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STRATEGIC ENVIRONMENTAL REGULATION AND INBOUND FOREIGN DIRECT INVESTMENT IN THE PEOPLE'S REPUBLIC OF CHINA

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Abstract

Using a new dataset on foreign direct investment (FDI) and a comprehensive measurement of environmental policy stringency and enforcement, this paper studies the spatial distribution of inbound FDI in manufacturing sectors by accounting for strategically determined environmental policies across Chinese cities over the period 2003–2014. In particular, we investigate how the stringency of environmental regulation affects the FDI inflow of a city and its neighbors. We find strong evidence that the pollution haven hypothesis applies to the People's Republic of China based on both spatial lag of X and two-stage least-squares estimates. In particular, the laxity of a city's own environmental regulation is positively associated with its inbound FDI. We further investigate the investment deflection effect and find that the laxity of neighboring environmental regulation is negatively related to the FDI inflows to a city.

Keywords: environmental regulation, inbound foreign direct investment, SLX model, two-stage least squares, pollution haven effect

JEL Classification: C31, L51, Q56, Q58, R1

Contents

1. INTRODUCTION

Continuous interest in the relationship between environmental policy, production location, and subsequent trade and capital flows has triggered a flurry of research. The popular theory of the "pollution haven hypothesis" (PHH)[1] claims that jurisdictions with inefficiently low environmental standards or weak enforcement may attract foreign investment that seeks to reduce pollution abatement costs and maximize economic gains, consequently aggravating the pollution in the host countries. However, "the empirical validity of pollution haven effects continues to be one of the most contentious issues in the debate regarding international trade, foreign investment, and the environment" (Kellenberg 2009) due to the difficulty of measuring regulatory stringency and the fact that studies determine stringency and pollution simultaneously. Besides, a radically changed perspective on emissions responsibility is also affecting the PHH (Savona and Ciarli 2019). Moreover, most supporting evidence of the PHH concerns inward FDI in industrial countries, while weak measures of environmental stringency and insufficient data to estimate variations in pollution intensity have hampered the studies in developing countries.

This paper assesses the validity of the PHH in a sub-national jurisdiction context of the People's Republic of China (PRC) by accounting for the strategic environmental policy across cities. Proper investigation of the PHH remains of critical importance for several reasons. Despite the recent significant retrenchment of trade following the global financial crisis in 2008, the global stock of FDI increased from 46% of the world GDP in 2007 to 57% in 2016 ($25 trillion to $41 trillion) (McKinsey Global Institute (MGI) 2017). Moreover, FDI, which reflects companies' long-term strategies and is the least volatile type of capital flow, has gained a larger share of the total gross capital flows, suggesting that financial globalization will be more stable in the future. While foreign investment stocks remain highly concentrated among a handful of advanced economies, FDI flows to developing economies reached their highest level of $681 billion in 2014. In the same year, the PRC, the focus of this study, became the world's largest recipient of FDI (UNCTAD 2015). In 2016, the aggregate inbound FDI stocks in the country amounted to $2,961 billion, accounting for 26% of its GDP (MGI 2017).

Furthermore, if the PHH is true, regulators may manipulate environmental regulations to attract FDI, implying the necessity of policy coordination to avoid Pareto-inefficient levels of regulation because competition for investment may initiate a "race to the bottom" in environmental standards (Levinson 1997, 2003). As Copeland (2008) pointed out, the PHH "could create a political backlash" in environmentally stringent countries due to "concerns about losses of jobs and investment" while it could "exacerbate the effects of pollution on health and mortality" in lower-income countries with lax regulation. Given that governments at the level of sub-national jurisdictions may also leverage the stringency of environmental policy to influence capital flows, it is possible to examine the PHH within an individual country (Millimet 2013; Millimet and Roy 2016). Although strategic interaction of regulation has emerged as a prime candidate for pollution havens, little research has examined the empirical validity of these considerations.[2] The PRC provides a compelling setting to explore the PHH within the interjurisdictional competition framework, because its cadre evaluation system has

1 Pethig (1976) and McGuire (1982) first developed the theory; and Copeland and Taylor (1994); Levinson and Taylor (2008); Dijkstra, Mathew, and Mukherjee (2011); and Tang (2015), among others, later improved it.

2 Fredriksson and Millimet (2002) and Fredriksson, List, and Millimet (2004) provided evidence that US states set environmental regulation strategically based on the regulation in neighboring states.

motivated local authorities to compete with one another for investment to generate high economic growth (Maskin, Qian, and Xu 2000; Li and Zhou 2005). Besides, being a large country, the PRC provides us with substantial variations across the country in the distribution of FDI and environmental quality to identify the effects of environmental regulation.

Finally, if the location of multinational enterprise (MNE) activity can change due to environmental regulations, bringing environmental policies under the purview of existing institutional structures, such as the national constitution, may be necessary to achieve the goal of pollution abatement. As pollution is becoming the PRC's greatest health threat, the Chinese government has introduced a series of regulatory policies over recent decades. For example, in its 10th Five-Year Plan (2001–2005), released in 2001, the central government added environmental protection and pollution reduction to its list of "national strategic goals" for the first time and set a target to reduce pollutant discharges by 10% by the end of 2005. Within the new regulation framework, it assigned each province a specific target and intended to evaluate the provincial government officials on, among other things, how well they met these targets. However, little improvement on environmental quality has been observable in the PRC, because the pollution mandates that the central government imposed triggered strategic polluting responses from its provinces (Cai, Chen, and Gong 2016).

For the empirical analysis, this paper examines the impact of environmental regulation on the spatial distribution of inbound FDI to the manufacturing sector across 210 Chinese cities over the period 2003–2014. We first construct a composite index to reflect the variation of environmental policy stringency and enforcement across cities. With detailed information on the investment time, location, and sector of each project, which we obtained from a new dataset on FDI, we can assess the impact of strategic environmental regulations on the distribution of inbound FDI across different sectors and cities. We employ the spatial lag of X model (SLX) to account for the strategic competition across cities. Furthermore, we infer the causal impact of environmental policy on the inbound FDI with the two-stage least-squares (2SLS) regression, which instruments the environmental regulation of each city with its meteorological ventilation coefficient. We find robust evidence supporting the pollution haven effect. The laxity of a city's own environmental regulation is positively related to its inbound FDI. Moreover, we detect a significant investment deflection effect; that is, the laxity of environmental regulation in neighboring cities is negatively related to FDI inflows.

Our research differs from the existing literature in several aspects. First, we use a comprehensive and new database—the *fDi* Market—to uncover the whole pattern of the manufacturing FDI projects that the PRC established in the period from 2003 to 2014. The detailed information on the operating industries of each FDI project allows us to investigate whether the effect of environmental regulation varies across industries, while the information on sourcing countries enables us to investigate whether the effects of environmental regulation stringency depend on sourcing countries with different degrees of environmental protection. In addition, the time span of this database allows for the examination of the PHH during the period from 2003 to 2014, when there was a significant increase in the multinational activity in the PRC and the environmental policy was at the forefront of debates.

Second, we construct a new index to explore the regional variations in regulation stringency. The measurement of environmental regulations is complex and involves multidimensional factors. As Shadbegian and Wolverton (2010, 13) pointed out, "Measuring the level of environmental stringency in any meaningful way is quite difficult, whether at the national, state, or local level." This is because different regulations typically cover different pollutants. Multiple levels of governments (e.g., federal and local)

may enact them, while monitoring and enforcement are imperfect. Several studies have attempted to measure environmental regulation with the emission cost or intensity. By combining two observable regulation tools of the differentiated industrial electricity pricing and industrial sewage treatment fee at the city level, Auffhammer et al. (2016) developed an environmental regulation index. Due to data availability, however, Xing and Kolstad (2002), Eskeland and Harrison (2003), and Co, List, and Qui (2004) used emission intensity as a proxy for cross-country differences in environmental regulation. Based on an entropy-weighted method, we construct a composite index covering the abatement of four major pollutants, industrial sulfur dioxide (SO_2), living wastewater, living waste, and industrial solid waste, for each city. As a robustness check, we compose another indicator by adding the ratio of consumption waste treated to the abatement of these four pollutants.

Third, we incorporate the geographic spillover of environmental regulations by including the attributes of the neighboring regions, which studies have found to influence the location choice of FDI (Blonigen et al. 2007; Millimet and Roy 2015). Recent theoretical models emphasize that the scale of MNE activity in one location depends not just on the attributes of that location but also on the attributes of other potential hosts. Failure to account for geographic spillovers in empirical analyses of the PHH may lead to biased inference. This may be particularly problematic in the context of empirical analyses of inbound FDI to the PRC, where the tournament competition among city leaders is an important feature of the political system (Li and Zhou 2005; Xu 2011). A city leader's chance of promotion largely depends on GDP growth, of which investment, including FDI, is a major driver (Yu, Zhou, and Zhu 2013). Our findings suggest that a city's environmental regulations are strongly related to the regulatory stringency of its neighbors, which is consistent with Fredriksson and Millimet (2002).

The remainder of this paper proceeds as follows. Section 2 describes the empirical strategy, data source, and measurement of key variables; section 3 presents the estimation results; and section 4 concludes.

2. EMPIRICAL STRATEGY

2.1 Empirical Specification

The primary goal of this research is to estimate the effects of environmental regulation on MNEs' location choice for their investment in manufacturing sector across the PRC. Particularly, we assume that lax environmental regulation is a potential source of local comparative advantage. We simultaneously incorporate environmental regulation and pollution intensity into our model. We also control industrial, regional, and global characteristics, respectively, in this study by setting the empirical specification as:

$$FDI_{ict} = \beta_0 + \beta_1 E_{ct} \times e_{it} + \gamma X_{ct} + \lambda_i + \mu_c + \nu_t + \varepsilon_{ict} \quad (1)$$

where FDI_{ict} denotes the inbound FDI to industry *i* in city *c* of year *t*; E_{ct} is the laxity of environmental regulation in city *c* of year *t*; e_{it} represents the pollution intensity of industry *i* in year *t*; and X_{ct} is a vector of control variables for city *c*. Various theoretical studies have identified many determinants of FDI, including differences in the marginal return to capital, market size of host countries, exchange rate risk, trade impediments, and market power (Helpman 2006). In our analysis, we employ the GDP per capita as a proxy for the market size, wage for the labor cost, share of trade in the GDP for openness, education for skill abundance, and transportation infrastructure for

accessibility. Specifically, we measure the education level using the ratio of the number of high school students to the population. The number of subscribers of local telephones to the total population and the area of paved roads to the total population are two indicators reflecting a city's infrastructure status. We obtained these data from the *China City Statistical Yearbook* (CCSY) and the CEIC China Premium Database. λ_i, μ_c and ν_t capture industry, city, and year fixed effects, respectively. A city with laxer environmental regulation is likely to attract more inbound FDI for industry. In other words, a positive value of β_1 indicates that the PHH holds.

Our theoretical discussion predicts that neighboring cities may compete for FDI by adopting lax environmental regulation as a comparative advantage. To test this hypothesis, we augment the baseline model by accounting for the existence of spatial correlation. We include a "lag" term ($E_{ct} \times e_{it}$), which reflects the situation in nearby locations, in a spatial regression in the form of

$$FDI_{ict} = \beta_0 + \beta_1 E_{ct} \times e_{it} + \rho W E_{ct} \times e_{it} + \gamma \cdot X_{ct} + \lambda_i + \mu_c + \nu_t + \varepsilon_{ict} \quad (2)$$

where $W = (\omega_{cd})_{N \times N}$ is the spatial weight matrix defining the relative distance between city *c* and city *d* in period *t*.

In our estimation, we restrict W to be row-normalized with zeros on the diagonal and ensure that all the weights are between zero and one. We can interpret the weighting operations as an average of the neighboring values. That is, $W = \begin{bmatrix} 0 & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & 0 \end{bmatrix}$. The matrix describes the spatial arrangement (connections) between city *c* and city *d*. As a robustness check, we also construct the road base distance (which we manually extracted from Google Maps) spatial weight matrix.

The potential endogeneity of environmental regulations complicates the estimation of Equations (1) and (2), because they are likely to be correlated with the error term ε due to measurement error, spatial error correlation, unobserved heterogeneity, or reverse causality. For instance, a city with a comparative advantage in polluting industries might avoid implementing stringent environmental regulations. Moreover, foreign investors might negotiate with local officials for laxer environmental regulations prior to making a location choice. As the OECD (2005) stated, local Environmental Protection Boards (EPBs) across the PRC often negotiate the levels of discharge fees with firms. They are even unable to enforce environmental regulations fully when people consider noncompliant enterprises to be important for the local economy. To address these concerns, we need to instrument environmental regulation with an exogenous variable that explains the variation in environmental regulations but does not affect inbound FDI through other channels. We follow Broner, Bustos, and Carvalho's (2016) strategy of using the ventilation coefficient (V_c) as an instrumental variable for environmental regulation (E_c). According to the Box model (Jacobson 2002), the two meteorological forces of wind speed and mixing height jointly determine the pollution dispersion. The faster wind speed is helpful for pollutants to disperse horizontally, while the mixing height causes pollutants to disperse vertically. We hence calculate the ventilation coefficient as the product of wind speed and mixing height, with higher values implying faster dispersion of pollutants. Specifically, a place with a higher ventilation coefficient would have a lower pollution concentration at a given level of emissions, indicating that its environmental regulation is laxer than that of its counterparts with lower ventilation coefficients. As weather and geographic characteristics determine them exogenously, the ventilation coefficients will satisfy the exogeneity requirement. Given that the

environmental regulation (E_c) has heterogeneous effects on industries with different levels of polluting intensity (e_i), the main interest of the coefficients is on the interaction between the environmental regulation in city *c* and the polluting intensity in industry *i*, that is, $E_c \times e_i$, which we instrument with the interaction between the ventilation coefficient in city *c* and the polluting intensity of industry *i*, or ($V_c \times e_i$).

2.2 Data and Variables

Our dataset consists of 210 prefectures and municipalities, which account for around 74% of all Chinese prefectures, during the years 2003–2014. As we discussed above, the key indicators that we need for this research are: i) the inbound FDI to industry *i* in city *c*; ii) the emission intensity of an industry; iii) the laxity of environmental regulation in a city; and iv) the meteorological conditions determining a city's air pollution dispersion potential. In the following, we detail the sources of each indicator.

2.2.1 FDI

For our analysis, we need information on the FDI inflow at the city, industry, and year levels. Our FDI data come from *fDi Markets*, which fDi Intelligence, a division of the Financial Times, compiles. This database is the most comprehensive source of firm-level information on cross-border greenfield investment available, covering all countries and sectors worldwide since 2003. It provides the name of the country in which a firm engaging in greenfield FDI is headquartered, the name of the destination city, the year of investment, the recipient sector, the function (nature) of the FDI project, the type of project (new or expansion), the capital investment (capital expenditures), and the new employment associated with the project. There is no minimum investment size for including a project, but the equity stake of the foreign investor cannot be lower than 10%. The database cross-references each project against multiple sources, with the focus on direct company sources. We aggregate the firm-level data from the *fDi Markets* database at the city sector level. Our empirical analysis focuses on the capital for newly established projects to reflect the impact of environmental regulation on the location choice of MNEs.

The detailed information on the operating industries of each FDI project allows us to investigate how the effect of environmental regulation differs across industries. This is critical for testing the validity of the PHH. Given that the mobility and emission intensity vary significantly across industries, the cross-industry regressions that average over multiple industries could mask the effect of environmental regulations (Ederington, Levinson, and Minier 2005). In addition, the information on sourcing countries enables us to investigate whether the effects of environmental regulation stringency vary across countries with different degrees of environmental protection. The aggregate FDI flows may mask the distinct patterns of environmental regulations across regions.

The FDI data used in this paper are unique not only for their information coverage but also for their time span. The existing studies usually leveraged FDI data that are only valid up to the late 1990s or the early 2000s. For example, Cai et al. (2016) used a city panel from 1992 to 2001 to evaluate the impact of the Two Control Zones policy on inbound FDI to the PRC. Building on Copeland and Taylor's (2004) firm production and abatement model, Dean, Lovely, and Wang (2009) employed a provincial panel for the years 1993–1996 to evaluate the location choice of a manufacturing equity joint venture in response to inter-provincial environmental stringency. The period that we analyze in this paper, extending from 2003 to 2014, allows for the examination of the PHH during a time when there was a significant increase in the multinational activity in the PRC and the environmental policy was at the forefront of debates. Since the early years of this century, the annual FDI inflow to the PRC has more than doubled, from

$46.88 billion in 2001 to $126.27 billion in 2015, enabling the PRC to supplant the US as the largest recipient of FDI.[3] However, environmental degradation has accompanied the phenomenal economic growth that the PRC has achieved in recent decades. At the same time, being alarmed by the deteriorating water quality, accelerated pollution-related disputes and accidents, and the haze frequently plaguing Chinese cities, the central government has substantially tightened the environmental regulation since 2001. The data used in this research are able to reflect these new changes.

2.2.2 Environmental Regulation

Quantifying environmental stringency is challenging for environmental economists. Some scholars, including List and Co (2000), Keller and Levinson (2002), Ederington and Minier (2003), Ederington, Levinson, and Minier (2004), Levinson and Taylor (2008), and Ederington, Levinson, and Minier (2005), have used the abatement cost as a proxy to investigate how environmental regulation stringency affects production location, imports, and the composition of industries in the United States. However, such data are not available for most countries and the United States is the only country that has published manufacturers' pollution abatement costs at the four-digit industry level for a significant amount of time.

As an alternative, researchers have made numerous efforts to measure environmental regulation with emission intensity. For instance, Xing and Kolstad (2002), Eskeland and Harrison (2003), and Co, List, and Qui (2004) leveraged emissions of various pollutants as proxies for cross-country differences in environmental regulation. In addition, Van Soest, List, and Jeppesen (2006) created such a measure of environmental stringency based on the shadow price of energy, which Galinato and Chouinard (2018) recently used. Broner, Bustos, and Carvalho (2016) measured the cross-country laxity of environmental regulation with the average grams of lead content per liter of gasoline, as this indicator correlates well with other proxies for the environmental stance of a country (Damania, Fredriksson, and List 2003). Moreover, multidimensionality, simultaneity, industrial composition, and capital vintage are the four fundamental conceptual obstacles to measuring the stringency of environmental regulations empirically (Brunel and Levinson 2016).However, emission-specific proxies, such as SO_2, energy intensity, and the lead content of gasoline, only capture one component of environmental stringency and will be biased toward affecting capital- and energy-intensive industries.

The existing research in the Chinese context suggests that local officials' incentives and efforts to regulate pollution differ across regions and cities. Zheng et al. (2014) found that people in richer cities are willing to pay more for the clean environment, and this incentivizes their local leaders to pursue more stringent environmental regulations. Chinese regulators employ two types of environmental regulation: one is a standard-driven administrative intervention, while the other relies on economic incentives, including a pollution levy (Wang and Wheeler 2005; Lin 2013). Following the existing studies (Broner, Bustos, and Carvalho 2016; Huang, Yu, and Ma 2018), we construct a composite environmental laxity indicator to measure the geographic variations of environmental regulation, which reflects the pollution abatement requirement across cities. To quantify the city-level pollution abatement effort (PAE), we mainly concentrate on command-and-control regulation and first source the data on the four pollution abatement indicators from the CCSY and the CEIC China Premium Database, including the industrial SO_2 removal rate, the utilization ratio of industrial solid waste, the treatment

[3] The data come from the *China Statistical Yearbook 2016*, which the National Bureau of Statistics of China published, available at http://www.stats.gov.cn/tjsj/ndsj/2016/indexch.htm.

rate of living waste, and the treatment rate of living wastewater. In the PRC, firms must meet the discharge standards of pollutants and pay for the environmental protection equipment, which enables local governments to use these standards to regulate pollution-intensive industries. We assume that the lower the abatement requirement, the greater the laxity of environmental regulation. We then employ the entropy method to construct a composite index of PAE covering all these four indicators (Zou, Yi, and Sun 2006). We label the index the environmental laxity index (ELI). As a robustness check, we compose another indicator by integrating the ratio of consumption waste treated into the abovementioned four types of pollutant abatements. Appendix A presents the details of the entropy-weighted approach.

2.2.3 Pollution Intensity

The pollution intensity not only reflects the production technology of an industry but also measures its intrinsic exposure to environmental regulation stringency. However, measuring the industry pollution intensity is as challenging as measuring the environmental regulation, because such data are unavailable in most developing countries. In this research, we calculate the ratio of emissions to value added or output for each sector to gauge the pollution intensity.

In the PRC, the official statistical information on industrial pollution is only available at the two-digit level. We first collect the emissions of industrial SO_2 for each sector from the *China Statistical Yearbook on Environment*. Given that pollution emissions increase monotonically with energy use (Chung 2014), we also collect the energy consumption for each sector from the CEIC China Premium Database as another emission indicator. To calculate the emission intensity, we source the data on output and value added for each manufacturing industry from the CEIC China Premium Database. As shown in equation (3), we measure the pollution intensity through four indicators of SO_2 emissions (or energy consumption) per unit of output and SO_2 emissions (or energy consumption) per unit of value added. The units are million tons for SO_2 and energy consumption, billion RMB for output, and one hundred thousand RMB for value added.

$$\text{Pollution intensity } (e_{it}) = \frac{\text{SO2 emissions or energy consumption by industry } i \text{ in year } t}{\text{Output or value added by industry } i \text{ in year } t} \quad (3)$$

2.2.4 Ventilation Coefficient

We adopt the ventilation coefficient, which is the product of the wind speed and the mixing height, as the instrument for environmental regulation in this study. We collect data from the European Centre for Medium-Term Weather Forecasting (ECMWF) ERA-Interim dataset, which contains satellite observations of the wind speed at 10 meters above the ground and the mixing height (named the boundary layer height in the dataset) on a global grid of 0.75° × 0.75° longitude and latitude data. We match each city and the corresponding grid, and then we obtain the annual ventilation coefficient of each city over the period from 2003 to 2014 by multiplying the wind speed and mixing height. Table 1 presents the definitions and data source of the main variables that we use in this paper and their summary statistics.

Table 1: Summary Statistics and Data Source of Different Variables

Variables	Definitions	Mean	Std Dev.
FDI[a]	Inbound FDI ($ million)	11.786	135.622
Ventilation coefficient[b]	Wind speed multiplied by mixing height (1,000 m^2/s)	1.670	0.467
GDP per capita[c]	Per capita GDP	31.364	24.619
Wage[c]	Logarithm of per capita real total trade (1,000 CNY)	2.834	1.424
Trade openness[d]	Ratio of trade (import and export) and GDP	0.257	0.443
Telephone ratio[c]	Ratio of number of subscribers of local telephones to population	0.274	0.286
High-school students ratio[c]	Ratio of number of high-school students to population	0.017	0.027
Road area ratio[c]	Ratio of area of paved roads to population	0.382	0.502

Note: We sourced variables with superscripts a, b, c, and d from *fDi Markets*, ERA-Interim, the CCSY, and the CEIC China Premium Database, respectively.

3. EMPIRICAL RESULTS

3.1 Main Results

3.1.1 OLS and 2SLS Estimations

Tables 2 and 3 report the baseline results that we estimated using OLS and 2SLS, respectively. We construct four measurements of industrial pollution intensity: 1) SO_2 emissions per billion RMB of GDP; 2) SO_2 emissions per thousand RMB of value added; 3) energy consumption per 10 million RMB of GDP; and 4) energy consumption per ten thousand RMB of value added. As Equation (1) describes, we estimate the coefficients of the interaction between the environmental laxity index (ELI) and the four indices of pollution intensity, respectively. The control variables include the GDP per capita, wage, trade exposure, infrastructure, and education. Note that we use the interaction of the ventilation coefficient in city *c* and pollution intensity in industry *i* $(\mathrm{V_{ct}} \times \mathrm{e_{it}})$ as an IV for the interaction of environmental regulation in city *c* and pollution intensity in industry *i* $(\mathrm{E_{ct}} \times \mathrm{e_{it}})$ in Equation (1).

The first column of both Table 2 and Table 3 presents the estimation results for the interaction between the ELI of the local city and the pollution intensity, which we measure using the SO_2/output, while the second, third, and fourth columns present the analogous estimate for the interaction of the ELI with the SO_2/value added, energy consumption/output, and energy consumption/value added, respectively. As Table 2 shows, we find strong evidence that environmental regulation laxity exerts positive impacts on FDI, mostly statistically significant at the 5% or 10% level. The estimated coefficients presented in the first column indicate that, if a city increases its ELI by one standard deviation from the mean, then its inbound FDI to an industry that is one standard deviation above the mean pollution intensity increases by 1.8% compared with an industry of which the pollution intensity is at the sample mean. The fourth column shows that the impacts of the ELI on FDI increase to 3.2% when we consider the share of energy consumption in value added as an alternative measurement of pollution intensity.

The coefficients of the 2SLS estimate are significant and even larger than the OLS estimate, confirming the robustness of our main findings. The IV selected in our study is valid, since the Kleibergen–Paap Wald rk F statistics are much large than 10. Note that the magnitude of coefficients varies across different proxies of pollution intensity, which we measure using different units. This finding indicates that the PHH of this paper is valid

in the PRC. The laxity of environmental regulations is both a statistically and an economically significant factor of attracting FDI to high-emission industries. The introduction of the ventilation coefficient as an instrument for environmental regulation excludes reverse causality and measurement error; thus, the effect of environmental regulation on FDI is likely to be causal.

Table 2: Effects of Environmental Laxity on Inbound FDI

Variables	**(1)**	**(2)**	**(3)**	**(4)**
ELI × share of SO_2 emissions in output	0.018*			
	(0.084)			
ELI × share of SO_2 emissions in value added		0.024**		
		(0.013)		
ELI × share of energy consumption in output			0.031**	
			(0.026)	
ELI × share of energy consumption in value added				0.032*
				(0.079)
Control variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	50,400	50,400	50,400	50,400
R-squared	0.079	0.079	0.079	0.079

Notes: 1) The robust *p* value is in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) the estimation results are clustered by city; 4) ELI denotes the environmental laxity index measured using the treatment rate and utilization rate of four pollutants.

Table 3: Two-Stage Least-Squares (2SLS) Regression Results

Variables	**(1)**	**(2)**	**(3)**	**(4)**
ELI × share of SO_2 emissions in output	0.028*			
	(0.076)			
ELI × share of SO_2 emissions in value added		0.036**		
		(0.021)		
ELI × share of energy consumption in output			0.044*	
			(0.054)	
ELI × share of energy consumption in value added				0.047*
				(0.059)
Control variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	50,400	50,400	50,400	50,400
R-squared	0.003	0.003	0.003	0.004

Notes: 1) The robust *p* value is in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) the estimation results are clustered by city; 4) the column presents the second-stage estimation results.

3.1.2 Spatial Lag of X Model

We assume that the competition effect of city-level environmental regulation exists because a city's leader is motivated to lower its own regulation relative to other cities to attract more FDI. Since the spatial econometric model fully considers spatial dependence and spatial heterogeneity (i.e., how the behavior of an observation depends on the behavior of its neighbors), we employ it for further analysis.

We start by estimating the reduced spatial lag of X model (SLX), as Equation (2) shows. Recall that β_1 captures the effect of city *c*'s environmental regulation on its FDI and $\boldsymbol{\rho}$ represents the effect of its neighboring cities' regulation on this city's FDI inflow. This specification contains spatially lagged terms for the explanatory variable, and the key issue is to specify the spatial weighting matrix, W, which has the dimensions N × N with N as the number of observations. The matrix describes the spatial arrangement (connections) between city ***c*** and city ***d***. There are several weight matrices that empirical studies have widely used: the inverse distance, contiguity, common border, and nearest-neighbor matrices. To investigate how robust the results are, we try different specifications of W. Besides, we further row-normalize W to ensure that we can interpret WX as the average of neighboring observations.

Inspired by Tobler's (1970) first law of geography, "everything is related to everything else, but near things are more related than distant things," we can define W based on the inverse distance:

$$\omega_{cd} = \begin{cases} \dfrac{1}{d_{cd}} & if\ c \neq d \\ 0 & if\ c = d \end{cases} \tag{4}$$

where d_{cd} denotes the distance between city ***c*** and city ***d***, which we calculate based on the latitude and longitude of each city. This specification assumes that the cities closer to city ***c*** have more influence on its environmental regulation than those farther away. For the sake of robustness checks, we also construct an alternative spatial weight matrix reflecting the road base distance (which we manually extract from Google Maps) between cities.

Table 4 reports the basic SLX estimation results using the inverse distance as the weighting matrix. The first column presents the estimate of β_1 for the interaction of environmental regulation laxity ELI of the city, with SO_2/output as the pollution intensity, and ρ for the spillover effect of neighboring cities' weighted regulation laxity with SO_2 as the pollution intensity. The second, third, and fourth columns report the analogous estimate for SO_2/value added, energy consumption/output, and energy consumption/value added.

The estimates of β_1 for the interaction of the ELI with SO_2/output and SO_2/value added are positive and significant at the 10% and 5% levels, respectively. The estimate coefficient $\boldsymbol{\rho}$ for the interaction of neighboring cities' weighted regulation laxity ELI with SO_2/value added is negative and statistically significant at the 10% level. Others have the expected sign but are insignificant to some extent, indicating that, when neighboring cities lower their environmental regulation standards, the local city attracts less inbound FDI.

Table 4: Spatial Strategy Interaction of Environmental Laxity on Inbound FDI

Variables	(1)	(2)	(3)	(4)
ELI × share of SO_2 emissions in output	0.162*			
	(0.086)			
W.ELI × share of SO_2 emissions in output	–0.144			
	(0.107)			
ELI × share of SO_2 emissions in value added		0.119**		
		(0.045)		
W.ELI × share of SO_2 emissions in value added		–0.094*		
		(0.084)		
ELI × share of energy consumption in output			0.125	
			(0.210)	
W.ELI × share of energy consumption in output			–0.094	
			(0.316)	
ELI × share of energy consumption in value added				0.083
				(0.117)
W.ELI × share of energy consumption in value added				–0.050
				(0.276)
Control variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	50,400	50,400	50,400	50,400
R-squared	0.079	0.079	0.079	0.079

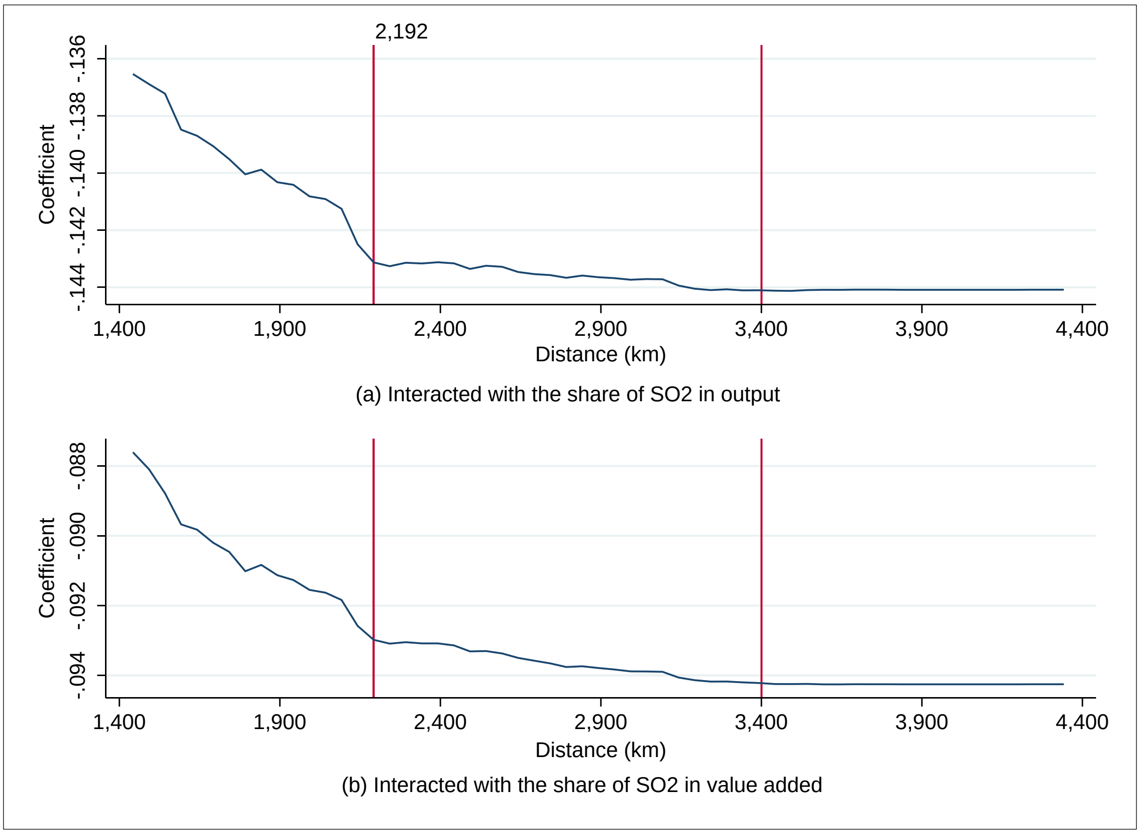
Notes: 1) The robust *p* value is in parentheses; 2) *** p < 0.01, ** p < 0.05, * p < 0.1; 3) the estimation results are clustered by city; 4) variables prefixed with "W" denote spatial lagged terms; 5) we use the SLX model (Vega and Elhorst 2015) to estimate the models.

Furthermore, we investigate the distance effect of environmental laxity on FDI by constructing spatial weighting matrices with different distance thresholds/cut-offs, which we specify as:

$$\widetilde{\omega}_{cd} = \begin{cases} \dfrac{1}{d_{cd}} & if\ d_{cd} \leq d_{threshold} \\ 0 & if\ d_{cd} > d_{threshold} \end{cases} \tag{5}$$

where $d_{threshold}$ denotes the distance threshold (km), ranging from 1,442 km (which ensures that each city has at least one neighbor, local spatial spillovers) to 4,342 km (the maximum distance between cities, global spatial spillovers) and steps equal to 50 km.

Figure 1: Distance Effects of Environmental Laxity on Inbound FDI (Color Figure Online)



We re-estimate the SLX model and focus primarily on the coefficients of $\boldsymbol{\rho}$. The results show that the spatial spillover presents obvious distance decay of which the trajectory is non-linear but with a wave-like decreasing process. Figure 1 graphically illustrates the relationship between spatial spillover coefficient $\boldsymbol{\rho}$ and geographic distance variation. According to the trend of the curve, we can divide it into three parts. The first part is the distance interval within 2,192 km, which is the interval that contains a greatly weakened spatial spillover, with the spatial spillover coefficient dropping to –0.141. The second part is the distance interval between 2,192 km and 3,400 km, for which the spatial spillover effect gradually declines. The third part is the distance in the range from 3,400 km to 4,342 km, for which the spatial spillover coefficient becomes very small. The decay curve of the spatial spillover effect with varying distance shows that closer neighbors of the local city have more weight in the spatial weighting matrix and therefore have a larger impact on the shift of investment.

To sum up, we find that the cities with laxer environmental regulations attracted more FDI, confirming the PHH in the PRC. Meanwhile, peer cities with laxer environmental regulations have a negative impact on the host city's FDI, indicating that the laxer the environmental regulations of peer cities, the lower the amount of FDI flowing to the host city. This provides evidence of geographic spillovers and strategic competition among peer cities in the PRC. Local governments indeed manipulate environmental regulation stringency and enforcement to attract FDI, which exacerbates the "race to the bottom" in environmental standards.

3.2 Robustness Checks

We construct alternative measures of the spatial weighting matrix and the ELI, respectively, to implement robustness checks. First, we manually extract the road base distance from Google Maps for each city and construct another inversed distance spatial weighting matrix based on the road base distance. Second, we compose an alternative measure of the ELI using both the ratio of consumption waste treated and the four types of pollutants (i.e., the industrial SO_2 removal rate, utilization ratio of industrial solid waste, treatment rate of living waste, and treatment rate of living wastewater). Table 5 summarizes the estimation results.

Table 5: Robustness Checks

	Alternative Specification of the Spatial Weighting Matrix				**Alternative Measure of ELI**			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ELI × share of SO_2 emissions in output	0.163*				0.215**			
	(0.087)				(0.036)			
W.ELI × share of SO_2 emissions in output	–0.145				–0.186*			
	(0.107)				(0.066)			
ELI × share of SO_2 emissions in value added		0.119**				0.121*		
		(0.046)				(0.064)		
W.ELI × share of SO_2 emissions in value added		–0.095*				–0.080		
		(0.084)				(0.166)		
ELI × share of energy consumption in output			1.255				0.227	
			(0.213)				(0.139)	
W.ELI × share of energy consumption in output			–0.948				–0.174	
			(0.318)				(0.210)	
ELI × share of energy consumption in value added				0.083				0.101
				(0.119)				(0.251)
W.ELI × share of energy consumption in value added				–0.050				–0.048
				(0.279)				(0.404)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,400	50,400	50,400	50,400	50,400	50,400	50,400	50,400
R-squared	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079

Notes: 1) The robust *p* value is in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) the estimation results are clustered by city.

Regarding the alternative specification of the spatial weighting matrix, our findings document that, as a city increases its ELI from the mean by one standard deviation, the inbound FDI of an industry that is one standard deviation above the mean pollution intensity increases by 16.3% of a standard deviation than the FDI of the mean pollution intensity (SO_2/output) and by 11.9% for SO_2/value added. At the same time, if the weighted ELI of a city's neighbors increases by one standard deviation from the mean, then the inbound FDI of an industry that is one standard deviation above the mean pollution intensity decreases by 14.5% of a standard deviation than the FDI of the mean pollution intensity (SO_2/output) and by 9.5% for SO_2/value added (significant at the 10% level).

We reach a similar conclusion with respect to the alternative measure of the ELI, as columns (5) and (6) show. The estimates of the interaction terms between the ELI and the share of energy consumption both in output and in value added are economically

consistent with our expectation. Thus, the results further support the PHH and strategic environmental regulation competition among Chinese cities.

3.3 Heterogeneous Effects

After assessing the average effect of a city and its neighboring cities' environmental regulation stringency on FDI flows over 12 years (2003–2014), we further investigate the heterogeneous effects across different time periods, regions, and industries by exploiting the detailed FDI project information.

3.3.1 Time Variation

We divide the sample into two subperiods of 2003–2010 and 2011–2014 based on the following institutional backgrounds. In 2010, the PRC basically reached the binding targets for energy conservation and emission reduction that the 11th Five-Year Plan (2006–2010) set and achieved remarkable results in energy conservation and emission reduction. During this period of time, the energy consumption elasticity coefficient dropped to 0.59, saving 630 million tons of standard coal.[4] In 2010, compared with 2005, the average annual concentration of SO_2 in key environmental protection cities decreased by 26.3%, and the environmental quality improved. The 12th Five-Year Plan (2011–2015) clearly set the target of reducing the total emissions of major pollutants by 8% to 10% and added two categories of pollution control indicators of ammonia nitrogen and nitrogen oxide. Pollution reduction projects have received substantial attention, and local performance assessment has gradually incorporated environmental quality assessment standards. In 2011, the State Council announced the 12th Five-Year Plan for national environmental protection, explicitly incorporating environmental protection into the performance appraisal of local governments at all levels for the first time and implementing a one-vote veto system for environmental protection. Given that, we further investigate the effects of the environmental laxity index on FDI during the two subperiods of time. Table 6 presents the estimation results. Our findings indicate that the coefficient of β_1 for the interaction term between ELI and SO_2/output for the second sample period is more than twice as large as that for the first sample period, implying that environmental regulation plays an even more important role in attracting FDI to a high-pollution industry when the overall regulation stringency escalates. We also find that the ELI of neighboring cities is negatively associated with the attraction of local FDI. The findings are consistent with our baseline results.

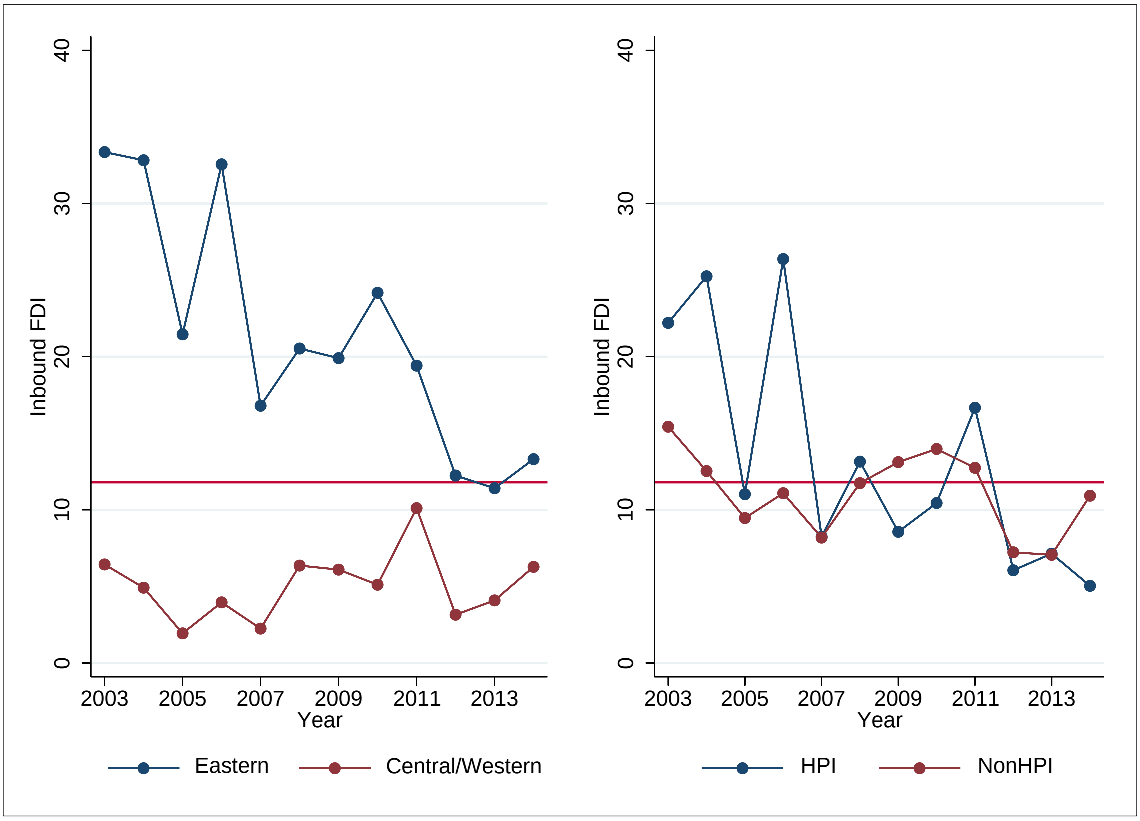
3.3.2 Regional Variation

Figure 2 further depicts the evolution of inbound FDI across regions and industries. To address the geographic heterogeneity and unobserved fixed factors, we divide the sample into coastal and inland cities. The coastal region, covering 11 provinces or manipulates (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan), attracts more FDI than the central/western region due to its location advantages. Table 7 shows that the PHH applies to the central/western region area but does not always hold in the eastern region (see column (3)). As the theory of the environmental Kuznets curve implies, the demand for a clean environment grows as the income increases. In the economically well-developed coastal region, environmental regulation is no longer a comparative advantage for attracting FDI (Fang, Huang, and Yang 2018). In contrast, the cities in inland areas of the PRC are

[4] Released by the 12th Five-Year Plan for Energy Conservation and Emission Reduction; for the official interpretation, please see http://www.gov.cn/zhengce/content/2012-08/12/content_2728.htm.

more likely to accept large firms' heavy pollution in return for the generation of local tax revenue, jobs, and economic growth.

Figure 2: Evolution of Inbound FDI across Both Regions and Industries (2003–2014) (Color Figure Online)



Note: The horizontal red line denotes the average inbound FDI.

3.3.3 Industrial Variation

According to the *Report of First National Census Blueprint on Pollution Sources* released by the State Council in 2007,[5] 6 manufacturing industries are heavily polluting in the PRC (**Appendix B** contains the classification and code of industrial sub-sectors), specifically food manufacturing (14), the textile industry (17), paper making and paper products (22), petroleum processing, coking, and nuclear fuels (25), raw chemical materials and chemical products (26), and non-metal mineral products (31). We first plot the distribution of the average inbound FDI across industries during the years 2003–2014 in Figure 3. Three industries (26, 37, and 40) attract much more FDI than the other seventeen industries. We then compare FDI in the six highly polluting industries (HPIs) and the remaining non-HPI industries. We find that the PHH holds in both HPI and non-HPI industries, as the signs of all the coefficients are consistent with our expectations (see Table 8). However, the impacts of the ELI for non-HPI industries are larger than those for HPI industries.

[5] The report is published at the website of China Bureau of Statistics http://www.stats.gov.cn/tjsj/tjgb/qttjgb/qgqttjgb/201002/t20100211_30641.html.

Figure 3: Distribution of Inbound FDI across Industries (Color Figure Online)

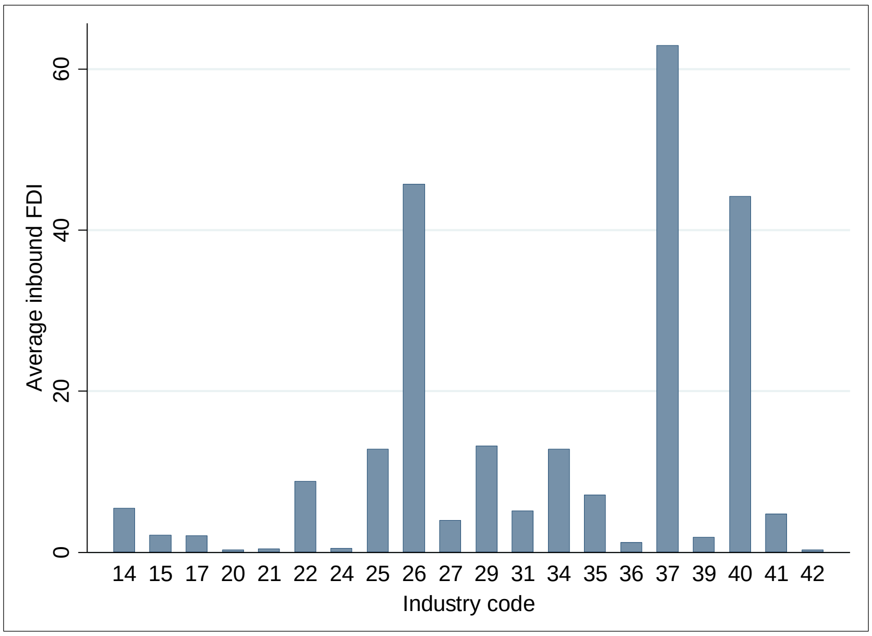


Table 6: Temporal Heterogeneity Analysis

	Period: 2003–2010				Period: 2011–2014			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ELI × share of SO_2 emissions in output	0.167*				0.483**			
	(0.070)				(0.023)			
W.ELI × share of SO_2 emissions in output	–0.147*				–0.154			
	(0.088)				(0.406)			
ELI × share of SO_2 emissions in value added		0.130**				0.197		
		(0.035)				(0.174)		
W.ELI × share of SO_2 emissions in value added		–0.100*				–0.022		
		(0.067)				(0.578)		
ELI × share of energy consumption in output			0.129				0.106	
			(0.189)				(0.219)	
W.ELI × share of energy consumption in output			–0.099				–0.007	
			(0.278)				(0.951)	
ELI × share of energy consumption in value added				0.094				0.076
				(0.111)				(0.304)
W.ELI × share of energy consumption in value added				–0.057				0.006
				(0.242)				(0.803)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,600	33,600	33,600	33,600	16,800	16,800	16,800	16,800
R-squared	0.092	0.092	0.092	0.092	0.065	0.065	0.065	0.065

Notes: 1) The robust *p* value is in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) the estimation results are clustered by city.

Table 7: Regional Heterogeneity Analysis

	Eastern Region				Central/Western Region			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ELI × share of SO_2 emissions in output	0.049				0.183*			
	(0.654)				(0.083)			
W.ELI × share of SO_2 emissions in output	–0.042				–0.163			
	(0.681)				(0.102)			
ELI × share of SO_2 emissions in value added		0.029				0.138**		
		(0.620)				(0.038)		
W.ELI × share of SO_2 emissions in value added		–0.012				–0.113*		
		(0.846)				(0.059)		
ELI × share of energy consumption in output			–0.067				0.171	
			(0.659)				(0.119)	
W.ELI × share of energy consumption in output			0.106				–0.151	
			(0.505)				(0.127)	
ELI × share of energy consumption in value added				–0.028				0.104*
				(0.601)				(0.085)
W.ELI × share of energy consumption in value added				0.069				–0.082*
				(0.365)				(0.086)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,080	16,080	16,080	16,080	34,320	34,320	34,320	34,320
R-squared	0.111	0.111	0.111	0.111	0.032	0.032	0.032	0.032

Notes: 1) The robust *p* value is in parentheses; 2) *** p < 0.01, ** p < 0.05, * p < 0.1; 3) the estimation results are clustered by city.

Table 8: Industrial Heterogeneity Analysis

	HPI				Non-HPI			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ELI × share of SO_2 emissions in output	0.108				0.368**			
	(0.182)				(0.044)			
W.ELI × share of SO_2 emissions in output	–0.120				–0.440**			
	(0.137)				(0.037)			
ELI × share of SO_2 emissions in value added		0.085*				0.169*		
		(0.087)				(0.085)		
W.ELI × share of SO_2 emissions in value added		–0.089*				–0.223**		
		(0.066)				(0.044)		
ELI × share of energy consumption in output			0.091				0.116*	
			(0.359)				(0.065)	
W.ELI × share of energy consumption in output			–0.071				–0.140*	
			(0.476)				(0.055)	
ELI × share of energy consumption in value added				0.065				0.034
				(0.207)				(0.462)
W.ELI × share of energy consumption in value added				–0.044				–0.070*
				(0.322)				(0.086)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,120	15,120	15,120	15120	35280	35280	35280	35280
R-squared	0.062	0.062	0.062	0.062	0.108	0.108	0.108	0.108

Notes: 1) The robust *p* value is in parentheses; 2) *** p < 0.01, ** p < 0.05, * p < 0.1; 3) the estimation results are clustered by city.

4. CONCLUSION

The empirical validity of the PHH and strategic environmental regulation are debated topics. In this paper, we first construct a composite index to measure environmental policy stringency across Chinese cities. Employing a spatial lag of X model (SLX), we present robust confirmation of a pollution haven effect. We find that stricter environmental regulations did indeed induce a relative reduction of FDI and show evidence that cities engage in strategic competition and intentionally lower their environmental regulation to attract more FDI.

To deal with the potential endogeneity of environmental regulations, we use the meteorological ventilation coefficient as an instrument for a city's environmental regulation laxity and show that the latter has a positive significant effect on FDI. We conclude that the laxity of environmental regulations is a statistically significant determinant of comparative advantage in FDI and that local cities manipulate environmental regulation to boost their FDI economic growth.

The policy implication of this research is obvious. Even though the central government issues strict regulation policies, the empirical results of this paper show that it is at local governments' discretion to adjust and enforce compliance. Along with the exodus of pollution-intensive firms from rich eastern areas and inter-regional industry transfer, the effect on social welfare and striking a balance between FDI and a better environment are particularly interesting issues for future research.

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APPENDIX A

Entropy-Weighted Approach to the Environmental Laxity Index

Information theory defines entropy as the average amount of information that a system presents. Suppose there are *m* evaluating indicators for *n* evaluation objects. We will have a system that the matrix of $\boldsymbol{Z} = (x_{pq})_{m\times n}$ represents. Our first measurement of environmental regulation consists of four indicators covering 210 cities, indicating values of 4 for *m* and 210 for *n*. Denoting the four indicators as x_p (*p* = 1,2,3,4), we can calculate the weight of each indicator in the following four steps.

We first standardize the original matrix *Z* to obtain Equation (A.1).

$$Y = (y_{pq})_{m\times n} \tag{A.1}$$

where y_{pq} is the standard value of the *q-th* city on the *p-th* indicator in the range of $[0,1]$. Since the four indicators play a negative role in deciding the environmental regulation laxity, when $x_{pq} = \max_q(x_{pq})$, while y_{pq} = 0; $x_{pq} = \min_q(x_{pq})$, y_{pq} = 1.

$$y_{pq} = \frac{\max_q(x_{pq}) - (x_{pq})}{\max_q(x_{pq}) - \min_q(x_{pq})} \tag{A.2}$$

The second step is to define entropy. For indicator x_p, the greater the difference in the index value x_{pq}, the smaller the entropy, the greater the information that the indicator provides, and the larger the weight of the indicator in the comprehensive assessment. In the *m* indicators, *n* objects evaluation problem, we define the information entropy of the *p-th* indicator as R_p:

$$R_p = -(\ln(n))^{-1}\sum_{q=1}^{n} f_{pq}\ln(f_{pq}), p = 1,2,\cdots \mathrm{m} \tag{A.3}$$

in which probability $f_{pq} = \frac{y_{pq}}{\sum_{q=1}^{n} y_{pq}}$, and suppose when $f_{pq} = 0$, $f_{pq}ln(f_{pq}) = 0$.

The third step is to define the weight of entropy of the *p-th* indicator δ_p:

$$\delta_p = \frac{1 - R_p}{m - \sum_{p=1}^{m} R_p} \tag{A.4}$$

where $0 \leq \delta_p \leq 1, \sum_{p=1}^{m} \delta_p = 1$.

Finally, Equation (A.5) shows the result of the ELI value for the *q-th* city, and a higher ELI indicates a higher level of environmental laxity.

$$\mathrm{ELI}_q = \sum_{p=1}^{m} \delta_p \times x_{pq} \quad (A.5)$$