t-1}$	129.597*	-5.696	103.324**
	(76.431)	(49.655)	(44.749)
Controls	Yes	Yes	Yes
City dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
First stage F statistics	21.37	20.55	25.51
N	3192	2791	3153

Table 8 shows the channels through which FDI affects air quality. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Controls include all of the variables shown in Table 1. 'Electricity' is industrial electricity consumption per capita (kilowatt hours), 'coal' is the industrial coal consumption per capita (tons), and 'gas' is the industrial natural gas consumption per capita (cubic meters).

Specifically, we check whether FDI increases various types of energy consumption. 'Electricity' represents industrial electricity use per capita (kilowatt hours), 'coal' represents industrial coal consumption per capita (tons), and 'gas' represents industrial natural gas consumption per capita (cubic meters). To address the potential endogeneity of FDI, we use the difference in the effects of the financial crisis on FDI in coastal and non-coastal areas, similar to our baseline regression. Again, controls include all of the variables shown in Table 1. City fixed effects and year fixed effects are included in all regressions.

Table 8 shows the results of 2SLS estimations of the various channels through which FDI affects air quality. The instruments are all significant at the 1% level for the various specifications, with all F-statistics well above the rule-of-thumb threshold. FDI increases the per capita industrial use of electricity and gas significantly, while the effect on per capita use of industrial coal is negative but not significant. Therefore, our results show that FDI significantly worsens air quality in China through the scale effect, that is, increased pollution emissions and resource depletion.

5.2 Foreign firms and domestic firms

Given our baseline results showing that FDI worsens air quality in China, we are also interested in examining whether FDI affects the emissions of domestic firms, thereby indirectly increasing PM2.5 concentrations. Thus, we implement a firm-level analysis that captures the difference between foreign and domestic firms.

The data we use are from the Annual Surveys of Industrial Production compiled by the National Bureau of Statistics of China, which contain firm-level information including the balance sheet, production, and ownership. These surveys cover all state-owned enterprises and all non-state-owned enterprises (including foreign enterprises) with total sales exceeding 5 million RMB in the industrial sector from 1995 to 2013. Unfortunately, there is no information about the firms' emissions, and thus we do not have a direct measure of the firms' pollution behavior. However, we can construct an indirect measure using the firms' industry information. Specifically, we identify whether the firm is in one of the polluting industries included in the Industrial Classification of Key Pollution Sources by the Ministry of Environmental Protection of China. In other words, we define a firm as a polluting firm if its industry is a polluting industry. In addition, industries on the list are classified into three categories based on the average level of emissions. Thus, we can use this information to divide firms into four groups (0, 1, 2, and 3) based on their level of pollution.

The results are shown in Table 9. We first test whether a foreign firm is more likely to be a polluting firm (i.e., in a polluting industry) than a domestic firm using a Probit model. The coefficient of foreign ownership is significantly negative, with or without controls and fixed effects. This implies that domestic firms are more likely than foreign firms to be polluters.[24] Control variables, age, asset, workers, and output are all significant. We also examine the effect of foreign ownership on pollution levels using an ordered Probit model. The results are robust. Overall, results show that domestic firms in China are more likely to be in highly polluting industries than foreign firms when all else equal.

[24] Note that this does not necessarily mean that foreign firms are not polluters. It simply means that they are less likely to be polluters than domestic firms.

Table 9. Channels through which FDI affects air quality: micro-level evidence

	Probit Polluting			Ordered Probit Pollution Level		
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign	-0.345***	-0.361***	-0.228***	-0.304***	-0.332***	-0.190***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Age		0.0003***	0.0007***		0.0003***	0.00008*
		(0.00006)	(0.0001)		(0.00004)	(0.00003)
ln Asset		0.115***	0.0907***		0.106***	0.0783***
		(0.0005)	(0.0006)		(0.0004)	(0.0006)
ln Labor		-0.179***	-0.174***		-0.151***	-0.155***
		(0.0009)	(0.001)		(0.0007)	(0.0009)
ln Output		0.076***	0.084***		0.067***	0.094***
		(0.0007)	(0.0009)		(0.0006)	(0.0009)
_cons	0.759***	-0.156***	0.531***			
	(0.0008)	(0.005)	(0.06)			
cut1				-0.748***	0.126***	-0.704***
				(0.0007)	(0.004)	(0.05)
cut2				-0.114***	0.771***	-0.0469
				(0.0007)	(0.004)	(0.05)
cut3				0.0804***	0.969***	0.162**
				(0.0007)	(0.004)	(0.05)
City FE	NO	NO	YES	NO	NO	YES
Year FE	NO	NO	YES	NO	NO	YES
N	3459628	3376488	2996192	3459628	3376488	2996550
R^2	0.0100	0.0311	0.0699	0.00488	0.0164	0.0434

Table 9 shows the channels through which FDI affects air quality. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Polluting' represents whether or not the firm is in a polluting industry, and 'pollution level' is the pollution level of the industry the firm is in.

There are two possible reasons why domestic firms are more likely to be polluters than foreign firms. First, foreign firms enter the market and bring the competition effect. Domestic firms are forced to switch to more polluting industries in response to increased competition. Second, some foreign polluting firms have demonstration effect. Domestic firms are incented to do more business in polluting industries. In either way, FDI increases the pollution in China indirectly.

6. Conclusion

During the past four decades, many emerging economies have experienced a growing inflow of FDI, which is now regarded as an important tool for expanding economic activities and overall progress. However, recent studies of FDI have focused on the positive impacts of FDI on economic progress and society, with little discussion of the negative effects of FDI. Whether FDI is good or bad for the environment has always been highly debated as a result of data differences and endogeneity issues.

This study deals with the endogeneity issue by using FDI as an instrumental variable. Specifically, using the exogenous shock of the 2008 financial crisis as a natural experiment, we construct instrumental variables representing FDI by distinguishing between the effects of FDI decreases on coastal and non-coastal cities. Using panel data for China's prefecture-level cities, we found that FDI has significantly worsened air quality in China. The effect of FDI on PM2.5 concentrations is economically and statistically more significant in big cities than in smaller cities. Robustness checks, using another instrumental variable, a different measure of the key independent variable, or a shorter time window, showed that the overall results were robust. It was found that FDI significantly worsened air quality in China by increasing pollution emissions and resource depletion.

There is one limitation to this study, which may provide an avenue for future research. Every dollar of FDI is considered equal in our analysis, and thus we were not able to discuss the heterogeneity of FDI in China without detailed information on FDI flows. It might also be interesting to distinguish FDI based on its country of origin. Foreign firms funded through Macao, Taiwan, and Hong Kong might have different effects on air quality compared to those funded through the US and European countries. Foreign multinationals from countries with better environmental protection regulations than those existing in China might behave differently to those from countries with worse environmental protection regulations than those in China. The effect of FDI on the environment could also be investigated based on whether it is in the export sector and whether it involves sole proprietorship or a joint venture.

References

Antweiler, Copeland, B. and Taylor, M., 2001, "Is free trade good for the environment?" *American Economic Review*, vol. 4, 877-908.

Barwick, Panle J., Shanjun Li, Deyu Rao, and Nahim Bin Zahur, 2018, "The morbidity cost of air pollution: evidence from consumers pending in China", working paper.

Blonigen, Bruce A., Ronald B. Davies, Glen R. Waddell, and Helen Naughton, 2007, "FDI in space: spatial autoregressive relationships in foreign direct investment", *European Economic Review*, 51, 1303-1325.

Blundell, R., A. Duncan, and C. Meghir, 1998, "Estimating labor supply responses using tax reforms", *Econometrica* 66, 827-861.

Cai, X., Y. Lu, M. Wu, and L. Yu., 2016, "Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China", *Journal of Development Economics*, 73-85.

Cheung, K.-Y., and Lin, P., 2004, "Spillover effects of FDI on innovation in China: evidence from the provincial data", *China Economic Review*, 15 (1): 25–44.

Chung, Sunghoon, 2014, "Environmental regulation and foreign direct investment: evidence from South Korea", *Journal of Development Economics*, 108, 222-236.

Cole, M.A., R.J.R. Elliott and J. Zhang, 2011, "Growth, foreign direct investment, and the environment: evidence from Chinese cities", *Journal of Regional Science*, 51(1): 121–138.

Dean, M. and M. Lovely, 2010, "Trade growth, production fragmentation, and China's environment", R. Feenstra and S.J. Wei (Eds.), 2010, China's growing role in world trade, NBER and University of Chicago Press, Chicago.

Dean, J.M., M.E. Lovely, and H. Wang, 2009. "Are foreign investors attracted to weak environmental regulations? Evaluating the evidence from China", *Journal of Development Economics*, 90(1): 1–13.

Deaton, A., 2005, "Measuring poverty in a growing world", *Review of Economics and Statistics*, 87, 1-19.

Dinda, Soumyananda, 2004, "Environmental Kuznets Curve hypothesis: a survey", *Ecological Economics*, 49, 431–455.

Eskeland, Gunnar S. and Harrison, Ann E., 2003, "Moving to greener pastures? Multinationals and the pollution haven hypothesis", *Journal of Development Economics*, vol.70, 1-23.

Frankel, J.A. and A.K. Rose, 2005, "Is trade good or bad for the environment? Sorting out the causality", *Review of Economics and Statistics*, 87(1): 85–91.

Freeman, Richard, Wenquan Liang, Ran Song, and Christopher Timmins, 2019, "Willingness to pay for clean air in China", *Journal of Environmental Economics and Management*, 94, 188-216.

Fleisher, B., Li, H., and Zhao, M., 2010, "Human capital, economic growth, and regional inequality in China", *Journal of Development Economics*, 92(2): 215–231.

Gaigné, C., Riou, S., and Thisse, J., 2012, "Are compact cities environmentally friendly?" *Journal of Urban Economics*, 72, 123–136.

Grossman, G., 1995, "Pollution and growth: what do we know?" In Goldin and Winter (Ed.), The Economics of Sustainable Development, Cambridge University Press.

Grossman, G. M., and Krueger, A. B., 1991, "Environmental impacts of a North American Free Trade Agreement", National Bureau of Economic Research Working Paper 3914, NBER, Cambridge MA.

Gunby, P., Jin, Y., and Reed, W., 2017, "Did FDI really cause Chinese economic growth? A meta-analysis", *World Development*, 90, 242–255.

Hanna, Rema, 2011, "US environmental regulation and FDI: evidence from a panel of US-based multinational firms", *American Economic Journal: Applied Economics*, 2, 158-189.

Hansen, H. and Rand, J., 2006, "On the causal links between FDI and growth in developing countries", *World Economy*, 29(1), 21-41.

Harris, I., Jones P. D., Osborn T. J., Lister D. H., 2014, "Updated high-resolution grids of monthly climatic observations–the CRU TS3. 10 Dataset", *International Journal of Climatology*, 34(3): 623-642.

Havranek, T. and Irsova, Z., 2011, "Estimating vertical spillovers from FDI: why results vary and what the true effect is", *Journal of International Economics*, 85(2), 234–244.

He, Jie, 2006, "Pollution haven hypothesis and environmental impacts of foreign direct investment: the case of industrial emission of sulfur dioxide in Chinese provinces", *Ecological Economics*, vol. 60, 228-245.

He, Q., 2015, "Fiscal decentralization and environmental pollution: evidence from Chinese panel data", *China Economic Review*, 36, 86-100.

Hering, Laura and Sandra Poncet, 2014, "Environmental policy and trade performance: evidence from China", *Journal of Environmental Economics and Management*, 68, 296-318.

Kellenberg, Derek K., 2009, "An empirical investigation of the pollution haven effect with strategic environment and trade policy", *Journal of International Economics*, 78, 242-255.

Keller, W. and Levinson A., 2002, "Pollution abatement costs and foreign direct investment inflow to U.S. states", *Review of Economics and Statistics*, vol.84, 691-703.

Lee, S. and D. Oh, 2015, "Economic growth and the environment in China: Empirical evidence using prefecture-level data", *China Economic Review*, 36, 73-85.

Liang, Feng Helen, 2005, "Does foreign direct investment harm the host country's environment? Evidence from China", *Academy of Management*.

Lin, P., Liu, Z., and Zhang, Y., 2009, "Do Chinese domestic firms benefit from FDI inflow? Evidence of horizontal and vertical spillovers", *China Economic Review*, 20(4), 677–691.

List, J. A., and Catherine, Y. Co., 2000, "The effects of environmental regulations on foreign direct investment", *Journal of Environmental Economics and Management*, vol. 40, 1-20.

List, John A., W. Warren McHone, and Daniel L. Millimet, 2004, "Effects of environmental regulation on foreign and domestic plant births: is there a home field advantage?" *Journal of Urban Economics*, 56, 303-326.

List, John A., Daniel L. Millimet, Per G. Fredriksson, and W. Warren McHone, 2003, "Effects of environmental regulations on manufacturing plant births: evidence from a propensity score matching estimator", *Review of Economics and Statistics*, 85, 944-952.

Markusen, J. R., 1999, "Foreign direct investment as a catalyst for industrial development", *European Economic Review*, vol. 42, 335-356.

Millimet, Daniel L., and Joyjit Roy, 2016, "Empirical tests of the pollution haven hypothesis when environmental regulation is endogenous", *Journal of Applied Economics*, 31, 652-677.

Su, Y. and Liu, Z., 2016, "The impact of foreign direct investment and human capital on economic growth: evidence from Chinese cities", *China Economic Review*, 37: 97-109.

Wang, S.X., Y.B. Fu, and Z.G. Zhang, 2015, "Population growth and the environmental Kuznets

curve", *China Economic Review*, 36: 146-16.

van Donkelaar, A., R.V Martin, M.Brauer, N. C. Hsu, R. A. Kahn, R. C Levy, A. Lyapustin, A. M. Sayer, and D. M Winker, 2016, "Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors", *Environmental Science & Technology*, 3762-3772.

Xu, X. and Sheng, Y., 2012, "Productivity spillovers from foreign direct investment: firm-level evidence from China", *World Development*, 40(1), 62–74.