The Effect of AIR POLLUTION on FOREIGN DIRECT INVESTMENT in CHINA: Evidence from SPATIAL ECONOMETRIC Analysis

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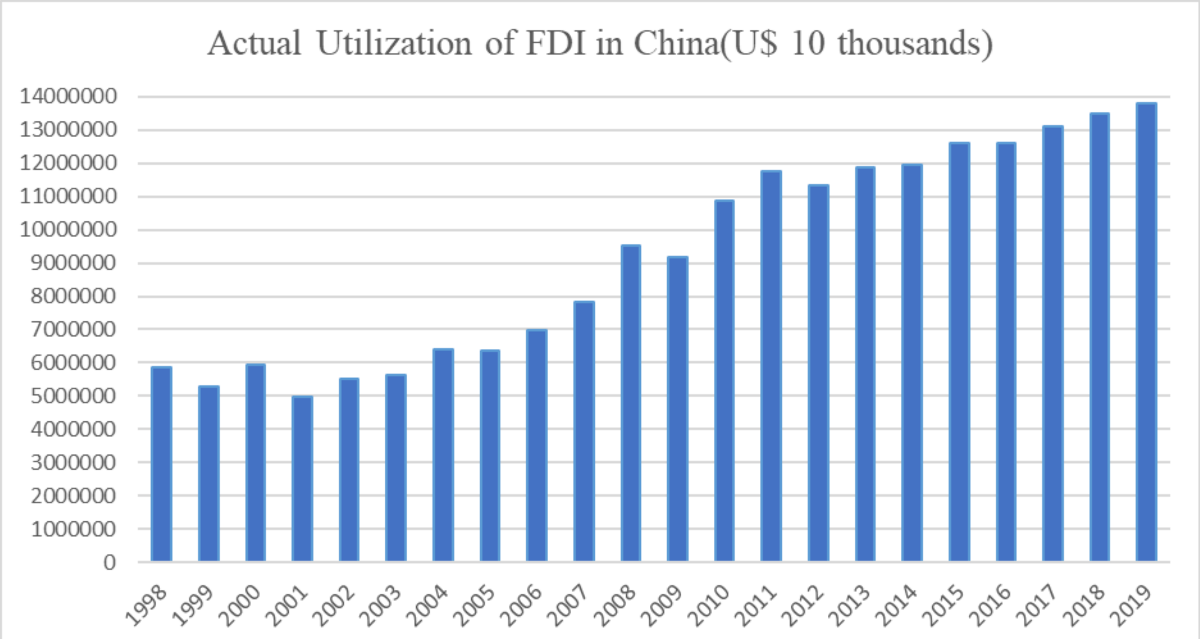
Foreign Direct Investment (FDI) in China

- FDI in China has increased from ***58.56 billion dollars in 1998*** to ***138.14 billion dollars in 2019.***
- The scale of FDI in China shows a continuously increasing overall trend with slightly fluctuation.



Foreign Direct Investment (FDI) in China

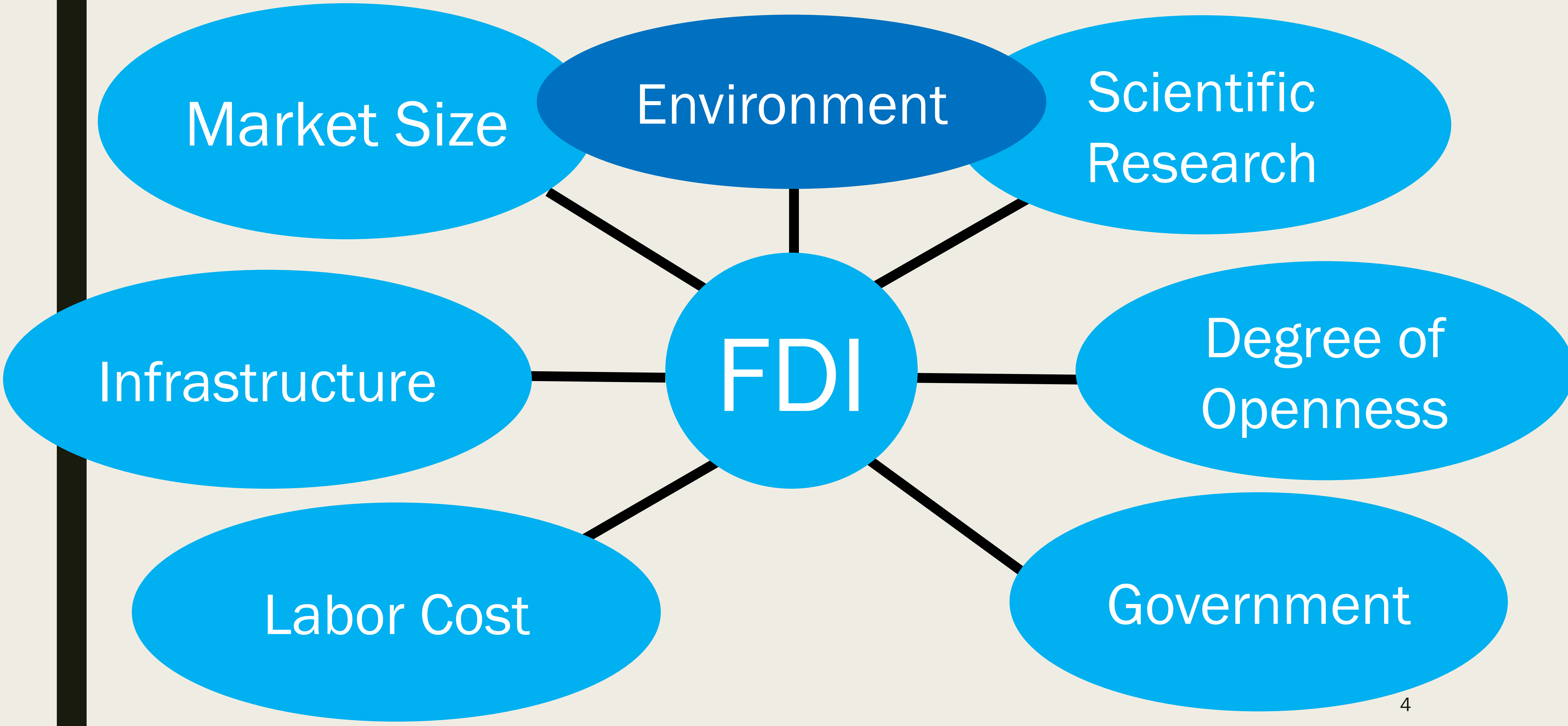
Regional Distribution of FDI in China by 2017

Region	Share of Accumulative Number of Enterprises	Share of Accumulative Actual Use of FDI
Eastern	90.4	87.5
Central	4.7	6.3
Western	4.9	6.2

Resource: Report on Foreign Investment in China 2018

- The distribution of FDI among China’s regions remains asymmetrical, showing a marked interest of investors towards the Eastern region.
- China continue to actively encouraged FDI to flow to the central and western regions and Northeast old industrial base, and 5 pilot free trade zones were set up in the central and western regions.

Determinants of FDI (Sun, Tong, and Yu 2002)



Literature Review

- One-Way of FDI inflows on environment.

(1) FDI exacerbate environmental pollution.

(2) FDI with clean technologies tends to the improvement of environment.

- Two-Way of FDI inflows on environment.
- The impact of Environment pollution on FDI.

One-Way of FDI Inflows on Environment

- Pollution Haven Hypothesis: Under the conditions of an open economy, the consequences of free trade will lead to the continuous migration of polluting industries from developed to developing countries (Walter and Ugelow 1979).
- A significant positive correlation between FDI inflows and environmental pollution (Waldkirch and Gopinath 2008; Kivyiro and Arminen 2014).
- The internal factors such as higher levels of corruption, faster economic growth, or higher human capital stock can indirectly influence the environmental quality through FDI inflows so that FDI inflows can exacerbate environmental pollution (Li and Liu 2013; Nie and Liu 2015).

One-Way of FDI Inflows on Environment

- Pollution halo hypothesis: FDI inflows can result in more clean technologies in host countries, generating technology spillovers effects and demonstration effects, which tends to contribute to the improvement of the environment (Hassaballa 2014).
- The implementation of stringent and uniform environmental standards by foreign firms also benefits host countries' environmental technology and reduces pollutant emissions (Eskeland and Harrison 2003).

Two-Way of FDI Inflows on Environment

- An increase in CO_2 emissions in low-income countries leads to FDI inflows; in middle-income countries, FDI inflows lead to an increase in CO_2 emissions; and for high-income countries, the causality is not obvious (Hoffmann et al. 2005).
- Environmental pollution can adversely affect the location decisions of FDI inflows, and heavily polluted areas do not have the ability to attract FDI inflows (Hassaballa 2014).
- The causality between environmental pollution and FDI inflows in the long run, there is a two-way causality between environmental pollution and FDI (Tang and Tan 2015).
- The causality is not obvious in the short run (Guo and Zhang 2012).

The impact of Environment pollution on FDI

- Due to the absence of geographical advantages, firms in areas with serious environmental problems are required to pay more compensation fees for pollution to employees to offset negative environmental impacts, which tends to increase the labor costs paid by the firms and may cause foreign firms to withdraw in the long run (Deng and Gao 2013).
- The improvement in human capital is a key factor to attract FDI inflows (Choi 2015).
- Air pollution negatively affects human capital (Stafford 2015).
- The deterioration of air quality enhances people’s immigration tendency (Qin and Zhu 2018).

Environmental Pollution Crowds out FDI inflows?

- Environmental pollution can damage human health and thus exert a negative impact on FDI inflows.
- Environmental pollution can increase the operating costs of firms by increasing the “hazard allowance” for pollution that they may pay, which causes the withdrawal of FDI.
- Environmental pollution can cause the loss of human capital, thereby reducing FDI.

Environmental Pollution Crowds out FDI inflows

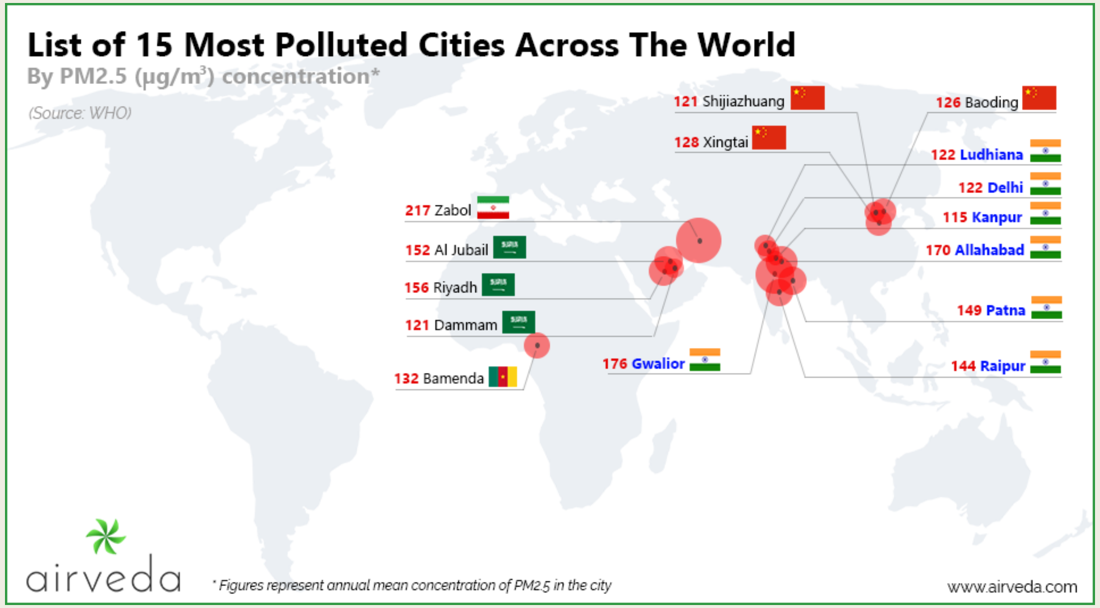
- Li and Zhang (2019) show that every 1% increase in $PM_{2.5}$ concentration, FDI flows decrease by 0.393%, and FDI stocks decrease by 0.015%.
- Air pollution may exert a negative impact on FDI inflows through its impact on the health risks of the labor force and health insurance spending of foreign firms.

$PM_{2.5}$

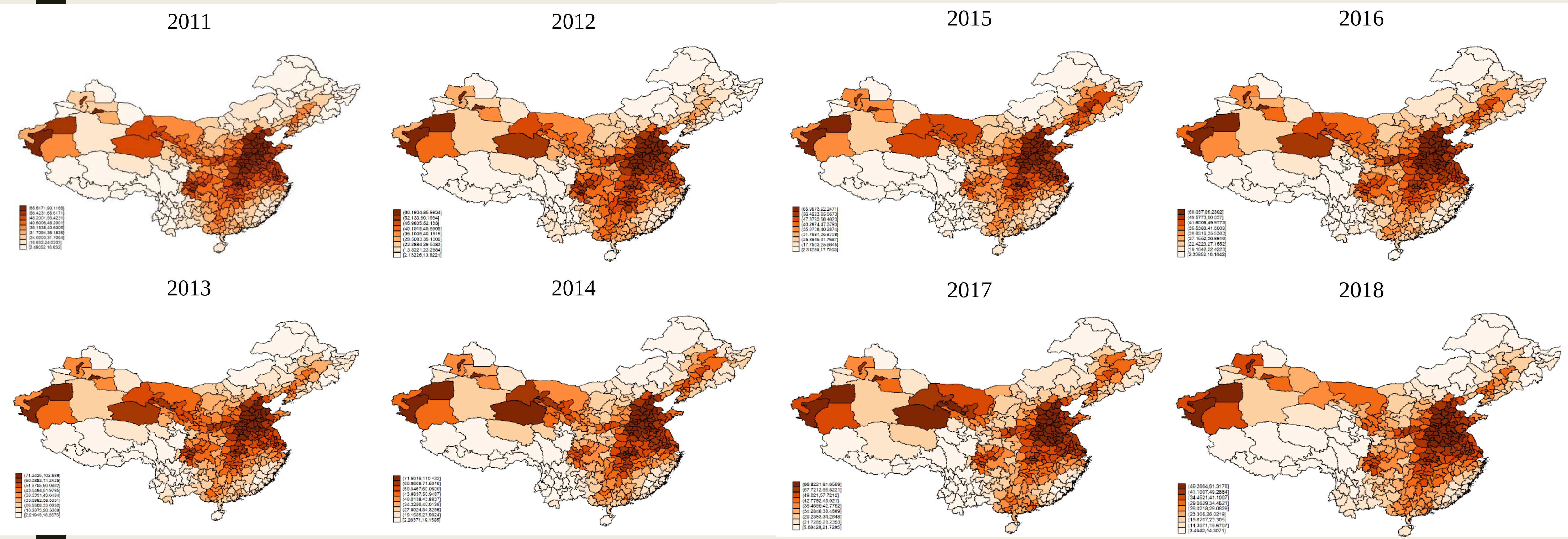
- An index of air pollution.
- Atmospheric particulate matter (PM) that have a diameter of less than 2.5 micrometers.
- About 3% the diameter of a human hair.

$PM_{2.5}$

- The air pollution indicator in this paper is concerned more with the annual average volume of prefecture-level cities' $PM_{2.5}$ concentration.
- We obtain air pollution data from Columbia University's Socioeconomic Data and Applications Center and further utilize the ArcGIS software to extract the annual PM2.5 concentration of prefecture-level cities in China from 2011 to 2018 as the main air pollution indicator.



Spatial Distribution of Prefecture-level's $PM_{2.5}$ Concentration



- *Sources: Columbia University's Socioeconomic Data and Applications Center*

The Importance of This Study

- Rare empirical literatures explore the impact of air pollution on FDI.
- The air pollution indicator in this paper is concerned more with the annual average volume of prefecture-level cities’ $PM_{2.5}$ concentration that is really the cause of FDI.
- Most of the empirical studies on the relationship between Chinese FDI and environmental pollution are based on provincial-level data, but this empirical study bases on the prefecture-level cities are rare.

The Goals of This Study

- How is the spatial dependence of FDI in prefecture-level cities of China?
- How does the air pollution affect the FDI among China's prefecture-level cities with different GRP level?

Challenge

- There may be a reverse causality between air pollution and FDI inflows, which tends to bias our estimates by endogeneity.
- Whether air pollution crowds out FDI inflows in the same way among any China’s prefecture-level cities or these with different GRP level.

Data Variable Selection

- The form of panel data from 288 prefecture-level cities in China from 2011 to 2018.
- For the data completeness by the fact Chaohu city in Anhui province was merged into Hefei city, as well as Bijie city and Tongren city in Guizhou province was established in 2011.
- The data resource is from China City Statistical Yearbook, CEIC database, and the Statistical Yearbook for each province in China.

Database Resource

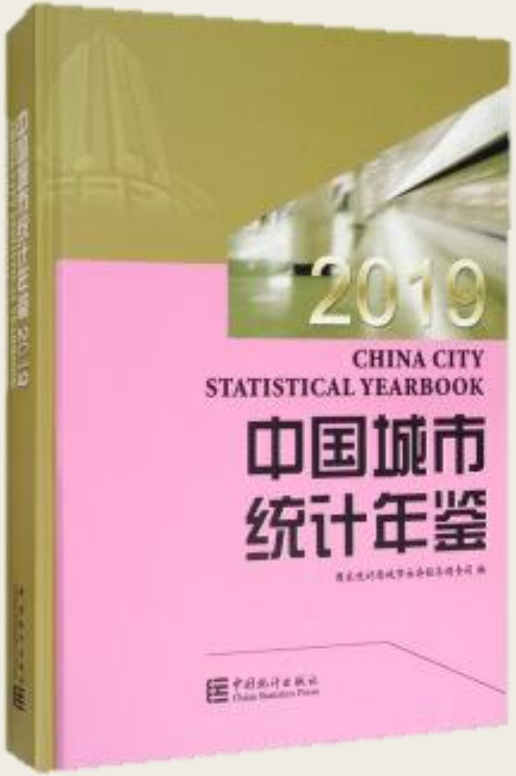


TABLE 1

Definitions and the Expected Signs of Impact of All Variables

Variables	Definition	Mean (S.D.)	LLC t-statistic	Exp. Sign
A. Dependent Variables				
$log(FDI_t)$	Logarithm of real foreign direct investment inflows.	11.44 (2.91)	-39.94 ***	
B. Independent Variables				
$PM25_t$	$PM_{2.5}$ concentration in cities, an index of air pollution. (unit: $\mu g/m^3$)	41.81 (14.66)	-25.52 ***	-
TAX_{t-1}	Corporate tax rate for the enterprises in the previous year.	0.43 (0.21)	-57.44 ***	-
SEC_{t-1}	Share of product of secondary industry to GRP in the previous year.	47.68 (10.51)	-13.91 ***	+
$log(GRP_{t-1})$	Logarithm of real gross regional product in the previous year.	16.30 (0.97)	-5.50 ***	+
$TRADE_{t-1}$	Share of sum of exports and imports in GRP in the previous year.	20.78 (41.58)	-2.89 ***	+
$log(WAGE_{t-1})$	Logarithm of real average wage of employed labors in the previous year.	10.69 (0.32)	-37.67 ***	-
$ROAD_{t-1}$	Share of area of city paved roads to land used for urban construction in the previous year.	13.6 (8.30)	-40.75 ***	+
$log(CFDI_{t-1})$	Logarithm of real cumulative foreign direct investment inflows from 1998 to the previous year.	14.68 (1.61)	-52.26 ***	+
D_{t-1}	A dummy equals to 1 if GRP is larger than the average GRP, and equals to 0 otherwise.	0.26 (0.14)		

Note: 1. The number in the parentheses are standard deviations.

*2. ***, **, and * indicate at 1%, 5%, and 10% significance level, respectively.*

3. All the variables measured by monetary values are converted into year 1998 constant prices denominated in RMB.

4. Data resources are taken from China City Statistical Yearbook, CEIC database, and the Statistical Yearbook for each province in China.

The Tax Rate for Enterprises

- TAX_{t-1} is the tax rate for enterprises for every dollar of profit invested by local investment in Chinese prefecture-level cities in the previous year.

$$TAX = \frac{VAT + STEC}{SR - SC}$$

- *VAT* is value-added tax payable, *STEC* is sales tax and extra charges, *SR* is sales revenue, and *SC* is sales cost.

Methodology

- Two-stage least squares (2SLS) method.
- The panel fix-effect estimation model in stage 1. (Huang 2018)
- The panel spatial Durbin model (SDM) in stage 2.

Spatial Econometric Model

- Spatial Durbin Model (SDM)

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \alpha + \beta \cdot x_{it} + \theta \sum_{j=1}^{n} w_{ij} x_{jt} + \mu_i + \lambda_t + \varepsilon_{it}$$

- Spatial Autoregressive Model (SAR)

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \alpha + \beta \cdot x_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

- Spatial Error Model (SEM)

$$y_{it} = \alpha + \beta \cdot x_{it} + \mu_i + \lambda_t + \varphi_{it}, \ \varphi_{it} = \pi \sum_{j=1}^{n} w_{ij} \varphi_{it} + \varepsilon_{it}$$

Spatial Econometric Model

- The SDM, extended from the SAR, was created by LeSage and Pace (2009), and includes the spatial-lag terms of both the dependent and independent variables.
- The advantage of the SDM is that it conquers the problems of omitted variables and spatial heterogeneity that might be ignored in the SAR and SEM.

Spatial Econometric Model

- Spatial Durbin Model (SDM)

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \alpha + \beta \cdot x_{it} + \theta \sum_{j=1}^{n} w_{ij} x_{jt} + \mu_i + \lambda_t + \varepsilon_{it}$$

- Spatial Autoregressive Model (SAR)

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \alpha + \beta \cdot x_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

- Spatial Error Model (SEM)

$$y_{it} = \alpha + \beta \cdot x_{it} + \mu_i + \lambda_t + \varphi_{it}, \quad \varphi_{it} = \pi \sum_{j=1}^{n} w_{ij} \varphi_{it} + \varepsilon_{it}$$

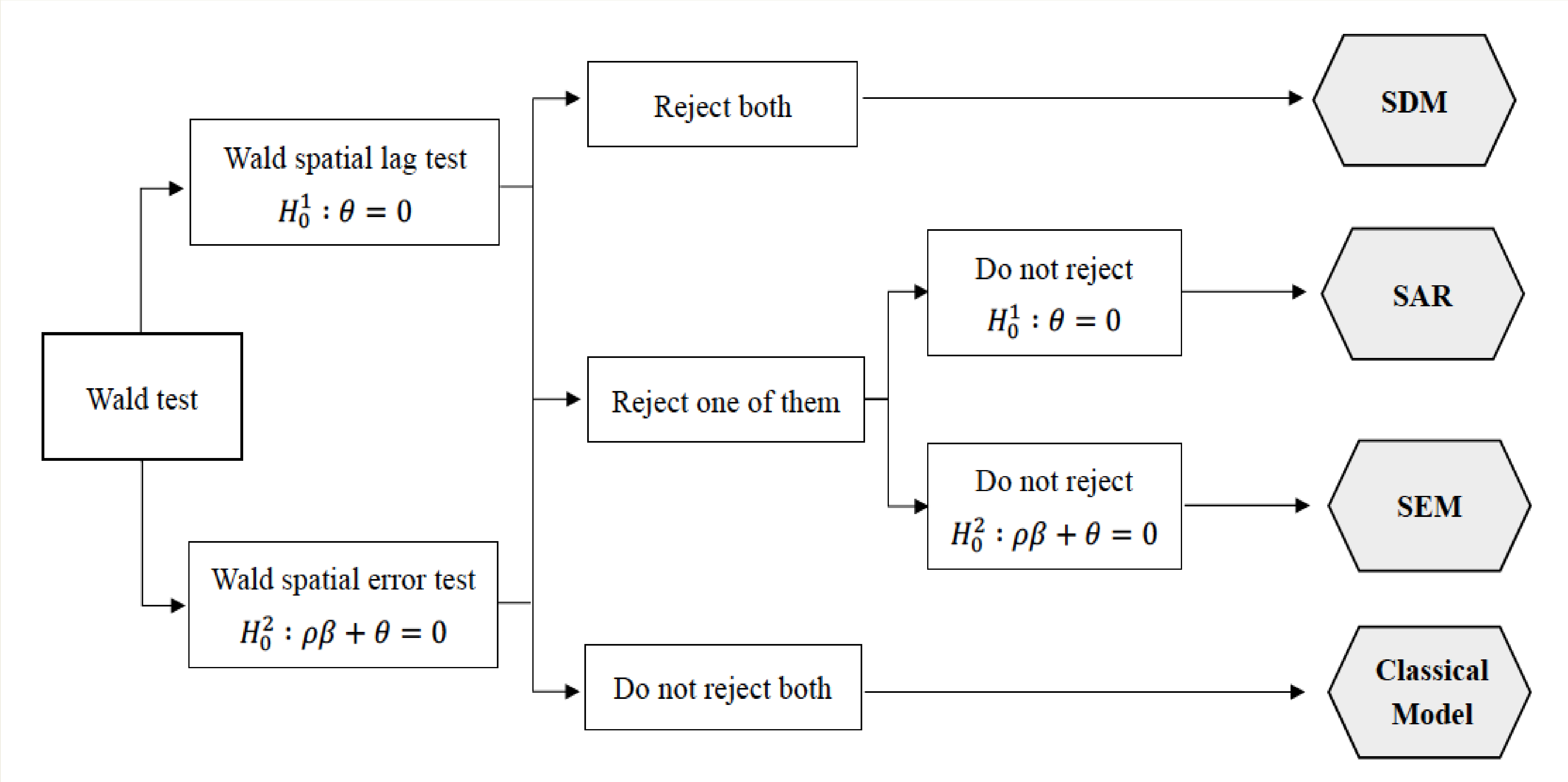
Wald Spatial Lag Test:

$H_0^1 : \theta = 0$

Wald Spatial Error Test :

$H_0^2 : \rho\beta + \theta = 0$

How to Choose Spatial Econometric Model



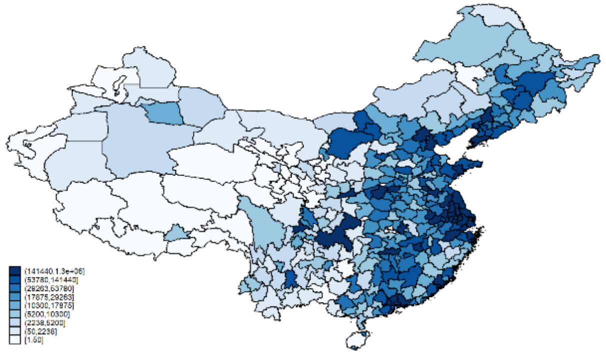
The Modeling Framework

- **Stage 1** $$PM25_{it} = \varphi_0 + \varphi_1 GRP_{it} + \varphi_2 GRP_{it}^2 + \varphi_3 GRP_{it}^3 + \varphi_4 \log(FDI_{it-1}) + \varphi_5 POP_{it} + \varphi_6 TRADE_{it} + \varphi_7 SEC_{it} + \lambda_i + \gamma_t + e_{it}$$

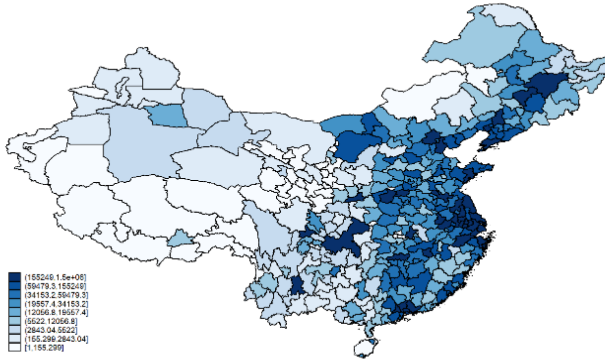
- **Stage 2** $$\begin{aligned} \log(FDI_{it}) = {} & \mu_i + \rho \sum_{j=1}^{N} w_{ij} \log(FDI_{jt}) + \alpha + \beta_1 PM25_{it} + \beta_2 PM25_{it} \times DUMMY_{it-1} \\ & + \beta_3 TAX_{it-1} + \beta_4 SEC_{it-1} + \beta_5 \log(GRP_{it-1}) + \beta_6 TRADE_{it-1} \\ & + \beta_7 \log(WAGE_{it-1}) + \beta_8 ROAD_{it-1} + \beta_9 \log(CFDI_{it-1}) \\ & + \theta_1 \sum_{j=1}^{N} w_{ij} PM25_{jt} + \theta_2 \sum_{j=1}^{N} w_{ij} PM25_{jt} \times DUMMY_{jt-1} + \theta_3 \sum_{j=1}^{N} w_{ij} TAX_{jt-1} \\ & + \theta_4 \sum_{j=1}^{N} w_{ij} SEC_{jt-1} + \theta_5 \sum_{j=1}^{N} w_{ij} \log(GRP_{jt-1}) + \theta_6 \sum_{j=1}^{N} w_{ij} TRADE_{jt-1} \\ & + \theta_7 \sum_{j=1}^{N} w_{ij} \log(WAGE_{jt-1}) + \theta_8 \sum_{j=1}^{N} w_{ij} ROAD_{ji-1} + \theta_9 \sum_{j=1}^{N} w_{ij} \log(CFDI_{jt-1}) \\ & + \varepsilon_{it}, \quad i \neq j \end{aligned}$$

Spatial Distribution of Prefecture-level’s FDI Inflows

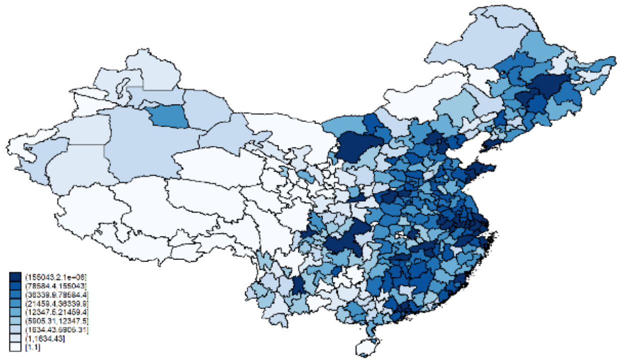
2011



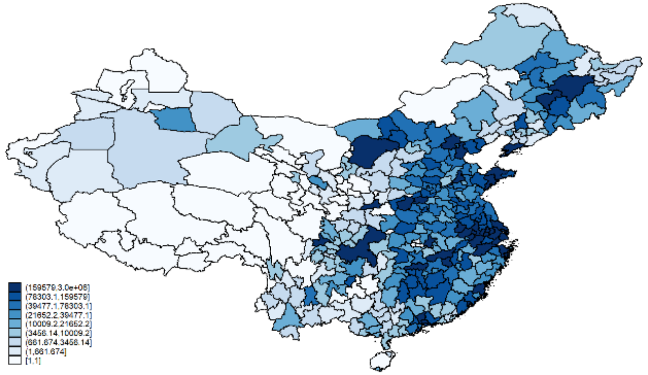
2012



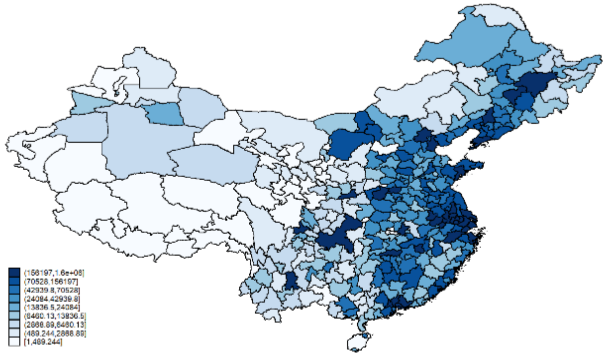
2015



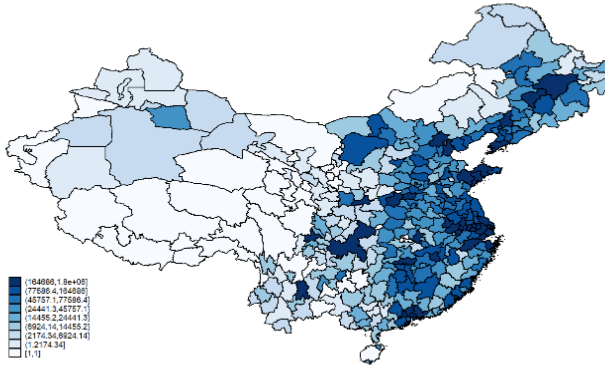
2016



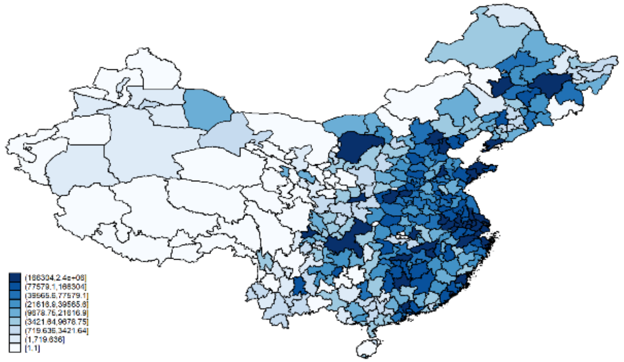
2013



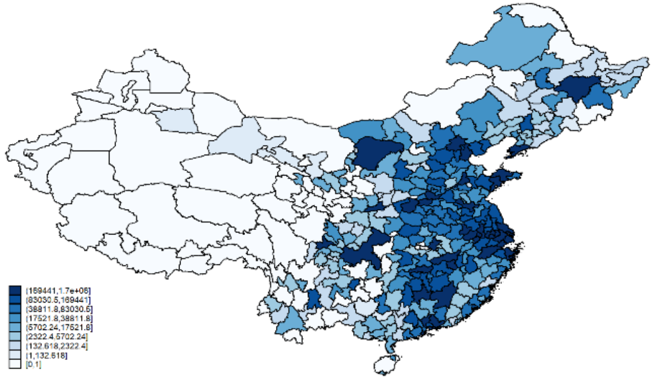
2014



2017



2018



- *Sources: China City Statistical Yearbook, CEIC database, and the Statistical Yearbook for each province in China.*

Moran's I

- A spatial correlation index proposed by Moran (1950).
- LeSage and Pace (2009) suggest that ignoring this feature in econometric models could give rise to inefficient or even biased estimates.
- According to the *p*-values, the null hypothesis of no spatial correlation is rejected at the 1% significance for each year from 2011 to 2018.
- the null hypothesis is statistically rejected, prefecture-level cities' FDI inflows in China might be characterized by positive spatial correlation.

Moran's I

Variables	I	
lfdi_2011	0.222	***
lfdi_2012	0.277	***
lfdi_2013	0.247	***
lfdi_2014	0.218	***
lfdi_2015	0.235	***
lfdi_2016	0.259	***
lfdi_2017	0.256	***
lfdi_2018	0.237	***

TABLE 2

Estimation Results of Fixed-effects SDM of FDI

Variables	β coefficient	θ coefficient	Direct Effect	Indirect Effect	Total Effect
PM25	0.01	-0.02	0.01	-0.02	-4.58×10^{-3}
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
PM25×DUMMY	5.4×10^{-4}	-0.02**	-5.5×10^{-4}	-0.02**	-0.02*
	(4.94×10^{-3})	(0.01)	(4.76×10^{-3})	(0.01)	(0.01)
TAX	-0.59***	-0.65*	-0.61***	-0.93**	-1.15***
	(0.19)	(0.35)	(0.18)	(0.43)	(0.48)
SEC	0.02**	1.47×10^{-3}	0.02***	0.01	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log(GRP)	0.32**	0.15	0.33**	0.27	0.60***
	(0.14)	(0.16)	(0.13)	(0.17)	(0.14)
TRADE	2.86×10^{-3}**	1.72×10^{-3}	3.03×10^{-3}***	2.79×10^{-3}	0.01**
	(1.11×10^{-3})	(1.77×10^{-3})	(1.1×10^{-3})	(2.06×10^{-3})	(2.39×10^{-3})
log(WAGE)	-0.86***	0.34	-0.86***	0.17	-0.69*
	(0.25)	(0.35)	(0.25)	(0.40)	(0.38)
ROAD	2.14×10^{-3}	0.01	2.36×10^{-3}	0.01	0.01
	(4.15×10^{-3})	(0.01)	(4.04×10^{-3})	(0.01)	(0.01)
Log(CFDI)	0.11	-0.02	0.12	4.32×10^{-3}	0.12
	(0.07)	(0.13)	(0.07)	(0.16)	(0.19)
ρ			0.23 ***		
			(0.03)		
Wald Spatial Lag Test			15.45*		
Wald Spatial Error Test			17.88**		
Hausman Test			38.53***		
Log-likelihood			-3788.41		
Observations			2304		

Note: 1. The number in the parentheses are standard deviations.

*2. ***, **, and * indicate at 1%, 5%, and 10% significance level, respectively.*

3. ρ denoting spatial autocorrelation parameter is the coefficient of variable of FDI.

Robust Estimation

- In order to ascertain the estimated results are robust and reliable.
- Put "the number of university (*UNIV*)" into the regression model to check whether the previous results can be changed or not.
- Education can measure human capital, and the number of universities as a rough proxy for the level of education is expected to have positive impact on the inflow of FDI (Sun, Tong and Yu 2002) .

TABLE 3
Robust Estimation Results of Fixed-effects SDM of FDI

Variables	β coefficient	θ coefficient	Direct Effect	Indirect Effect	Total Effect
PM25	0.01	-0.02	0.01	-0.02	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
PM25×DUMMY	4.2×10^{-4}	-0.02**	-6.3×10^{-4}	0.02*	-0.02*
	(4.96×10^{-3})	(0.01)	(4.77×10^{-3})	(0.01)	(0.01)
TAX	-0.59***	-0.65*	-0.62***	-0.97**	-1.61***
	(0.19)	(0.35)	(0.18)	(0.41)	(0.43)
SEC	0.02**	-1.56×10^{-4}	0.02***	0.01	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log(GRP)	0.30**	0.14	0.33**	0.25	0.58***
	(0.14)	(0.16)	(0.13)	(0.17)	(0.14)
TRADE	2.85×10^{-3}**	1.66×10^{-3}	3×10^{-3}***	2.77×10^{-3}	0.01**
	(1.11×10^{-3})	(1.77×10^{-3})	(1.11×10^{-3})	(2.14×10^{-3})	(2.63×10^{-3})
log(WAGE)	-0.86***	0.33	-0.86***	0.17	-0.68*
	(0.25)	(0.35)	(0.26)	(0.39)	(0.40)
ROAD	2.18×10^{-3}	0.01	2.34×10^{-3}	0.01	0.01
	(4.15×10^{-3})	(0.01)	(4.02×10^{-3})	(0.01)	(0.01)
Log(CFDI)	0.11	-0.02	0.12	-4.18×10^{-3}	0.11
	(0.07)	(0.13)	(0.07)	(0.16)	(0.19)
UNIV	4×10^{-3}	0.01	14.3×10^{-3}***	0.01	0.02
	(0.02)	(0.04)	(0.01)	(0.05)	(0.05)
ρ			0.23 ***		
			(0.03)		
Wald Spatial Lag Test			65.07***		
Wald Spatial Error Test			60.13***		
Hausman Test			24.02***		
Log-likelihood			-378.36		
Observations			2304		

Note: 1. The number in the parentheses are standard deviations.

*2. ***, **, and * indicate at 1%, 5%, and 10% significance level, respectively.*

3. ρ denoting spatial autocorrelation parameter is the coefficient of variable of FDI.

Concluding Remark

- A positive spatial correlation of FDI inflows among 288 prefecture-level cities in China from 2011 to 2018 exists.
- FDI can be reduced statistically by air pollution with a positive spatial correlation only in the prefecture-level cities of which GRP is larger than the average.
- The corporate tax rate for the enterprises decreases, FDI can be increased.
- The prefecture-level cities with higher GRP, shares of secondary industries to GRP, and share of sum of exports and imports in GRP will attract FDI inflows.
- prefecture-level cities with higher average wage of employed labors will cause the withdrawal of FDI inflows.

Implications

- The Chinese government must actively manage environmental problems, intensify environmental governance, and raise the market access threshold for FDI inflows in the prefecture-level cities of which GRP is larger than the average..
- Stringent environmental policies may cause the withdrawal of heavily polluting foreign firms in the short run. However, in the long run, good air quality will attract more high-quality FDI inflows, which contributes to form a good circular economic system.


Thank you