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Research article

Labor market distortion and air pollution: An empirical analysis based on spatial effect modeling

Siling Yao [a], Rui Xie [a], Feng Han [b,*], Qi Zhang [c,**]

[a] School of Economics and Trade, Hunan University, Changsha, Hunan, 410079, China
[b] School of Economics, Nanjing Audit University, Nanjing, Jiangsu, 211815, China
[c] Department of Geography, University of North Carolina at Chapel Hill, Chapel Hill, NC, 27599, USA

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ABSTRACT

In China, along with the rapid development of economy, air pollution has become a hot issue of public concern, particularly in many cities. The distortion in the labor factor market can cause air pollution, but the underlying mechanism is not yet clear. To investigate this question, this article examines the effect of labor market distortion on air pollution focusing on SO_2 emissions based on data of China's 283 cities during 2003–2015. The main objectives are to examine the direct and spillover effects of labor market distortion on air pollution using panel fixed-effects models, including the spatial Durbin model and the mediated-effects model. Results show that labor market distortion directly aggravates air pollution in cities. Mechanism analysis suggests that labor market distortion incurs air pollution through mechanisms of suppressing technological progress, hindering the upgrading of industrial structure, and reducing the efficiency of energy use. Divided the cities by their locations into those in eastern, central, and western regions, we find that such unfavorable effects are more prominent in eastern and western regions of the country. These findings highlight the impetus of mitigating the distorted labor market to ameliorate air quality and promote sustainable development.

1. Introduction

China's past decades have been a period of rapid economic and industrial development (He, 2006; Yin and Wu, 2022). Many regions in China have nevertheless experienced environmental degradation with severe air pollution problems (Yang et al., 2022). According to China's National Bureau of Statistics report, in 2017, sulfur dioxide (SO_2) emissions approached nearly nine million metric tons while nitrogen oxides (NO_x) emissions reached more than 12 million metric tons nationwide, making the country face challenges of air pollutant emissions. Evidence showed that the ultra-speed economic growth has aggravated the level of atmospheric pollution in China (Liu and Liang, 2017; Xu and Zhang, 2020; Jiang et al., 2020). To tackle this issue, the report by Chinese central government pointed out the necessity of accelerating the reform of the ecological civilization system, emphasizing prominent environmental issues, and strengthening air pollution prevention and regulation actions (He et al., 2018; Liu et al., 2022b). In 2018, the working report of the State Council further proposed to make efforts to control air pollution: the SO_2 and NO_x emissions should altogether be reduced by 3%, and the concentration of fine particles ($PM_{2.5}$) in key areas should be substantially mitigated.[1]

Under the "GDP-oriented" assessment for governmental performance, China's local governments continuously intervene the regulations of price and configuration of labor production factors. The intervened flow of labor elements subsequently causes the imbalance between labor price and its marginal output phenomenon (Yang et al., 2018). As such, labor market development lags the product market, associated with underestimated labor value and distorted labor market. Along the pathway of achieving the coordination and unification of socioeconomic development and energy preservation and emission mitigation (Xiao et al., 2019), unraveling the relationship between labor market distortion and air pollution and understanding its mechanisms is a critical prerequisite for solving environmental pollution problems in contemporary China. Current studies have not yet emphasized how labor market distortion affects air pollution within the economic context in China. In this study, we hypothesize that labor market distortion

* Corresponding author.
** Corresponding author.
E-mail addresses: yaosiling8023@163.com (S. Yao), xrxrui@126.com (R. Xie), hf8417@126.com (F. Han), qz@unc.edu (Q. Zhang).

[1] http://www.gov.cn/zhuanti/2018lh/2018zfgzbg/zfgzbg.htm.

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affects air pollution by forming an intermediary effect via influencing technological progress, industrial structure, and energy efficiency. We test our hypothesis based on data of Chinese prefecture-level cities.

The literature review on labor market distortion and air pollution can be divided into two main parts. The first part is devoted to the discussion of the factors underlying air pollution, and the second examines the socioeconomic effect of labor market distortion. Most studies suggest that economic growth, urbanization, fiscal decentralization, and environmental regulations are key factors contributing to air pollution (Schleich et al., 2009; Elgin and Mazhar, 2013; Schmalensee and Stavins, 2013; Gao et al., 2017). Notably, there is not always a linear correlation between increase in economy and environmental quality (Grossman and Krueger, 1991; Panayotou, 1997). Environmental pollution tends to have the Kuznets inverted U-curve relationship with economic growth (Grossman and Krueger, 2000; Dinda, 2004; Markandya et al., 2006; Cheng et al., 2017). Empirical results suggest that although urbanization rate and urban construction are the main factors of atmospheric pollutant generation (Wang and Fang, 2016), urban administrative boundary expansion improves urban air quality through source management and production process control (Jiang et al., 2022). Moreover, there is an ambivalent correlation between fiscal decentralization and air pollution mitigation. On the one hand, higher fiscal decentralization brings higher environmental standards and makes fiscal decentralization beneficial to environmental improvement (Fredriksson and Millimet, 2002; Levinson, 2003). On the other hand, due to the negative externalities of pollution, fiscal decentralization may hinder the improvement of environmental quality (Silva and Caplan, 1997; Ogawa and Wildasin, 2009). Finally, environmental regulation is a double-edged sword for China's air pollution (Biswas et al., 2012). Measures of environmental protection attempt to restrict pollutant emissions by reducing the size in formal economy, but such protecting regulations can exacerbate environmental pollution via enlarging the size of the shadow economy (Baksi and Bose, 2010; Elgin and Mazhar, 2013).

Labor market distortion is not a unique phenomenon in China, but it is also commonly observed in many developing economic markets, such as in Pakistan, India, and Russia (Norbäck, 2001; Cai, 2015; Takeda et al., 2019; Danzer and Grundke, 2020). Lau and Yotopoulos (1971) and William and Kevin (1988) argued that factor market distortions are based on information asymmetries and the restricted free flow of factors in the market. Hsieh and Klenow (2009) pioneered the study of the relationship between factor allocation distortions and total factor productivity. Banerjee and Moll (2010) and Midrigan and Xu (2014) considered that factor market distortions generate losses in the static allocative efficiency of firms. Li et al. (2014) explored that skilled labor outflows and unskilled labor inflows improve the environment under the condition of free mobility of labor factors among countries. This proves from the opposite side that if labor factor mobility is restricted, the environment will be polluted. Liu et al. (2022a) found that rural labor migration would contribute to air pollution from agricultural activities by altering the labor supply in the agricultural sector, the budget lines of rural residents, the scale of agricultural production, and the structure of crop cultivation. Their study is based on rural agricultural data for counties in Hubei and Hunan provinces of China from 2007 to 2017, which lacks a nationwide city-level exploration. In this study, we utilize panel data for 283 prefecture-level and above cities in China during 2003–2015, which covers a broader range. Moreover, we provide a distinct perspective by exploring the effect of labor market distortion in aggravating SO_2 by inhibiting technological progress, industrial structural upgrading, and energy use efficiency.

Based on studies in the existing literature, evidence on the explicit impact of distortion in China's labor market on air pollution is lacking. Meanwhile, little research has addressed the spatial spillover effects of labor market distortion that spread over time and space. Furthermore, differences in influencing channels necessitate the inspection of mechanisms of such effects. Therefore, the value of the present study lies in three aspects relating to our major research objectives: 1) This research fills the gaps in theoretical research by examining the effect of labor market distortion on air pollution, especially for SO_2. 2) This study integrates labor market distortion and air pollution into the space economic theory and examines the spatial spillover effects of labor market distortion on air pollution with spatial Durbin model. 3) This paper uses a set of panel data on China's 283 cities (prefecture-level and above) to systematically investigate the internal mechanism and realized mechanism of labor market distortion influencing air pollution with mediated-effects model.

This remaining structure of the article is arranged as follow. Section 2 formulates theoretical hypotheses. Section 3 describes the model, variables, and data. Sections 4 presents and discusses the empirical findings. Finally, Section 5 provides major conclusions and policy suggestions.

2. Mechanism analysis

To specifically investigate the effect of labor market distortion (LPD) on air pollution (SO_2) in urban China, we propose a conceptual framework (Fig. S1). Chinese local government officials have been intervening in the price and allocation of factors of production such as labor to achieve economic performance during their tenure. The intervention can impede the free flow of labor factors and leading to a distorted labor market in which the actual price deviates from the equilibrium price. Labor market distortion thus induces enterprises to adopt low-cost production factors, which may generate massive industrial pollution gases in the production process and drive the production factors to traditional enterprises with high pollution, high emission, and high energy consumption. LPD affects urban SO_2 emissions through four main mechanisms, including technological progress, industrial structure upgrading, energy efficiency, and spatial spillover effects.

2.1. Channels of technological progress

When the market is distorted, production factors such as labor and capital are less likely to reach the "Pareto optimality" according to the market mechanism, i.e., the optimal market allocation cannot be achieved (Stiglitz et al., 2019). Labor price distortion can directly cause human resource mismatches and hinder technological progress of enterprises (Bartelsman et al., 2013; Oberfield, 2013; Sandleris and Wright, 2014). Labor market distortion hinders the free movement of the population, especially the enormous number of high-quality talents who cannot be appropriately allocated according to market mechanisms. Due to government intervention, employment of high-quality human resources tends to be in large state-owned heavy industrial enterprises, which makes technological progress lean towards capital intensive sectors. Thus, it is be a difficult task to effectively display these labors' innovation ability and maintain or upgrade the efficiency level of innovative production (Bai and Bian, 2016). Moreover, to achieve economic performance, local government officials may influence decision-making in financial sectors through credit interventions and exercise an elevated level of monopoly over the capital factor market. Capital factors are biased toward traditional-styled enterprises such as heavy industrial enterprises to boost local GPD (Cong et al., 2019). However, for firms with innovations such as SMEs, the increased high financing costs and distorted financing structure can reduce the incentive for enterprises to invest in R&D manpower, thus inhibiting the ability of enterprises to be independently innovate (Amore et al., 2013; Hsu et al., 2014). Therefore, labor market distortion may reduce the innovation efficiency or technological progress of enterprises while forming an extensive economic development mode. This influence tends to suppress the effects of technological spillovers and knowledge spillovers and promote enterprises' bias towards heavy industrial development. The industrial sector is also an important source of intensive pollution emissions and energy consumption, which will in turn lead to intensified urban air pollution.

- H1: By inhibiting technological progress or innovation efficiency, labor market distortion leads to the inability of brining technological and knowledge spillover effects, thus pushing enterprises to favor a heavy-industrial development model and forming an extensive economic growth, which in turn leads to the intensification of air pollution.

2.2. Channels of industrial structural upgrade

Labor market distortion is conducive to the increase of the proportion of industry, especially manufacturing industry. Before the reform and opening policy, China adopted a planned economic system, which strategically prioritized the heavy industry and weakened the service industry. Thus, the prices of numerous factors of production were artificially low to support the development of heavy industry. At present, the “growth-competitive” local governments continue to pursue GDP growth with industry-favoring factor market distortions to enhance the attractiveness of foreign investment (Huang and Du, 2017), such as lower wages and other benefits for rural-urban workers than what would be expected in a free market equilibrium. Government support for the industrial sector to obtain labor resources at low prices can lead to a tendency having a large flow of labor factors to high-energy, high--output heavy industries or low-level processing industries (Lin and Du, 2013). Meanwhile, low wages constrain the ability of workers to update their knowledge and upgrade their skills, indirectly hindering the possibility of labor migration to higher-level industries and exacerbating industrial structural imbalances.

In addition, significant industry characteristics and differences exist between industry and services. Compared to service industry, which allocates advanced factors of production such as knowledge and technology, heavy industry generally uses traditional factors such as labor, capital, and land more intensively as input factors. Although China possesses abundant labor force, low-skilled and unskilled laborers provide the most. The preferred industry for such unskilled laborers after migrating from rural to urban areas is the manufacturing industry, which performs processing and assembly. It is difficult for them to enter advanced service industries with high technology and knowledge requirements at large scales. This has promoted the development of heavy industry, especially manufacturing, while the service sector lagged behind (Tan, 2015). The distortion of factor market shows the characteristics of industry preference, which leads to the relative fast development of industry comparing to service industry in China. This would inhibit the transformation of Chinese industry to the developing mode of high quality and cleaner energy, incurring the deterioration of the ecological environment and the aggravation of air pollution.

- H2: Labor market distortion is conducive to increasing the proportion of industry, especially manufacturing industry, and leading to lagging service industry; this low quality and high energy consumption development model has caused the deterioration of the ecological environment and the escalation of urban air pollution.

2.3. Channels of energy efficiency

The literature discussed a locking effect of factor price distortion on the extensive growth model. The underestimation of factor prices allows the backward production capacity that should have been eliminated to survive. Relatively low-cost factors allow enterprises to earn profits by increasing factor inputs, which inhibits the incentive for firms to invest in R&D and technology (Chu et al., 2019). Factor market distortions hinder the upgrading and transformation of regional industries and forms a lock on the extensive growth model, which in turn consolidates energy consumption in production (Lin and Du, 2013). Moreover, local governments are more inclined to give the priority to the distribution of production factors such as labor to enterprises in their jurisdictions under the incentive of the GDP-based performance evaluation index system. The price discrimination against enterprises in other regions has hindered the improvement of resource liquidity and production efficiency, and thus inhibited the technological progress of enterprises. Under such circumstances, enterprises lack the motivation to use clean production processes, clean energy, and pollution treatment equipment, resulting in high energy consumption per unit output with subsequent reduced energy efficiency. Finally, rent-seeking behaviors caused by distortion in the labor market make factors more allocated to politically connected enterprises, and these enterprises are usually less efficient than ordinary enterprises (Yang, 2011). It violates the market’s principle of prioritizing the allocation of resources to highly efficient enterprises, i.e., the impropriate allocation of resources.

- H3: Labor market distortion inhibits the improvement of energy efficiency, resulting in copious amounts of energy input in production process, and energy consumption often generates smoke and exhaust gas, which can aggravate urban air pollution.

2.4. Channels of spatial spillover effect

Labor factors have the characteristics of mobility and agglomeration, which are conducive to the formation of spatial correlation. However, the labor force, especially the high-quality labor force, is more likely to gather in space, which leads to a sharp rise in the distortion of the local labor factor market (Wang et al., 2019). Furthermore, if there is a high degree of factor price distortion in a region, factors would be transferred outward to achieve reasonable allocation of resources (Bai and Bian, 2016). The strict household registration system leads to extremely inefficient labor allocation inter-city in China, and the mobility of high-quality talent depends primarily on the effect of the relative wage compensation gap among cities. In regions with more distorted labor markets, lower wages can have an “exclusion effect” that inhibits the inflow of high-quality talent from other regions. It may also lead to the outflow of high-quality talents in the region and then reduce the level of agglomeration of high-quality talents in the city.

- H4: The human resource flow caused by the distortion of labor market will produce spatial spillover effect, and then affect urban air pollution.

3. Methodology

3.1. Data collection

The research sample selects a panel dataset from 283 cities (which are at the prefecture scale and above, hereafter referred as to city) in China during 2003–2015. To consider the integrity and continuity of the data, ten cities with serious missing data are excluded, which are Bijie, Chaohu, Danzhou, Haidong, Longnan, Lhasa, Longnan, Sansha, Tongren and Zhongwei. The sample covers 30 provinces, autonomous regions, and municipalities directly under the central government, not including Hong Kong, Macao, Taiwan, and Tibet. Data sources are City Statistical Yearbook, City Construction Statistical Yearbook, and Statistical Yearbook of China. Although the China City Statistical Yearbook is incomplete due to the lack of open-accessed data for cities or missing information of indicator data for published cities, it is the only official certified data covering all prefecture-level cities in China (Han et al., 2020). The indicators currently counted in the China Statistical Data of County-level Cities are few and insufficient to measure variables such as labor market distortion. Furthermore, while China’s county-level data covers a broader range, the uneven level of economic development characteristic of China’s counties and the unscientific statistical methods of some counties may lead to inaccurate statistics. Therefore, we finally select the authoritative certified statistics of Chinese prefecture-level cities. Since data involve income information associated with the inflation effects, all currency values are deflated using the 2003 prices as the base.

3.2. Variable derivation

3.2.1. Dependent variable

Dependent variable reflects urban air pollution. At present, main pollutants in the urban atmosphere include mainly respirable suspended matter (e.g., $PM_{2.5}$), SO_2, NO_x, CO (i.e., carbon monoxide), among which SO_2 can be viewed as a serious pollutant compound that induces far-reaching environmental adversities such as acid rain (Schmalensee et al., 1998). In this article, China's SO_2 emission by urban industries each year in a city is specifically accounted as an indicator for air pollution. Fig. 1a and b map the distributions of industrial sulfur dioxide emissions in 283 Chinese cities in 2003 and 2015, respectively. The spatial distributions demonstrate that industrial sulfur dioxide emissions in cities across the country exhibit a gradual upward trend from 2003 to 2015. Moreover, the spatial performance of sulfur dioxide emission growth varies. In 2015 (Fig. 1b), the increase of SO_2 emissions in the east and middle regions exceeded that in the west region. Among them, the increase of SO_2 emissions in the east region is especially significant in the Yangtze River Delta Industrial Base and Beijing-Tianjin-Tangshan Industrial Base. The increase of SO_2 emissions in the middle region is most obvious in the Hunan Province, Hubei Province, Inner Mongolia Autonomous Region, and Central and southern Liaoning Industrial base.

3.2.2. Independent variable

In this study, labor market distortion (LPD) is the core independent variable. In China's context of labor factor market, strict household registration management systems restrict the free movement of labor (Mohino and Ureña, 2020; Zhang et al., 2020). Local government regulations on labor wages reduce the enthusiasm of enterprises to conduct innovative production activities. The characteristics of the dual urban-rural economic structure formed therefrom also lead to the fragmentation and distortion in labor market (Bai and Bian, 2016). As such, indicators of labor price distortion are used to characterize labor market distortion. Following the methods by Drucker and Feser (2012), the marginal output of labor factors is calculated as the form of transcendental logarithmic production function; then, the index of labor price

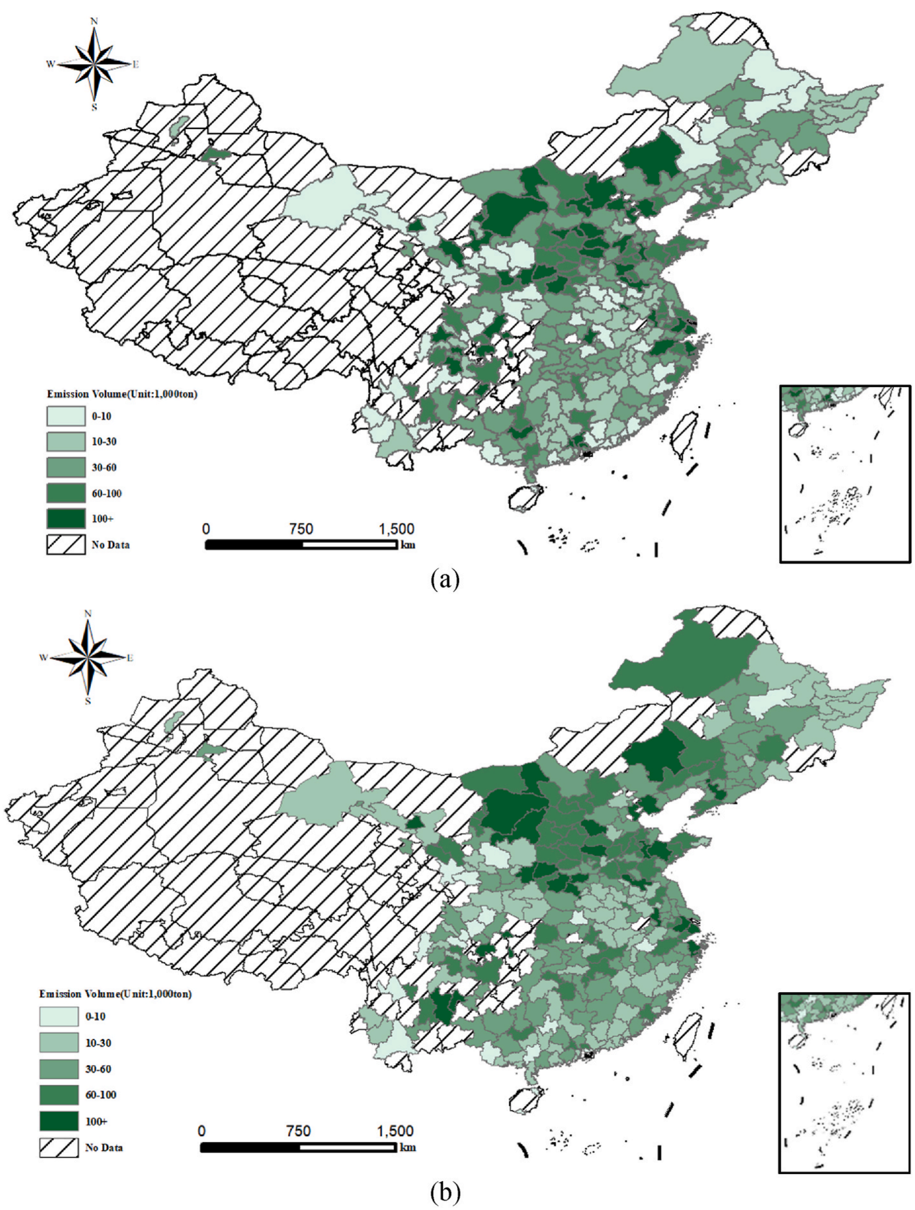

Fig. 1. Distribution map of China's industrial SO_2 emissions in 2003(a) and 2015(b), respectively.

distortion can be obtained by dividing the marginal output of labor factors by its real price. The formula of calculating the output is:

$$\ln Y_{it} = \gamma_0 + \gamma_1 \ln P_{it} + \gamma_2 \ln C_{it} + \frac{1}{2}\gamma_3(\ln P_{it})^2 + \frac{1}{2}\gamma_4(\ln C_{it})^2 + \gamma_5 \ln P_{it} \ln C_{it} + \xi_{it} \quad (1)$$

where t and i are year and city, respectively, γ_0 is constant, $\gamma_1 \sim \gamma_5$ are elastic coefficients, and ξ_{it} is random disturbance term. Meanwhile, Y is the regional industrial output, characterized by the secondary industry's GDP; P is the amount of labor in the industrial sector, calculated as the total number of employees from the secondary industry within the municipal urban area; C denotes the urban capital stock, formulated as $C_{i,t} = (1-\pi)C_{i,t-1} + I_t/\eta_{i,t}$ ($C_{i,t}$, domestic capital stock; π, annual depreciation rate of 5%; I_t, fixed asset investment; $\eta_{i,t}$, cumulative capital price index). With the partial derivative corresponding to Pin Eq. (1), the marginal output of labor factors (MP_P) can be obtained as:

$$MP_P = \frac{(\gamma_1 + \gamma_3 \ln P + \gamma_5 \ln C)Y}{P} \quad (2)$$

With the actual price (A) of the marginal output labor factors, the estimation of the distortion degree is:

$$LPD = MP_P/_A \quad (3)$$

A LPD value of 1 indicates no distortion in the labor factor market. When LPD is lower than 1, value of labor force is smaller than its real price, with the labor factor market presenting a positive mismatch; when LPD is greater than 1, namely labor force's value is larger than the actual price, a negative mismatch for labor factor market is observed.

3.2.3. Control variables

The models include a set of other explanatory variables to control their confounding effects when assessing the impacts of LPD on SO_2. Infrastructure level in urban, density in population, R&D investment, and governmental intervention are control variables. To estimate their elasticities, the natural logarithmic forms for all these control variables are derived for model estimations. The descriptive statistics of the dependent and independent variables in the sampled cities of China are reported in Table S1. The justification and derivation of each control variable are described as follows.

1) Urban infrastructure (*PURL*): As the area of urban roads increases, the number of car trips also increases proportionately or disproportionately, and the resultant heavy traffic volumes in turn negatively affect air quality (Grote et al., 2016). This study uses the urban road area per capita of each prefecture-level city to characterize the construction of urban infrastructure.
2) Population density (*PD*): The density of population reflects the distributions and activities of people in urban area, which can have impacts on air quality.
3) R&D investment (*SE*): The increase in R&D investment can promote green technology innovation, which not only helps reduce the operating costs of enterprises or/and increase their market share, but also gain the benefits of green technology transfer. This would ultimately be conducive to environmental improvement including air pollution mitigation (Hammar and Löfgren, 2010). Here, the R&D investment is indicated by the expenditure of scientific undertakings at the city level.
4) Government intervention (*FES*): Under China's current official evaluation and promotion system, local governments have the motivation and ability to interfere in the production and operation activities of enterprises, and then affect the local environmental quality (Bali Swain et al., 2020). Therefore, degree of intervention by the local government is expressed by the share of fiscal expenditure to GDP in each city.

3.3. Design of econometric models

3.3.1. Benchmark econometric model

The main research purpose is to analyze how labor market distortion impact air pollution. The modeling efforts evaluate the effect by using a standardized OLS panel estimation method that captures both dual fixed effects of individual and temporal. This estimation is treated as a benchmark measurement model, expressed as follows:

$$\ln SO_{2it} = a + \varphi_1 \ln LPD_{it} + \theta_1 \ln PURL_{it} + \theta_2 \ln PD_{it} + \theta_3 \ln SE_{it} + \theta_4 \ln FES_{it} + \beta_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where SO_2 represents the industrial sulfur dioxide emissions; LPD represents labor market distortion; φ_1 is the elastic coefficient of LPD, a is constant, $\theta_1, \theta_2, \theta_3, \theta_4$ are elastic coefficients of control variables with respective to urban infrastructure (ln *PURL*), population density (ln *PD*), R&D investment (ln *SE*), and government intervention (ln *FES*). β_i is the individual fixed effect, while λ_t is the temporal fixed effect. ε is the error bearing with the normal distribution assumption.

3.3.2. Spatial econometric models

Air pollution itself has unavoidable spatial autocorrelation that potentially leads to spatial spillover effects. The environmental quality of a region can be influenced not only by its own economic development, but also by the environmental quality of the surrounding areas. The OLS approach assumes that the samples are isolated from each other, neglecting the spatial error of and interdependence between the samples. However, the spatial econometric model organically integrates geographic location with spatial connection and can consider such error. In addition, unobservable contextual factors with high spatial interdependence such as regional policy, geographic conditions, and institutional environment may be omitted in the measurement model setting. It is arguably essential to test and incorporate spatial effects into the modeling analysis. To address the above issues, the modeling process further introduces spatial econometric models for labor market distortion and air pollution with spatial effects considered. A general form of the model is:

$$\ln SO_{2it} = \Lambda + \sigma \sum_{j=1, j\neq i}^{N} W_{ij} \ln SO_{2jt} + \vartheta X_{it} + \sum_{j=1, j\neq i}^{N} W_{ij} X_{ijt} \Theta + \mu_i + \nu_t + \varepsilon_{it}$$
$$\varepsilon_{it} = \Omega \sum_{j=1, j\neq i}^{N} W_{ij} \varepsilon_{jt} + \varphi_{it} \quad (5)$$

where ν_t and μ_i capture unobserved effects with respect of time and space; Ω and σ are coefficients corresponding to spatial error and spatial lag; W_{ij} is a spatial weight matrix; X contains explanatory variables including LPD and covariates. Note Eq. (5) is a generalized nested model, and the determination of a specific model should follow a series of procedures of rigorously designed tests. According to the test outcome revealed in Table S2, the spatial-temporal fixed-effects Spatial Durbin Model (SDM) outperforms others as well as the benchmark model in Eq. (4) (Gutiérrez-Portilla et al., 2020). The regular SDM and its alternative form can be reformulated and rewritten, respectively, in Eq. (6) and Eq. (7):

$$\ln SO_{2it} = \Lambda + \sigma \sum_{j=1, j\neq i}^{N} W_{ij} \ln SO_{2jt} + \vartheta X_{it} + \sum_{j=1, j\neq i}^{N} W_{ij} X_{ijt} \Theta + \mu_i + \nu_t + \varepsilon_{it} \quad (6)$$

$$O = (I - \sigma W)^{-1}(X\beta + WX\Theta) + R \quad (7)$$

where O is the outcome, and R denotes the remainder that consists of intercept and the error components. At this point, direct and indirect effect can be derived as follows:

$$dirst = \left[(I - \sigma W)^{-1}(\vartheta_k + W\Theta_k)\right]^{\overline{d}} \quad (8)$$

$$indst = \left[(I - \sigma W)^{-1}(\vartheta_k + W\Theta_k)\right]^{\overline{rsum}} \quad (9)$$

Where, $\overline{d}$ is a function of averaging diagonal elements of the matrix, while $\overline{rsum}$ computes the matrix diagonal and non-diagonal element rows and averages. Given one city, the direct effect (*dirst*) reflects the effect of LPD on SO_2 within that city, while the indirect effect (*indst*) characterizes the spatial spillover effect of LPD in the city on SO_2 in its nearby cities.

4. Results and discussions

4.1. Spatial metrology inspection

4.1.1. Spatial correlation

Because the city observations are distributed in areas with spatial properties, Moran's I estimate (Moran, 1950) is adopted to detect the correlation of air pollution among sampled cities over space. The measurement accuracy relies on the suitability of the spatial weight matrix (w). Currently, the adjacent matrix and the geographic distance matrix are two most widely applied matrices (Getis, 2009). The latter is more adept at reflecting the spatial effects of discrete spatial samples than the former, which is based on adjacent cells sharing common boundaries and vertices, thus revealing the economic correlation between urban units in this circumstance. Consequently, to maximize the performance of capturing spatial characteristics, distributions, and interrelationships among cities, we construct the geographic distance w with cities' Latitude-Longitude positions using the approach described by Ren et al. (2023). The specific formula is:

$$W_{dij} = 1 \Big/ D_{ij}^2, i \neq j \quad (10)$$

where D_{ij}^2 symbolizes the squared distance from city i to city j (two different cities), W_{ij} denotes the spatial weight matrix. Note that when referring to the same city, namely i equals to j, the weight is set at 0 and the geographically attenuating coefficient should be 2.

Two space units with different economic genius by horizontal division of labor between industry, at which point their economic attribute of the two will converge. It may also be caused by vertical intra-industrial subdivision of labor, and the economic properties of the two will become increasingly different at that point. Therefore, we consider economic factors when modeling the spatial measurements. The method by Bavaud (2010) is used to set up the economic distance spatial weight matrix and define:

$$W_{eij} = \overline{E}_i \times \overline{E}_j, i \neq j \quad (11)$$

where $\overline{E}_i$ and $\overline{E}_j$ represent the actual per capita GDP of two cities, respectively.

Finally, the gravitational model space weight matrix is a comprehensive matrix that considers geographical distance factors and economic distance factors. The gravity model matrix is also added to measure the spatial correlation of urban air pollution.

$$W_{gij} = \begin{cases} \left(\overline{E}_i \times \overline{E}_j\right) \Big/ D_{ij}^2 & i \neq j \\ 0 & i = j \end{cases} \quad (12)$$

where the symbols present the same as those in Eq. (10) and Eq. (11).

Note that all the matrices are standardized before model estimations. Under various spatial weight matrices, the measurement results (Table S3) reveal that, for matrices of geographic distance, economic distance, and gravitational model, the panel index values for SO_2 air pollution are 0.148, 0.063, and 0.157, respectively (p-values all below 0.01). This suggests a significant correlation over space in terms of China's SO_2 situations in urban.

4.1.2. Estimated results of benchmark and spatial econometric models

Based on the research ideas proposed by Elhorst (2012), this analysis finds that the spatial Durbin model with dual fixed effects of space and time is the best designed model for the present case (Table S2). To make comparison straightforward, we present the estimated effects of the OLS panel model and SDM models with diverse types of weight matrix (spatially constructed) shown in Table 1. Overall empirical outcomes reveal that spatial autoregressive estimates are 0.087 and 0.093 (both with p-values less than 0.05) with respect to geographic distance and gravity model weights. This indicates that air pollution produces endogenous space interaction effects between cities after controlling for the exogenous spatial interaction effects of explanatory variables on air pollution, and demonstrates a form of spatial agglomeration, meaning that air pollution has a space spillover effect.

To further reveal direct and indirect effects (LeSage and Pace, 2009), Table 2 offers the modeling results, based on which findings are interpreted and discussed. Regarding the key explanatory variable, in all three spatial econometric models, the direct and indirect effects of labor market distortion (ln *LPD*) on air pollution are both positive, the former (direct) having passed the significance level test of 10% but the latter (indirect) not. Hence, given one city, labor market distortion has significantly aggravated the city's air pollution. This may be because of the gradually slow transformation from centrally planned to market-oriented economy in China under the opening reform during out defined study period (Xu and Mei, 2018). The marketization process makes the development of factor market lag the product market (Du and Li, 2021), which leads to the long-term undervaluation of labor factor prices and the formation of labor market distortion. Distortion in the labor market will entice companies to adopt low-cost production factors, resulting in backward production capacity not being eliminated in a

Table 1
Benchmark regression and spatial estimation results under various weight matrices.

Variable	OLS	Geographic distance	Economic distance	Gravitational model
ln *LPD*	0.097**	0.084*	0.096**	0.086*
	[0.047]	(0.065)	(0.032)	(0.058)
ln *PURL*	0.085**	0.080**	0.078**	0.079**
	[0.033]	(0.012)	(0.013)	(0.013)
ln *PD*	−0.723***	−0.810***	−0.702***	−0.831***
	[0.192]	(0.000)	(0.000)	(0.000)
ln *SE*	−0.041**	−0.040**	−0.044***	−0.037**
	[0.017]	(0.015)	(0.006)	(0.025)
ln *FES*	0.108*	0.103*	0.103*	0.099*
	[0.061]	(0.086)	(0.079)	(0.096)
$W*$ ln *LPD*	/	0.206	0.104	0.176
	/	(0.184)	(0.455)	(0.226)
$W*$ ln *PURL*	/	0.135	0.136	0.112
	/	(0.190)	(0.116)	(0.263)
$W*$ ln *PD*	/	1.619**	0.120	1.944***
	/	(0.022)	(0.824)	(0.005)
$W*$ ln *SE*	/	0.019	−0.139***	−0.026
	/	(0.686)	(0.002)	(0.583)
$W*$ ln *FES*	/	0.061	0.431***	0.093
	/	(0.758)	(0.005)	(0.615)
ρ	/	0.087**	−0.012	0.093**
	/	(0.023)	(0.707)	(0.012)
Log-Likelihood	/	−2754.254	−2751.671	−2753.426
Observations	3679	3679	3679	3679
Number of City	283	283	283	283
R-squared	0.047	0.787	0.787	0.787

Note: p-values are shown in parentheses and standard errors are shown in square brackets. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 2
Estimated results of spatial econometric models.

Variable	Geographic distance		Economic distance		Gravitational model	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
ln *LPD*	0.085*	0.238	0.095**	0.094	0.087*	0.211
	(0.067)	(0.166)	(0.036)	(0.490)	(0.058)	(0.201)
ln *PURL*	0.080**	0.151	0.079**	0.134	0.079**	0.134
	(0.015)	(0.181)	(0.010)	(0.112)	(0.016)	(0.233)
ln *PD*	−0.795***	1.677**	−0.707***	0.135	−0.805***	2.075***
	(0.000)	(0.027)	(0.000)	(0.797)	(0.000)	(0.006)
ln *SE*	−0.040**	0.017	−0.044***	−0.139***	−0.037**	−0.031
	(0.016)	(0.741)	(0.005)	(0.002)	(0.028)	(0.528)
ln *FES*	0.101*	0.081	0.102*	0.421***	0.100*	0.115
	(0.090)	(0.697)	(0.076)	(0.006)	(0.099)	(0.585)

Notes: p-values are shown in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

timely manner. Subsequently, a large amount of industrial pollution gases will be produced in the production process.

4.2. Inspection of influencing mechanisms

4.2.1. Model specification

The model inspection here uses the intermediate effect step-by-step test method (Baron and Kenny, 1986; He and Shi, 2023) to examine the transmission mechanisms of the distorted labor market affecting air pollution. The method specifically constructs a recursive model with three intermediary variables separately, described as follows. 1) Technical Progress (DEA). This article adopts the non-radial SBM model (Xie et al., 2019) and utilizes total factor productivity (computed in MaxDEA) as the proxy variable for technological progress. Production input uses labor input and capital stock of local cities, of which the former is the total employment at the end of each year and the latter is computed following the perpetual inventory approach (Han and Ke, 2013). The output data uses the GDP of secondary and tertiary industries. 2) Industrial Structure (IS). This variable is characterized by the share of the output value of the secondary industry in the regional GDP. 3) Energy Efficiency (EE). The method by Xie et al. (2017) is employed to calculate the energy consumption, and then compute the ratio of regional GDP to energy consumption to obtain the energy efficiency measurement index. The sequential recursive model constructed is specifically expressed as:

$$\ln SO_{2it} = \Theta + \varphi_0 \ln LPD_{it} + \varphi_j \sum_{j=1}^{n} \mathrm{T}_{j,it} + \varsigma_{it} \tag{13}$$

$$\ln Z_{it} = \Pi + \varphi_0^{'} \ln LPD_{it} + \varphi_j \sum_{j=1}^{n} \mathrm{T}_{j,it} + \xi_{it} \tag{14}$$

$$\ln SO_{2it} = \Psi + \varphi_0^{''} \ln LPD_{it} + \eta Z_{it} + \varphi_j \sum_{j=1}^{n} \mathrm{T}_{j,it} + \Im_{it} \tag{15}$$

where Θ, Π and Ψ are constant terms; Z is an intermediate variable; T is a control variable (total number of n); ς, ξ and $\Im$ are random errors. The first step is to quantitatively estimate the model of Eq. (13) to evaluate whether the regression parameter of labor market distortion is significantly positive (i.e., aggravating air pollution). The second is to perform the regression of Eq. (14) to assess whether labor market distortion have a significant effect on the identified mediation variable (Z). If statistically significant, it indicates that labor market distortion has significantly affected technological progress, industrial structure upgrade and/or energy usage efficiency. The third is to execute Eq. (15) model, where if both φ_0'' and η are significant and φ_0'' is lower than φ_0, there would be a partial mediation effect. If the coefficient φ_0'' is not significant, but the coefficient η is significant, each intermediary variable has played a full intermediary role in labor market distortion affecting air pollution.

4.2.2. Reports of mechanism inspection

The results for examining the intermediate effects are shown in Table 3. Models-A reports the effects by the sequential recursive model under the mediating transmission mechanism of labor market distortion through technological progress. Herein, Model-A1 reveals that the effect of labor market distortion is significantly positive (1% significance level); Model-A2 shows that the estimated parameter of labor market distortion is significantly negative at the level of 10%; Model-A3 shows that the parameter estimation coefficient value of labor market distortion variable is significantly positive, and the parameter estimation coefficient value of the technological progress variable is significantly negative. Moreover, the estimated coefficient value of labor market distortion in Model-A3 is 0.199, a value lower than the coefficient of 0.204 in Model-A1, which proves that technological progress plays a part of the mediating effect of labor market distortion on air pollution effect. This shows that labor market distortion can inhibit the technological progress or the improvement of innovation efficiency as an intermediary transmission mechanism to form an industry-led extensive economic growth model, which in turn significantly aggravates air pollution.

Models-B provides the effects of labor market distortion on air pollution mediated by industrial structure upgrading. The estimation shows that the parameter estimation coefficient of the labor market distortion variables is significantly positive in all three models, and the coefficient value of industrial structure in Model-B3 is also significantly positive. Meanwhile, the coefficient of labor market distortion in Model-B3 (0.15) is lower than that in Model-B1 (0.204), which also verifies that the upgrading of the industrial structure has partially intervened the impacts of labor market distortion on air pollution. Thus, the distortion in labor market can inhibit the transformation of Chinese industries into a high-quality, low-energy-consumption, and low-pollution development mode, being ineffective in mitigating the deterioration of the ecological environment and the increase in urban air pollution.

Models-C reports how labor market distortion affects air pollution through energy use efficiency. Herein, Model-C2 shows that the estimated parameter of labor market distortion is significantly negative (5% significance level); Model-C3 shows that the parameter estimation coefficient value of labor market distortion variable is significantly positive, but the coefficient of the energy efficiency variable is not statistically significant. As such, the exploration of the effects of labor market distortion mediated by energy use efficiency on air pollution has not passed the test. However, because the stepwise test is used to evaluate $H_0 : \varphi_0{'} \cdot \eta = 0$, it may have a lower type I error rate, which is lower than the significance level set up. If both $\varphi_0{'}$ and η are significant in the stepwise test result, then $\varphi_0{'} \cdot \eta$ is significant. However, the step-by-step test also has a lower test strength, i.e., the coefficient product is actually significant, but the step-by-step test is easy to draw a "not-significant" conclusion (MacKinnon et al., 2002). Therefore, this article utilizes the Bootstrap method (Preacher et al., 2007) to further test whether labor market distortion can take on the mediating transmission

Table 3
Intermediate effect test.

Variable	Models-A			Models-B			Models-C		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	ln SO_2	ln *DEA*	ln SO_2	ln SO_2	ln *IS*	ln SO_2	ln SO_2	ln *EE*	ln SO_2
ln *LPD*	0.204***	−0.035*	0.199***	0.204***	0.118***	0.150***	0.204***	−0.051**	0.206***
	(0.044)	(0.018)	(0.044)	(0.044)	(0.009)	(0.045)	(0.044)	(0.023)	(0.044)
ln *DEA*	/	/	−0.152***	/	/	/	/	/	/
	/	/	(0.041)	/	/	/	/	/	/
ln *IS*	/	/	/	/	/	0.460***	/	/	/
	/	/	/	/	/	(0.080)	/	/	/
ln *EE*	/	/	/	/	/	/	/	/	0.040
	/	/	/	/	/	/	/	/	(0.032)
ln *PURL*	0.112***	0.054***	0.120***	0.112***	0.034***	0.096***	0.112***	0.116***	0.116***
	(0.032)	(0.013)	(0.032)	(0.032)	(0.006)	(0.032)	(0.032)	(0.017)	(0.032)
ln *PD*	−0.582***	0.004	−0.581***	−0.582***	−0.059	−0.554***	−0.582***	0.275***	−0.571***
	(0.190)	(0.079)	(0.190)	(0.190)	(0.040)	(0.189)	(0.190)	(0.101)	(0.190)
ln *SE*	0.004	0.001	0.004	0.004	0.027***	−0.008	0.004	0.093***	0.008
	(0.009)	(0.004)	(0.009)	(0.009)	(0.002)	(0.010)	(0.009)	(0.005)	(0.010)
ln *FES*	0.126**	−0.032	0.121**	0.126**	0.011	0.121**	0.126**	0.075**	0.129**
	(0.055)	(0.022)	(0.054)	(0.054)	(0.012)	(0.054)	(0.054)	(0.029)	(0.054)
_bs_1	/	/	/	/	/	/	/	/	0.013***
	/	/	/	/	/	/	/	/	[0.004]
_bs_2	/	/	/	/	/	/	/	/	0.761***
	/	/	/	/	/	/	/	/	[0.049]

Notes: standard errors are shown in parentheses and p-values are shown in square brackets. *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01.

mechanism of air pollution through energy utilization efficiency. The test results are shown along with Models-C in Table 3. In the regression Model-C3, the parameter estimation coefficient values of bootstrap1 (bs1) and bootstrap2 (bs2) are both significantly positive and the confidence interval does not include 0, suggesting a significant coefficient product. Labor market distortion can restrain the improvement of energy efficiency, resulting in the need for a vast amount of energy input in the production process. The restrain may ultimately generate for instance smoke and exhaust gas, aggravating urban air pollution.

4.3. Analysis on regional heterogeneity

The effects and modes of labor market distortion on air pollution may differ with varying geographic regions and economic development level given the enormous size of the country. Therefore, we need to divide the cities into eastern, central, and western regions and apply SDM to each region for further analysis. Although there are two criteria for classifying eastern, central, and western regions including geographical location and economic development level, we cannot simply rely on one criterion alone to classify them since we are studying social and environmental issues, which involve economic, climatic, and geographical aspects. We divided 283 cities into eastern (101), central (100), and western (82) cities for sub-sample regressions according to the division criteria of the relevant national departments (Xie et al., 2019).

The estimated results by region (Table S4) show heterogeneous effects of labor market distortion on air pollution by geographic regions. Focusing on the explanatory variables, the coefficient for the indirect effect of labor market distortion in the eastern region is 0.33, marginally significant. This indicates that labor market distortion in the eastern region have significantly increased air pollution in neighboring cities. Cities in the eastern region, especially those along the coastal areas, are among the earliest open economic markets during the transformation processes (Wei, 1995). This, together with policy environment, make the governments' intervention in the factor market relatively low and labor market distortion gradually eased, so the impact on the city has decreased. At the same time, in order to actively respond to the "energy saving and emission reduction" policies, a large number of inefficient, energy-consuming and highly polluting enterprises, which are subject to "demographic dividends" due to the underestimated labor factor prices, were transferred to surrounding cities (Cheng et al., 2012; Wu et al., 2015; Gao et al., 2017), their air pollution being consequently worsened. Regardless of the direct or indirect effects, the distortion in labor market in the central region did not have a significant impact on air pollution. This may be because the central region is affected by the "central rise" strategy. The preferential policies introduced by the state have gradually shifted the "demographic dividends" from the eastern region to the central region, increasing the number of high-quality and high-tech talents, thereby reducing the distortion of the labor market, and then weakening the impact on air pollution in the city and neighboring cities. In the western region, only the direct effect passed the significance test (P $<$ 0.1). This shows that the distortion in labor market in western China has significantly aggravated the cities' air pollution. The western region is still in the initial stages of industrialization due to its harsh geographical and economic conditions, compared to the eastern and central regions. To achieve the performance goal with economic growth embedded as the core, the local governments artificially intervene in the price of labor factors in exchange for economic boost in a brief period, causing factor resources to flow into low-cost, high-energy/pollution industries.

5. Conclusion and policy implication

This article integrates labor market distortion and air pollution into the framework of the spatial economic theory, utilizing a panel data of cities in China over a decade to systematically test the mechanisms of the effects. The results of the study demonstrate that labor market distortion significantly exacerbates air pollution in the city. Labor market distortion can incur air pollution by intervening mechanisms such as inhibiting technological progress, hindering the upgrading of industrial structures, and reducing energy efficiency. Labor market distortion is more likely to cause air pollution problems in the east and west regions of China. A major conclusion is that mitigating the distorted labor market can provide the impetus to amelioration of air quality and policymakers must consider the regional difference when designing and executing environmental regulations. Policy recommendations are as follows.

First, we verified that labor market distortion exacerbates urban air pollution. Therefore, we propose that local governments should promote the free flow of labor factors and optimize the labor factor marketization process. The government needs to consolidate the reform of urban and rural household registration system and reduce the cost of labor mobility to promote the free flow of labor factors between urban and rural areas.

The control of labor prices by local governments should be abolished, and labor prices are to be determined through market mechanisms. In addition, local governments should loosely manage the control and monopoly of factor resources, and gradually reduce the preferences and privileges possessed by the state-owned sector in the distribution of factor resources, to promote the rational distribution and efficient use of factor resources. Second, in the theoretical mechanism framework, we verified hypothesis 1 (H1), hypothesis 2 (H2), and hypothesis 3 (H3). Thus, we propose that the government should support the progress of green technology in cities, promote the upgrading of industrial structure, and enhance energy efficiency. When optimizing the process of marketization of labor factors, it is necessary to increase investment in scientific research, improve the capacity of independent innovation and cultivate innovative talents, and guide technological innovation in a green direction. Moreover, policy makers should implement energy conservation and emission reduction, improve energy use efficiency, and accelerate the transformation and upgrading of industrial structure. Finally, labor market distortion is more likely to cause air pollution problems in east and west China. When formulating policies to optimize the marketization of labor factors, policymakers should consider the impact of labor market distortion on air environmental quality in the eastern and western regions. Specifically, local governments need to initiate labor factor price reforms and create a better-off market system for the free flow of high-tech talents. It will further elevate the level and quality of economic development among cities in the eastern, central, and western regions, transform the regional economic development model, and improve the regional atmospheric environment.

Author contributions

Siling Yao: Conceptualization, Data curation, Formal analysis, Writing – original draft. Rui Xie: Data curation, Formal analysis, Writing – original draft. Feng Han: Conceptualization, Writing – review & editing, Supervision. Qi Zhang: Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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References

Amore, M.D., Schneider, C., Žaldokas, A., 2013. Credit supply and corporate innovation. J. Financ. Econ. 109, 835–855. https://doi.org/10.1016/j.jfineco.2013.04.006.

Bai, J., Bian, Y., 2016. Factor market distortion and the efficiency losses of Chinese innovative production. China Ind. Econ. 39–55 https://doi.org/10.19581/j.cnki.ciejournal.2016.11.005 (in Chinese).

Baksi, S., Bose, P., 2010. Environmental Regulation in the Presence of an Informal Sector. The University of Winnipeg Working Papers.

Bali Swain, R., Kambhampati, U.S., Karimu, A., 2020. Regulation, governance and the role of the informal sector in influencing environmental quality? Ecol. Econ. 173, 106649 https://doi.org/10.1016/j.ecolecon.2020.106649.

Banerjee, A.V., Moll, B., 2010. Why does misallocation persist? Am. Econ. J. Macroecon. 2, 189–206. https://doi.org/10.1257/mac.2.1.189.

Baron, R.M., Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Pers. Soc. Psychol. 51, 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173.

Bartelsman, E., Haltiwanger, J., Scarpetta, S., 2013. Cross-country differences in productivity: the role of allocation and selection. Am. Econ. Rev. 103, 305–334. https://doi.org/10.1257/aer.103.1.305.

Bavaud, F., 2010. Models for spatial weights: a systematic look. Geogr. Anal. 30, 153–171. https://doi.org/10.1111/j.1538-4632.1998.tb00394.x.

Biswas, A.K., Farzanegan, M.R., Thum, M., 2012. Pollution, shadow economy and corruption: theory and evidence. Ecol. Econ. 75, 114–125. https://doi.org/10.1016/j.ecolecon.2012.01.007.

Cai, W., 2015. Structural change accounting with labor market distortions. J. Econ. Dynam. Control 57, 54–64. https://doi.org/10.1016/j.jedc.2015.05.006.

Cheng, C.-T., Shen, J.-J., Wu, X.-Y., Chau, K., 2012. Operation challenges for fast-growing China's hydropower systems and respondence to energy saving and emission reduction. Renew. Sustain. Energy Rev. 16, 2386–2393. https://doi.org/10.1016/j.rser.2012.01.056.

Cheng, Z., Li, L., Liu, J., 2017. Identifying the spatial effects and driving factors of urban PM2.5 pollution in China. Ecol. Indicat. 82, 61–75. https://doi.org/10.1016/j.ecolind.2017.06.043.

Chu, Geng, Guo, 2019. How does energy misallocation affect carbon emission efficiency in China? An empirical study based on the spatial econometric model. Sustainability 11, 2115. https://doi.org/10.3390/su11072115.

Cong, L.W., Gao, H., Ponticelli, J., Yang, X., 2019. Credit allocation under economic stimulus: evidence from China. Rev. Financ. Stud. 32, 3412–3460. https://doi.org/10.1093/rfs/hhz008.

Danzer, A.M., Grundke, R., 2020. Export price shocks and rural labor markets: the role of labor market distortions. J. Dev. Econ. 145, 102464 https://doi.org/10.1016/j.jdeveco.2020.102464.

Dinda, S., 2004. Environmental Kuznets curve hypothesis: a survey. Ecol. Econ. 49, 431–455. https://doi.org/10.1016/j.ecolecon.2004.02.011.

Drucker, J., Feser, E., 2012. Regional industrial structure and agglomeration economies: an analysis of productivity in three manufacturing industries. Reg. Sci. Urban Econ. 42, 1–14. https://doi.org/10.1016/j.regsciurbeco.2011.04.006.

Du, W., Li, M., 2021. The impact of land resource mismatch and land marketization on pollution emissions of industrial enterprises in China. J. Environ. Manag. 299, 113565 https://doi.org/10.1016/j.jenvman.2021.113565.

Elgin, C., Mazhar, U., 2013. Environmental regulation, pollution and the informal economy. Stata Bank Pak. SBP Res. Bull. 9, 62–81.

Elhorst, J.P., 2012. Dynamic spatial panels: models, methods, and inferences. J. Geogr. Syst. 14, 5–28. https://doi.org/10.1007/s10109-011-0158-4.

Fredriksson, P.G., Millimet, D.L., 2002. Is there a 'California effect' in US environmental policymaking? Reg. Sci. Urban Econ. 32, 737–764. https://doi.org/10.1016/S0166-0462(01)00096-5.

Gao, J., Woodward, A., Vardoulakis, S., Kovats, S., Wilkinson, P., Li, L., Xu, L., Li, J., Yang, J., Li, J., Cao, L., Liu, X., Wu, H., Liu, Q., 2017. Haze, public health and mitigation measures in China: a review of the current evidence for further policy response. Sci. Total Environ. 578, 148–157. https://doi.org/10.1016/j.scitotenv.2016.10.231.

Getis, A., 2009. Spatial weights matrices. Geogr. Anal. 41, 404–410. https://doi.org/10.1111/j.1538-4632.2009.00768.x.

Grossman, G.M., Krueger, A.B., 2000. Economic growth and the environment. Q. J. Econ. 110, 353–377.

Grossman, G.M., Krueger, A.B., 1991. Environmental Impacts of the North American Free Trade Agreement. NBER Working Paper.

Grote, M., Williams, I., Preston, J., Kemp, S., 2016. Including congestion effects in urban road traffic CO2 emissions modelling: do local government authorities have the right options? Transport. Res. Part Transp. Environ. 43, 95–106. https://doi.org/10.1016/j.trd.2015.12.010.

Gutiérrez-Portilla, M., Villaverde, J., Maza, A., Hierro, M., 2020. A spatial approach to the impact of immigration on wages: evidence from Spain. Reg. Stud. 54, 505–514. https://doi.org/10.1080/00343404.2018.1424994.

Hammar, H., Löfgren, Å., 2010. Explaining adoption of end of pipe solutions and clean technologies—determinants of firms' investments for reducing emissions to air in four sectors in Sweden. Energy Pol. 38, 3644–3651. https://doi.org/10.1016/j.enpol.2010.02.041.

Han, F., Ke, S., 2013. Spatial externalities, comparative advantages, and manufacturing agglomeration. J. Quant. Tech. Econ. 30, 22–38+116 (in Chinese).

Han, W., Zhang, X., Zheng, X., 2020. Land use regulation and urban land value: evidence from China. Land Use Pol. 92, 104432 https://doi.org/10.1016/j.landusepol.2019.104432.

He, J., 2006. Pollution haven hypothesis and environmental impacts of foreign direct investment: the case of industrial emission of sulfur dioxide (SO2) in Chinese provinces. Ecol. Econ. 60, 228–245. https://doi.org/10.1016/j.ecolecon.2005.12.008.

He, L., Zhong, Z., Yin, F., Wang, D., 2018. Impact of energy consumption on air quality in Jiangsu province of China. Sustainability 10, 94. https://doi.org/10.3390/su10010094.

He, X., Shi, J., 2023. The effect of air pollution on Chinese green bond market: the mediation role of public concern. J. Environ. Manag. 325, 116522 https://doi.org/10.1016/j.jenvman.2022.116522.

Hsieh, C.-T., Klenow, P.J., 2009. Misallocation and manufacturing TFP in China and India. Q. J. Econ. 124, 1403–1448. https://doi.org/10.1162/qjec.2009.124.4.1403.
Hsu, P.-H., Tian, X., Xu, Y., 2014. Financial development and innovation: cross-country evidence. J. Financ. Econ. 112, 116–135. https://doi.org/10.1016/j.jfineco.2013.12.002.
Huang, Z., Du, X., 2017. Government intervention and land misallocation: evidence from China. Cities 60, 323–332. https://doi.org/10.1016/j.cities.2016.10.006.
Jiang, B., Li, Y., Yang, W., 2020. Evaluation and treatment analysis of air quality including particulate pollutants: a case study of Shandong province, China. Int. J. Environ. Res. Publ. Health 17, 9476. https://doi.org/10.3390/ijerph17249476.
Jiang, M., Chen, W., Yu, X., Zhong, G., Dai, M., Shen, X., 2022. How can urban administrative boundary expansion affect air pollution? Mechanism analysis and empirical test. J. Environ. Manag. 322, 116075 https://doi.org/10.1016/j.jenvman.2022.116075.
Lau, L.J., Yotopoulos, P.A., 1971. A test for relative efficiency and application to Indian agriculture. Am. Econ. Rev. 61, 94–109.
LeSage, J., Pace, L., 2009. Introduction to Spatial Econometrics. Chapman Hall/CRC.
Levinson, A., 2003. Environmental regulatory competition: a status report and some new evidence. Natl. Tax J. 91–106.
Li, X., Xu, Y., Wang, D., 2014. Environment and labor movement of skilled labor and unskilled labor between sectors. Econ. Modell. 38, 367–371. https://doi.org/10.1016/j.econmod.2014.01.018.
Lin, B., Du, K., 2013. The impact of distortion of factor market on energy efficiency. Econ. Res. J. 125–136 (in Chinese).
Liu, L., Liang, Q., 2017. Changes to pollutants and carbon emission multipliers in China 2007–2012: an input-output structural decomposition analysis. J. Environ. Manag. 203, 76–86. https://doi.org/10.1016/j.jenvman.2017.07.061.
Liu, Y., You, S., Li, N., Fang, J., Jia, J., Li, X., Ren, J., 2022a. Study on the agricultural air pollution aggravated by the rural labor migration. Atmosphere 13, 174. https://doi.org/10.3390/atmos13020174.
Liu, Q., Zhu, Y., Yang, W., Wang, X., 2022b. Research on the impact of environmental regulation on green technology innovation from the perspective of regional differences: a quasi-natural experiment based on China's new environmental protection law. Sustainability 14, 1714. https://doi.org/10.3390/su14031714.
MacKinnon, D.P., Lockwood, C.M., Hoffman, J.M., West, S.G., Sheets, V., 2002. A comparison of methods to test mediation and other intervening variable effects. Psychol. Methods 7, 83–104. https://doi.org/10.1037/1082-989X.7.1.83.
Markandya, A., Golub, A., Pedroso-Galinato, S., 2006. Empirical analysis of national income and SO2 emissions in selected European countries. Environ. Resour. Econ. 35, 221–257. https://doi.org/10.1007/s10640-006-9014-2.
Midrigan, V., Xu, D.Y., 2014. Finance and misallocation: evidence from plant-level data. Am. Econ. Rev. 104, 422–458. https://doi.org/10.1257/aer.104.2.422.
Mohino, I., Ureña, J.M., 2020. Mobility, housing and labour markets in times of economic crises. Reg. Stud. 54, 443–449. https://doi.org/10.1080/00343404.2020.1711879.
Moran, P.A.P., 1950. Notes on continuous stochastic phenomena. Biometrika 37, 17–23. https://doi.org/10.2307/2332142.
Norbäck, P.-J., 2001. Cumulative effects of labor market distortions in a developing country. J. Dev. Econ. 65, 135–152. https://doi.org/10.1016/S0304-3878(01)00131-6.
Oberfield, E., 2013. Productivity and misallocation during a crisis: evidence from the Chilean crisis of 1982. Rev. Econ. Dynam. 16, 100–119. https://doi.org/10.1016/j.red.2012.10.005.
Ogawa, H., Wildasin, D.E., 2009. Think locally, act locally: spillovers, spillbacks, and efficient decentralized policymaking. Am. Econ. Rev. 99, 1206–1217. https://doi.org/10.1257/aer.99.4.1206.
Panayotou, T., 1997. Demystifying the environmental Kuznets curve: turning a black box into a policy tool. Environ. Dev. Econ. 2, 465–484. https://doi.org/10.1017/S1355770X97000259.
Preacher, K.J., Rucker, D.D., Hayes, A.F., 2007. Addressing moderated mediation hypotheses: theory, methods, and prescriptions. Multivariate Behav. Res. 42, 185–227. https://doi.org/10.1080/00273170701341316.
Ren, X., Zeng, G., Gozgor, G., 2023. How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. J. Environ. Manag. 330, 117125 https://doi.org/10.1016/j.jenvman.2022.117125.
Sandleris, G., Wright, M.L.J., 2014. The costs of financial crises: resource misallocation, productivity, and welfare in the 2001 Argentine crisis. Scand. J. Econ. 116, 87–127. https://doi.org/10.1111/sjoe.12050.
Schleich, J., Rogge, K., Betz, R., 2009. Incentives for energy efficiency in the EU emissions trading scheme. Energy Effic 2, 37–67. https://doi.org/10.1007/s12053-008-9029-3.
Schmalensee, R., Joskow, P.L., Ellerman, A.D., Montero, J.P., Bailey, E.M., 1998. An interim evaluation of Sulfur Dioxide emissions trading. J. Econ. Perspect. 12, 53–68. https://doi.org/10.1257/jep.12.3.53.
Schmalensee, R., Stavins, R.N., 2013. The SO2 allowance trading system: the ironic history of a grand policy experiment. J. Econ. Perspect. 27, 103–122.
Silva, E.C.D., Caplan, A.J., 1997. Transboundary pollution control in federal systems. J. Environ. Econ. Manag. 34, 173–186. https://doi.org/10.1006/jeem.1997.1008.
Stiglitz, J., Yun, J., Kosenko, A., 2019. Characterization, Existence, and Pareto Optimality in Markets with Asymmetric Information and Endogenous and Asymmetric Disclosures: Basic Analytics of Revisiting Rothschild-Stiglitz (No. W26251). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w26251.
Takeda, S., Arimura, T.H., Sugino, M., 2019. Labor market distortions and welfare-decreasing international emissions trading. Environ. Resour. Econ. 74, 271–293. https://doi.org/10.1007/s10640-018-00317-4.
Tan, H., 2015. Is there an industrial bias in China's factor market distortion? Empirical research based on Chinese provincial panel data. Manag. World 96–105 (in Chinese).
Wang, H., Xu, J., Lv, B., 2019. Factor market distortion and TFP growth of high-tech industry from the spatial perspective: an empirical test based on manufacturing of electronic and communication equipment. Econ. Geogr. 131–139 (in Chinese).
Wang, Z., Fang, C., 2016. Spatial-temporal characteristics and determinants of PM2.5 in the Bohai Rim urban agglomeration. Chemosphere 148, 148–162. https://doi.org/10.1016/j.chemosphere.2015.12.118.
Wei, S., 1995. The open door policy and China's rapid growth: evidence from city-level data. In: Growth Theories in Light of the East Asian Experience. University of Chicago Press, pp. 73–104.
William, T.D., Kevin, L., 1988. The reemergence of segmented labor market theory. Am. Econ. Rev. 78, 129–134.
Wu, J., Lv, L., Sun, J., Ji, X., 2015. A comprehensive analysis of China's regional energy saving and emission reduction efficiency: from production and treatment perspectives. Energy Pol. 84, 166–176. https://doi.org/10.1016/j.enpol.2015.05.005.
Xiao, H., Ma, Z., Zhang, P., Liu, M., 2019. Study of the impact of energy consumption structure on carbon emission intensity in China from the perspective of spatial effects. Nat. Hazards 99, 1365–1380. https://doi.org/10.1007/s11069-018-3535-1.
Xie, R., Fang, J., Liu, C., 2017. The effects of transportation infrastructure on urban carbon emissions. Appl. Energy 196, 199–207. https://doi.org/10.1016/j.apenergy.2017.01.020.
Xie, R., Yao, S., Han, F., Fang, J., 2019. Land finance, producer services agglomeration, and green total factor productivity. Int. Reg. Sci. Rev. 42, 550–579. https://doi.org/10.1177/0160017619836270.
Xu, X., Mei, W., 2018. Educational Policies and Legislation in China. Springer Singapore.
Xu, X., Zhang, T., 2020. Spatial-temporal variability of PM2.5 air quality in Beijing, China during 2013–2018. J. Environ. Manag. 262, 110263 https://doi.org/10.1016/j.jenvman.2020.110263.
Yang, M., Yang, F., Sun, C., 2018. Factor market distortion correction, resource reallocation and potential productivity gains: an empirical study on China's heavy industry sector. Energy Econ. 69, 270–279. https://doi.org/10.1016/j.eneco.2017.11.021.
Yang, Q., 2011. The growth of enterprises: to build political connections or capability? Econ. Res. J. 54–66 (in Chinese).
Yang, W., Gao, H., Yang, Y., Liao, J., 2022. Embodied carbon in China's export trade: a multi region input-output analysis. Int. J. Environ. Res. Publ. Health 19, 3894. https://doi.org/10.3390/ijerph19073894.
Yin, L., Wu, C., 2022. Promotion incentives and air pollution: from the political promotion tournament to the environment tournament. J. Environ. Manag. 317, 115491 https://doi.org/10.1016/j.jenvman.2022.115491.
Zhang, X., Wan, G., Li, J., He, Z., 2020. Global spatial economic interaction: knowledge spillover or technical diffusion? Spatial Econ. Anal. 15, 5–23. https://doi.org/10.1080/17421772.2019.1578402.