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Original Research

The Impact of Factor Market Distortion on Firm Emissions: Evidence from China

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Abstract

Despite the extensive literature on the effects of factor market distortions (FMD) on economic performance, only a limited number of studies have investigated their environmental impacts, and empirical evidence and mechanistic analysis from a micro level remain scarce. Against the backdrop of China's significant factor market distortions, this study examines the influence of such distortions on firms' pollution intensity empirically. Our research findings indicate that FMD increases the intensity of firms' sulfur dioxide (SO_2) emissions, and this conclusion remains valid after accounting for instrumental variable regression. Mechanistic tests indicate that FMD enhance the SO_2 emissions intensity of firms through three channels: by increasing their consumption of fossil energy, by impeding their willingness and ability to innovate, and by diminishing their ability to control pollution.

Keywords: firm, factor market distortion, pollution intensity, sulfur dioxide

Introduction

Ambient air pollution is becoming increasingly serious due to anthropogenic effects such as industrial activities and motor vehicles [1]. Ambient air pollution threatens human health and the environment. For example, atmospheric trace metal deposition in industrial areas has toxic effects on human and non-human biota [2]. Environmental pollution has become a significant global issue in recent decades, and determining the primary factors contributing to it and developing more focused policies is of great interest to both academics and policy makers. A large amount of literature has shown that economic growth [3-6], industrial restructuring [7] and technological innovation [8, 9] are important factors driving changes in pollution. Recently, a few studies have explored changes in emissions through the lens of factor market distortion (FMD), offering a fresh perspective on the study of factors influencing pollution. [10, 11].

Distortions in the factor market are reflected in two aspects, namely, factor price distortion and factor misallocation. Factor price distortion refers to deviation of market prices of factors from their opportunity cost, leading to suboptimal factor allocation in production and resulting in factor allocation distortion within firms. [11, 12]. Factor misallocation occurs when factors are not allocated to the most efficient firms due to government intervention instead of market forces determining the allocation. Local government officials, for their own political purposes, can distort the allocation of factors among firms, regions or industries through administrative intervention [10, 13].

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Both the factor allocation distortion that occurs within firms and the factor misallocation that occurs among firms can lead to an increase in pollution emissions. The former results in overconsumption of polluting resources and decreased investment in innovation and pollution control. The latter leads to an excess of resources for firms with low production efficiency and low environmental technology but insufficient resources for firms with high production efficiency and high environmental technology, thus leading to a misallocation of pollution emissions (undesired outputs) among firms and an increase in total emissions. Considering that our interest is in exploring the environmental effects of FMD at the firm level, we focus only on the effects of factor price distortion and the resulting intra-firm factor allocation distortions on the pollution intensity of the firm; we do not focus on the environmental effects of factor misallocation that occurs among firms. This is because exploring the environmental effects of factor misallocation must be done at a higher level than the firm (e.g., region or industry) level.

As the largest developing country and economy in transition, China has made great progress in establishing a market economy system since its reform and opening up, but due to the lag in factor market reforms, the marketisation of factor markets has lagged behind that of commodity markets [11, 14]. Local governments that are responsible for local economic development have strong and powerful control over the allocation, pricing and regulation of factor resources [15, 16], leading to serious FDM. Over the past few years, the Chinese government has implemented a sequence of reform initiatives with the goal of expediting the marketization process of factor markets.[1] Nevertheless, the degree of marketization in factor markets in China continues to significantly trail that of product markets, thereby substantially diminishing the influence of market mechanisms in the allocation of factors. In China, the coexistence of FMD and severe environmental pollution provides a suitable context for exploring the environmental effects of FMD.

This study makes two contributions over existing studies. Firstly, this study analyzes the effect of FDM on pollution emissions from a micro level perspective. Although some studies have discussed the relationship between FDM and pollution emissions at the regional level, empirical evidence is lacking on whether and how factor allocation distortion within firms affects their pollution emission behaviors. For firms, pollution emissions are byproducts of economic outputs. The factor allocation condition of a firm affects not only its productivity and economic outputs but also its pollution emissions and pollution intensity. Therefore, our study further extends the investigation of the environmental effects of FMD. Second, we analyze in detail and empirically test the microlevel mechanisms by which FMD affects pollution intensity. Firm-level empirical studies not only add microlevel evidence to the relationship between FMD and pollution emissions but also help us to better explain how FDM affects firms' emission behavior. In contrast to studies using aggregated data at the regional or industrial level, studies based on microlevel data can uncover information that may be obscured by aggregated data. Our study finds that FMD increases the intensity of firms' consumption of fossil energy, inhibits firms' willingness and ability to innovate, reduces their ability to control pollution, and ultimately increases their pollution intensity.

The rest of the paper is structured as follows: Section 2 reviews relevant literature and analyzes the mechanisms by which FMD affects firms' pollution intensity. Section 3 introduces the data, variables, and econometric models. Section 4 shows and discusses the results of benchmark estimates, robustness tests, and mechanism analysis, and Section 5 concludes the paper.

Literature Review and Mechanism Analysis

FDM in China

Since China's reform process is gradual, government intervention is a common phenomenon, especially in firms and banks, giving a distinctly nonmarket-oriented character to resource allocation [17]. Studies have found that imperfect factor market development can also lead to distortion in factor allocation. For example, David et al. [18] find that the adjustment costs of capital can lead to distortions in factor allocation for Chinese manufacturing firms. Wu [13] defines the existence of information imperfections or enforcement imperfections in the capital market as financial frictions and confirms that financial frictions can lead to capital misallocation. However, as Wu (2017) and David et al. [18] argue, capital adjustment costs and financial frictions do not fully explain capital misallocation, and policy distortions are the main cause of capital misallocation. Government intervention in the factor market will undoubtedly lead to severe FDM [19]. Ouyang et al.[20] also note that the factor market in China is still distorted compared to the commodity markets and that factor price and allocation are still determined by administrative forces rather than the market mechanism. Therefore, the reason for the distortion in China's factor markets mainly stems from government intervention. Next, we describe how government intervention leads to FDM from three perspectives: ownership preferences of local governments, firms' political ties, and assessment criteria for the promotion of officials.

First, the ownership preferences of local governments have led to distortion in the factor market. Due to the strong linkages between the government and

[1] The Chinese State Council approved a plan to implement a piloted comprehensive reform of the market-based allocation of production factors, according to a circular released on Jan 6, 2022.

state-owned enterprises (SOEs), numerous resources governed by local authorities remain disproportionately allocated to SOEs. For example, in order to avoid layoffs or plant closures during economic contraction, local governments often ask state-owned banks to bail out loss-making SOEs [21]. Compared to non-SOEs, SOEs can provide employees with stable jobs, as well as higher wages and nonwage benefits; furthermore, there is employment protection behavior, which attracts a large amount of labor to SOEs, resulting in SOEs employing too much labor [22, 23]. Many banks also tend to allocate credit resources to SOEs, which discourages the investment of private firms [24].

Second, firms' political ties can exacerbate FDM. While the role of market mechanism in resource allocation continues to expand, the distinction between the functions of the market and government remains ambiguous. The Chinese government has strong control over the economy and society [16]. In regions where market-supporting institutions are lacking, social ties are the key to accessing resources for firms [25]. At the same time, the Chinese governance system also has unique characteristics, manifesting itself as a relation-based governance system [26]. Moreover, the development of China's markets for essential productive factors (such as capital, labor, land) still lags behind, and there is serious allocation distortion among enterprises, various sectors or regions [12]. According to Khwaja et al. [27] and Claessens et al. [28], firms in developing countries often establish political connections with the government in order to engage in rent-seeking behavior. Such ties allow firms to gain access to factor resources allocated by government officials who wield the power to allocate them. Similar findings have been found in other studies. For example, Li et al. [29] find that party membership helps private entrepreneurs obtain loans from banks. In addition, companies run by government-linked CEOs face looser financial constraints [30, 31].

Third, local economic performance as the main assessment criterion for official promotion is also an important cause of FDM. After the reform and opening up, the promotion criteria for local officials in China changed from the previous political conformity to an economic performance assessment system, which greatly stimulated the willingness of the local government to develop the economy [32]. Under a promotion contest with strong incentives based on GDP growth, local officials, to maintain the stable growth of employment and output in their jurisdictions, will intentionally favor local enterprises by providing them with cheap factor resources and not treating firms from other places equally. The imposition of severe local protectionism results in the creation of artificial barriers to interregional trade, leading to significant market segmentation. As a consequence, the unimpeded flow of resources is constrained, resulting in a reduction in the efficiency of resource allocation [33]. In addition, some local governments, to stabilize employment and output, will even provide cheap bank credit to zombie enterprises that should have left the market, thus keeping them alive in the market [34]. The existence of such zombie enterprises has seriously crowded out the share of resources that normal enterprises can access and distorted factor allocation.

Mechanisms by which FDM Affects Pollution Intensity

In China, severe FDM has led to many discussions about the effect of FDM on the environmental pollution. Lin et al. [35] supplemented the widely confirmed proposition that factor misallocation inhibits total factor productivity growth from an environmental perspective. They argued that factor misallocation leads to low factor prices, which exacerbates excessive energy use and pollution emissions. Based on provincial data from China, they confirmed the negative impact of FMD on green total factor productivity (GTFP) growth. Hao et al. [36] measured regional resource misallocation by using Chinese provinces as the basic production unit, and included local corruption factors in their study on the effect of FDM on GTFP. They found that both labor and capital misallocation have a negative effect on GTFP, and that local corruption exacerbates the negative impact of labor misallocation on GTFP.

Many scholars have also investigated the effect of FMD on pollution emissions. For instance, Bian et al. [10] studied the effect of resource misallocation on pollution emissions from the perspective of market segmentation. They argued that local protectionism causes market segmentation, restricts the free flow of labor and capital, leads to factor misallocation, hinders industrial and technological upgrading, and ultimately exacerbates environmental pollution problems. Ji [11] measures the FDM index at the provincial level in China and finds that FDM increases pollution intensity at the province level. She explains that a low price of production factors not only increases the probability of factor overuse, leading to less efficient use of energy factors, but also allows inefficient and low-tech firms to persist, leading to increased emissions and reduced energy efficiency. Finally, Han et al. [37] used panel data from Chinese provinces and measured FMD by the deviation between factor marginal product values and factor prices. They found that both labor market distortions and capital market distortions lead to an increase in carbon dioxide emissions.

Although a large number of studies have explored the environmental effects of FDM in the Chinese context, empirical evidence is lacking on whether and how factor allocation distortion within firms affects their pollution emission behaviors. Next, this study analyzes the mechanisms of FMD on firms' pollution intensity in terms of firms' nonclean energy consumption, innovation activities, and pollution control.

First, FDM increases the intensity of firms' consumption of nonclean energy, thus exacerbating their pollution intensity. Local economic performance, as the main assessment criterion for official promotion, tends to make local government officials focus on economic development at the expense of the environment [5, 16, 38]. Moreover, the decentralization that has occurred since the reform and opening up can also lead to the creation of collusion between local governments and enterprises [26]. Local governments, prioritizing short-term growth, will not only provide supportive policies such as tax incentives and cheap factors of production (lower energy, land, and capital prices) but also even lower environmental regulatory standards for some firms [38, 39].

Although these policies have facilitated short-term output growth for enterprises, they have also resulted in the clustering of production factors in firms that receive preferential treatment from local governments. Those enterprises have access to large amounts of cheap resources; thus, this results in overconsumption of resources and high emissions, perpetuating an unsustainable development approach [11, 40]. A large amount of pollution (especially air pollution) comes from the consumption of nonclean energy such as fossil energy [41], and if such resources are obtained cheaply by enterprises, it will increase the intensity of their nonclean energy consumption and thus increase their pollution intensity. In addition, companies with limited access to clean factors such as capital and labor may increase their consumption of nonclean energy such as fossil energy to compensate for the lack of production factors [36].

Second, FDM can inhibit the willingness and ability of enterprises to innovate, thus discouraging the reduction of pollution intensity through technological innovation. Due to the favoritism of local governments, some enterprises suffer from the overallocation of production factors. These enterprises have access to cheap resources. For example, local governments provide large amounts of financial support to local enterprises and provide zombie enterprises with cheap bank credit to support their continued survival in the market. In addition, local governments may dominate investment through subsidies, distort the market prices of production factors and resources, and interfere with the market activities of firms. For these firms, the ability to earn excess profits through the low price of factors given by the government may discourage firms from earning profits through innovative activities [40]. The competitive advantage of these companies does not hinge on their internal innovation capabilities, but rather on their ability to maintain access to inexpensive resources as a means of survival in the market. For example, SOEs have easy access to various social resources but are inefficient in using these resources and lack the motivation and ability to innovate [19, 42]. The importance of technological innovation in economic development and environmental protection has been widely recognized [9]. Some empirical studies have shown that FMD leads to inefficient factor allocation and inhibits innovation efficiency [19, 43, 44].

Moreover, resources within the market are limited; thus, when the enterprises that are favored by local governments gain access to a large amount of resources, it results in limiting the amount of resources that other enterprises can access. Those enterprises that face constraints in access to resources can engage in irrational factor allocation [45]. To ensure stable production, such companies may devote all their resources to production factors at the expense of R&D investments. Some studies have shown that financing constraints can limit firms' R&D investments and reduce their innovation efficiency [46, 47]. As a result, companies with insufficient factor allocation are constrained in their R&D investment, which is not conducive for them to achieve emission reductions through technological innovation.

Third, FDM can inhibit enterprises' pollution control, which is detrimental to pollution reduction. The favoritism of some local governments toward local enterprises has gradually shifted from rigid restrictions such as the price controls on commodities originating from other places or the price subsidies for locally sourced commodities to implicit modes of providing investment subsidies, lower land prices, and lower environmental regulation standards for local enterprises [10]. These enterprises, when faced with cheap factors of production, serve the political purposes of economic growth and employment stability and have significant economic status. As a result, local officials tend to protect them by laxly enforcing regulations or levying only nominal fines [38, 48].

Moreover, the firms with close ties to the government, while receiving significant resources, are also more susceptible to the pressures exerted by officials in pursuit of economic growth. Since funds spent on environmental amenities do not translate into economic growth, officials will reduce spending on environmental amenities to enhance the likelihood of promotion [49] and then pass these pressures on to firms with close ties to the government. Thus, in the face of lower environmental regulation and the pressure transmitted by local officials' economic growth targets, firms will care more about output growth and thus neglect to improve their pollution control capacity, which will increase their pollution intensity. Those enterprises that face constraints in access to resources can lead to irrational factor allocation [45]. To ensure stable production, those companies may devote all their resources to production factors at the expense of investments in environmental protection. Differences in companies' environmental investments largely determine their environmental performance [50].

Data, Models and Variables

Data

The sample interval of this study ranges from 1999 to 2013. The data are mainly drawn from the Annual

Survey of Industrial Enterprises (ASIE), the Chinese Environment Statistics Database (CESD), and the China City Statistical Yearbook (CCSY). The ASIE, compiled by China's National Bureau of Statistics, covers both SOEs and non-SOEs with annual revenues exceeding 5 million RMB.[2] The firms listed in the ASIE account for 90% of China's industrial output, 70% of employees, and 97% of exports, providing a comprehensive representation of the industrial sector's operating conditions [51]. To address potential inaccuracies due to misreporting by some firms, this study adopts the methodology of Feenstra et al. [52] by excluding observations if any of the following criteria are met: (1) average annual number of employees is less than 8; (2) total assets are zero or negative; (3) total industrial output is zero or negative; (4) current assets are higher than total assets; (5) fixed assets are higher than total assets; and (6) total wages are zero or negative.

The CESD is compiled by China's Ministry of Environmental Protection and covers China's major industrial pollutants, including sulfur dioxide (SO_2), soot and other pollution emission data, as well as fossil energy consumption data such as coal. City-level control variables are sourced from the CCSY. In this study, we calculate the FDM index at the firm level using the ASIE and then match the index with the CESD to obtain unbalanced panel data of approximately 174,000 observations.

Baseline Estimation Model and the Dependent Variable

We use a multiple linear regression model with two-way fixed effects to examine the effects of FMD on firms' pollution intensity. The model specification is as follows:

$$EI_{it} = \alpha + \beta Dis_{it} + X_{ict}\varphi + \rho_i + \tau_t + \varepsilon_{it} \tag{1}$$

where subscript *i* refers to a firm; subscript *c* refers to a city; subscript *t* refers to a year; *X* is a vector of control variables; φ is the coefficient vector of the control variables; ρ_i and τ_t refer to firm and year fixed effects, respectively; and ε_{it} is the error term. In Equation (1), the dependent variable *EI* represents the logarithm of sulfur dioxide (SO_2) emissions intensity, i.e., SO_2 emissions per unit of total output. The CESD records a wide range of pollutant emissions from industrial enterprises in China, such as solid waste, soot, industrial dust, nitrogen oxides, and chemical oxygen demand (COD). However, due to the relative completeness of sulfur dioxide (SO_2) data and the close relationship between SO_2 emissions and the energy consumption of enterprises, the logarithm of SO_2 emissions intensity is used as the dependent variable. *Dis* is the distortion index measured at the firm level. To address potential heteroskedasticity and serial correlation, standard errors are clustered at the firm level.

Explanatory Variables

Building on the work of Choi [53], we describe the production behavior of firms under FDM. Considering that FDM persists even though the Chinese commodity market has a higher degree of marketization, this study assumes that commodity market distortion does not exist [20]. We assume that all firms use three factors of production: capital stock (*K*), labor (*L*), and intermediate input (*M*). There are a large number of firms with differences within industry *s*. Firm *i* in industry *s* produces output (*Y*) by using Cobb-Douglas production technology:

$$Y_{si} = A_{si}{K_{si}}^{\alpha_s}{L_{si}}^{\beta_s}{M_{si}}^{\mu_s} \tag{2}$$

where *A* represents total factor productivity. α_s, β_s, and μ_S represent the factor shares of capital stock, labor and intermediate input, respectively ($0<\alpha_s, \beta_s, \mu_s<1$, $0<\alpha_s + \beta_s + \mu_s \leq 1$). Since intermediate input mainly comes from commodity markets that are not heavily distorted, we mainly consider the distortion of capital and labor. Building on the work of Choi [53], we introduce two types of distortions (or wedges) on capital cost and labor cost, namely, capital distortion, which is denoted as τ_{ksi}, and labor distortion, which is denoted as τ_{lsi}. FDM leads to the existence of τ_{ksi} and τ_{lsi}. The nonzero wedges of τ_{ksi} and τ_{lsi} induce discrepancies between the marginal output of the factor and the cost of the factor. The profit of firm *si* is given by the following:

$$\pi_{si} = P_s Y_{si} - (1 + \tau_{lsi})W_{si}L_{si} - (1 + \tau_{ksi})R_{si}K_{si} - Z_{si}M_{si} \tag{3}$$

where P_s, W_{si}, R_{si}, Z_{si} are the price of Y_{si}, labor wage, capital cost, and the cost of intermediate input, respectively. The marginal revenue product of capital, labor, and intermediate inputs are given by the following:

$$MRPK_{si} = \alpha_s \frac{P_s Y_{si}}{K_{si}} = (1 + \tau_{ksi})R_{si} \tag{4}$$

$$MRPL_{si} = \beta_s \frac{P_s Y_{si}}{L_{si}} = (1 + \tau_{lsi})W_{si} \tag{5}$$

$$MRPM_{si} = \mu_s \frac{P_s Y_{si}}{M_{si}} = Z_{si} \tag{6}$$

When there is no distortion in the factor market, the marginal revenue product of a factor should be equal to its cost, and the values of τ_{ksi} and τ_{lsi} are 0. However, when there is FDM, the allocation of capital and labor of the enterprise cannot be optimal, and the values of τ_{ksi} and τ_{lsi} are not equal to 0. For example, some firms have close ties to the government and have access to cheap

[2] Since 2010, the threshold for inclusion of non-state-owned enterprises (non-SOEs) has been raised from 5 million to 20 million RMB in total sales.

bank credit, which drives them to allocate too much capital and thus induces discrepancies between the marginal revenue product of capital and the cost of capital (τ_{ksi} would be less than 0). We use $\left|\left[(1+\tau_{ski})^{\alpha_s}(1+\tau_{sli})^{\beta_s}\right]^{\frac{1}{\alpha_s+\beta_s+\mu_s}}-1\right|$ to measure the overall distortion degree for the firm (denoted as *Dis*, and the specific solution procedure of *Dis* is shown in Appendix).

Before calculating *Dis*, specific estimates of the parameters α_s, β_s, and μ_S in Equation (2) need to be obtained. Using ASIE data from 1999-2013, we use the method of Levinsohn et al. [54] to estimate Equation (2) at the two-digit industry level to obtain α_s, β_s, and μ_S and other parameters.[3] Total output value and total fixed assets are deflated in accordance with the ex-factory price index for industrial products and the price index for fixed assets investment, respectively, with 1999 as the base period.

Labor wage is measured by the per capita wage of the firm. Following Livdan et al. [55] and Yu et al. [56], we define capital cost as the sum of the firm's fixed capital depreciation rate and the bank lending rate. The fixed capital depreciation rate is obtained by calculating the ratio of the depreciation to the original value of fixed assets.[4] The bank lending rate is calculated by the Chinese yuan (CNY) benchmark lending rate published by the People's Bank of China.[5] Based on Chinese Accounting Standards and the CNY benchmark lending rate, we remove data where R_{si}<0.1 or R_{si}>0.43.[6] Finally, to avoid the effect of extreme values of $MRPK_{sj}$, $MRPL_{sj}$, R_{si}, W_{si}, $1 + \tau_{ksi}$, and $1 + \tau_{lsi}$, observations above and below three times the standard deviation of the mean of these variables are removed at the city level.

Control Variables

At the firm level, we use the studies of Wang et al. [57] and Du et al. [58] to consider the following control variables: whether the firm has state-owned capital (*SOC*), whether the firm has foreign-owned capital (*FOC*), total factor productivity (*TFP*), firm age (*Age*), fixed capital per capita (*FCPC*), firm size (*Size*), firm profit (*Profit*), and whether the firm exports (*Export*).

At the city level, we draw on Chen et al.[59] and consider four control variables, namely, the stringency of local regulations on SO_2 (ER_SO_2), the degree of local government intervention in the economy (*GI*), GDP per capita (*GDP_P*), and population density (*PD*).

Table 1 describes the definitions and data sources of the control variables. Table 2 reports the descriptive statistics of each variable, and Table 3 reports the correlation coefficient of the variables. The vast majority of correlation coefficients have absolute values below 0.4, indicating minimal multicollinearity. To be cautious, VIF values for independent variables were checked and found to be lower than 3, indicating no multicollinearity issue. This conclusion is supported by the fact that the VIF values are well below the commonly used threshold of 10 [60].

Empirical Results and Discussion

Benchmark Regression

We use Equation (1) to test the effect of FDM on firms' pollution intensity, and the regression results are shown in Table 4. In Table 4, Columns (1) and (2) show the regression results without and with city-level control variables, respectively. Since data for the city-level control variable ER_SO_2 are only available for the period 2003-2010, the data involved in the regression results including the city-level control variable span

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[3] We use total output value as Y, total fixed assets as K, average number of employees as L, and the value of intermediate goods as M to estimate Equation (2). The α_s, β_s, and μ_S estimates for industry codes 7 (oil and gas extraction industry), 11 (other mining industry), 16 (tobacco products industry), 29 (rubber products industry), 45 (gas production and supply industry), and 46 (water production and supply industry) are removed because the results are not significant.

[4] Since the original value of fixed assets is missing in the ASIE for 2008 and 2009, we do not consider the data for 2008 and 2009 in the benchmark regression. However, in the robustness tests, we estimate the missing original value of fixed assets in 2008 and 2009 using the sum of accumulated depreciation and net fixed assets and include the data for these two years in the regression to verify the results of the benchmark regression.

[5] The bank lending rate is the arithmetic average of the benchmark lending rates within six months (including six months) and between six months and one year (including one year) within the same year. In addition, during the period of 1998-2011, the People's Bank of China set the lower limit of the floating range of lending rate for financial institutions at 0.9 times the benchmark rate, which was changed after 2012; however, the level of lending rate for financial institutions basically remained within 10% below the benchmark lending rate after 2012. Therefore, the calculated bank lending rate was floated down by 10%.

[6] Referring to the Chinese Accounting Standards on the depreciable life of fixed assets, the depreciable life of buildings is 20 years; the minimum depreciable life of aircraft, trains, ships, machines, machinery and other production equipment is 10 years; the minimum depreciable life of fixed assets related to production and operation activities, such as apparatus, tools and furniture, is 5 years; the minimum depreciable life of means of transportation other than aircraft, trains and ships is 4 years; and the minimum depreciable life of electronic equipment is 3 years. Considering that our research sample is industrial enterprises, nonbuilding fixed capital occupies a major part of the production process of enterprises, and the lending rate is greater than 0.05 and less than 0.1 during 1999-2013, the should be greater than 0.1 (0.05+0.05) and less than 0.43 (0.33+0.1) in a conservative situation.

Table 1. Control variable definitions and data sources.

Variable	Definition	Source
SOC	Whether the capital composition of the enterprise includes state-owned capital – if so, the value is 1; otherwise, it is 0.	ASIE
FOC	Whether foreign-owned capital is included in the capital structure of the enterprise – if so, the value is 1; otherwise, it is 0.	ASIE
TFP	TFP of firm, calculated by drawing on the method of Levinsohn et al.[54]	ASIE
Age	Age of enterprise, the logarithm of years since business started.	ASIE
FCPC	Fixed capital per capita, the logarithm of fixed capital stock per capita (in units of 1 thousand yuan).	ASIE
Size	Firm size, the logarithm of total industrial output value of enterprises in the year (in units of 1 thousand yuan).	ASIE
Profit	Firm profit, the logarithm of total profit of the enterprise for the year (in units of 1 thousand yuan).	ASIE
Export	The export status of the enterprise – if there is, export takes the value of 1; otherwise, it is 0.	ASIE
ER_SO_2	The stringency of city-specific SO_2 regulation is expressed as the city's SO_2 removal rate, SO_2 removal/SO_2 production.	CCSY
GI	The degree of local government intervention in the economy; following Mao et al.[61], local fiscal expenditure/GDP.	CCSY
GDP_P	The logarithm of GDP per capita (in units of yuan).	CCSY
PD	The logarithm of population density (in units of people/km^2).	CCSY

the period 2003-2010. The regression results show that the coefficient of *Dis* is positive and passes the significance test regardless of whether city-level control variables are considered. This result indicates that an increase in the degree of FDM of firms significantly increases the pollution intensity of firms.

Regarding the control variables, only *Age* and *Size* showed relatively significant results in the regression analysis with city-level controls. The positive coefficient of *Age* indicates that age is positively related to the pollution intensity of firms. The older the enterprise is, the stronger the link between the enterprise and the government is likely to be, and these enterprises can bring stable jobs to the area and generate GDP. Local officials tend to protect polluters, who hold significant economic importance, by enforcing regulations loosely or imposing nominal fines [38, 48]. The negative coefficient of *Size* suggests that there may be a scale effect in terms of pollution reduction. Larger enterprises are well capitalized and have resources to invest in environmental protection. The results also show that the coefficient of *ER_SO2* is significantly negative, indicating that stricter environmental regulations can curb pollution emissions by firms and lead to a reduction in their pollution intensity.

Table 2. Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
EI	125468	–1.25	2.23	–16.21	4.62
Dis	174173	0.17	0.11	0.00	0.79
SOC	174173	0.10	0.29	0.00	1.00
FOC	174173	0.11	0.32	0.00	1.00
TFP	174173	2.48	0.63	0.16	6.86
Age	174173	2.29	0.78	0.00	4.17
FCPC	174173	4.10	1.07	–0.76	8.77
Size	174173	11.07	1.35	5.81	19.18
Profit	142473	7.80	2.17	0.00	16.23
Export	174173	0.29	0.45	0.00	1.00
ER_SO_2	85127	0.33	0.22	0.00	1.00
GI	115541	0.10	0.05	0.03	1.49
GDP_P	102514	9.94	0.74	7.41	12.07
PD	115590	6.18	0.73	1.55	7.90

Robustness Tests

To verify whether the conclusion that FDM increases the pollution intensity of firms has good robustness, we verify it in three ways: regression by groups, supplementing data, and instrumental variable regression.

Regression by Groups

China faces significant regional imbalances in development. The eastern region holds advantages over the central and western regions in terms of economic development. To assess the generalizability of the benchmark regression results to different levels of development and industries with varying emission levels, this study performs regressions by region

Table 3. Correlation matrix.

Variables	EI	Mis	SOC	FOC	TFP	Age	FCPC	Size	Profit	Export	ER_SO2	GI	GDP_P	PD
EI	1.00													
Dis	0.04	1.00												
SOC	-0.04	0.17	1.00											
FOC	-0.20	0.01	0.00	1.00										
TFP	-0.26	0.32	0.07	0.07	1.00									
Age	-0.08	0.09	0.21	-0.03	0.13	1.00								
FCPC	-0.04	0.25	0.13	0.12	0.01	-0.04	1.00							
Size	-0.37	-0.01	0.20	0.17	0.33	0.18	0.37	1.00						
Profit	-0.27	0.09	0.16	0.16	0.30	0.12	0.37	0.74	1.00					
Export	-0.24	-0.03	0.02	0.22	0.11	0.09	0.04	0.29	0.20	1.00				
ER_SO2	-0.08	-0.02	-0.02	0.03	0.03	0.07	0.00	0.07	0.05	0.05	1.00			
GI	0.00	0.08	0.04	-0.03	0.02	0.03	0.00	-0.02	-0.03	-0.08	0.03	1.00		
GDP_P	-0.20	-0.06	-0.10	0.13	0.07	0.10	0.06	0.15	0.10	0.17	0.28	-0.20	1.00	
PD	-0.15	-0.08	-0.09	0.09	0.06	0.08	-0.02	0.07	0.04	0.13	0.05	-0.29	0.47	1.00

Table 4. Benchmark regression results.

Variables	(1)	(2)
Dis	0.371***	0.293***
	(0.081)	(0.102)
SOC	0.024	0.051
	(0.028)	(0.043)
FOI	0.004	0.000
	(0.032)	(0.043)
TFP	–0.130***	–0.012
	(0.036)	(0.044)
Age	0.174***	0.137***
	(0.028)	(0.046)
FCPC	0.006	0.022
	(0.010)	(0.017)
Size	–0.713***	–0.800***
	(0.017)	(0.025)
Profit	0.004	0.007
	(0.004)	(0.006)
Export	0.041**	0.011
	(0.018)	(0.022)
ER_SO_2		–0.168***
		(0.051)
GI		0.555**
		(0.236)
GDP_P		0.096
		(0.071)
PD		0.006
		(0.321)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Constant	6.705***	6.313***
	(0.148)	(2.166)
Observations	102,418	49,599
R-squared	0.181	0.129

Note that: Robust standard errors are presented in parentheses. To economize on space, we have excluded the estimation outcomes for city fixed effect and year dummy. The significance levels are denoted by ***, **, and *, which correspond to statistical significance at 1%, 5%, and 10%, respectively.

and by industry.[7] Table 5 and Table 6 present the results of the regressions by region and by industry, respectively. The results in Table 5 indicate that the coefficient of *Dis* is positive and statistically significant in both the eastern and non-eastern regions. Table 6 shows that the coefficient of *Dis* is positive and passes the significance test in both high- and low-polluting industries. The above results indicate that the regional development level and industry emission level do not affect the environmental effect of FMD.

Supplementing Data

Since the original value of fixed assets is missing in the ASIE for 2008 and 2009, this causes us to be unable to calculate the user cost of capital R_{si} during 2008 and 2009. Therefore, the data for 2008 and 2009 are not included in the sample of the benchmark regression. Additionally, the results of Table 7 also suggest that the results of the benchmark regression are robust, even when the data from 2008 and 2009 is included. The positive and significant coefficient of *Dis* still indicates that FMD has a negative impact on firms' pollution behavior.

Instrumental Variable Regression

In benchmark regressions, we control firm and year fixed effects, which mitigates the endogeneity problem caused by omitted variables. To mitigate the endogeneity problem, we use instrumental variables combined with two-stage least squares (2SLS) to address this issue. Following Fisman et al. [62], we instrument for *Dis* using province-industry averages (DisIV) as instruments. In the calculation of *DisIV*, the enterprise's own *Dis* is excluded. As a result, *DisIV* varies slightly for each firm in the same industry within the same province. The construction of *DisIV* satisfies the hypothesis of correlation and exogeneity of instrumental

[7] The eastern region encompasses Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The remaining areas are categorized as non-eastern regions. According to China's Bulletin on the Second National Pollution Source Census, 22 double-digit industries are highly polluting industries, including the coal mining and washing (06); oil and gas mining (07); ferrous metal mining (08); nonferrous metal mining (09); nonmetallic mining (10); other mining (11); beverage manufacturing (15); textiles (17); textile clothing, shoes, hats manufacturing (18); leather, fur, feathers (down) and its products (19); paper and paper products (22); petroleum processing, coking and nuclear fuel processing (25); chemical raw materials and chemical products manufacturing (26); pharmaceutical manufacturing (27); chemical fiber manufacturing (28); rubber products (29); plastic products (30); nonmetallic mineral (31); ferrous metal smelting and rolling processing (32); nonferrous metal smelting and rolling processing (33); metal products (34); and electricity, heat production and supply (44) industries. Other industries are low-pollution industries.

Table 5. Regression results by region.

Variables	Eastern region		Non-eastern region	
	(1)	(2)	(3)	(4)
Dis	0.346***	0.293**	0.524***	0.400*
	(0.092)	(0.117)	(0.156)	(0.204)
Observations	60,990	29,710	41,428	19,889
R-squared	0.205	0.161	0.159	0.099
Control variables (firm level)	Yes	Yes	Yes	Yes
Control variables (city level)	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note that: Robust standard errors are presented in parentheses. To economize on space, we have excluded the estimation outcomes for city fixed effect and year dummy. The significance levels are denoted by ***, **, and *, which correspond to statistical significance at 1%, 5%, and 10%, respectively.

Table 6. Regression results by industries.

Variables	Eastern region		Non-eastern region	
	(1)	(2)	(3)	(4)
Dis	0.321***	0.221**	0.652***	0.737**
	(0.086)	(0.109)	(0.231)	(0.296)
Observations	77,884	39,184	24,534	10,415
R-squared	0.183	0.131	0.180	0.132
Control variables (firm level)	Yes	Yes	Yes	Yes
Control variables (city level)	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note that: Robust standard errors are presented in parentheses. To economize on space, we have excluded the estimation outcomes for city fixed effect and year dummy. The significance levels are denoted by ***, **, and *, which correspond to statistical significance at 1%, 5%, and 10%, respectively.

variables. This is because, within the same province and the same industry, different firms face similar cultural traditions and development in factor markets; therefore, there may be a greater correlation between the *Dis* of different firms in the same industry within the same province. The dependent variable in this study is the pollution intensity at the firm level, which is a factor at the firm level, and *DisIV* represents the degree of FDM of other firms within the province-industry level. In general, the FDM of other firms within the province-industry level does not directly affect the pollution emissions of firms. *DisIV* can satisfy the exogeneity hypothesis.

We test the effect of FDM on firms' pollution intensity through 2SLS. The results in Table 8 are the results of the second stage of the 2SLS regression (the estimation results of the first stage are shown in Table 9). The results show that the Kleibergen-Paap rk Wald F values are larger than the critical values of the Stock-Yogo weak ID test's 10% maximal IV size (16.38), indicating the absence of weak instrument issue. However, in the regression results without controlling for city-level control variables, the endogeneity test result was 0.06, thereby rejecting the original hypothesis that *Dis* values are exogenous. However, the original hypothesis that *Dis* values are exogenous cannot be rejected after controlling for city-level control variables. Since the *Dis* coefficient is significantly positive, the positive effect of FDM on firms' pollution intensity still holds in the case of regression with instrumental variables.

Mechanism Analysis

In Section 3, this study analyzes the mechanisms by which FDM affects pollution intensity in terms of firms'

Table 7. Regression results after supplementing data.

Variables	(1)	(2)
Dis	0.333***	0.259***
	(0.070)	(0.079)
Observations	126,757	71,252
R-squared	0.186	0.154
Control variables (firm level)	Yes	Yes
Control variables (city level)	NO	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes

Note that: Robust standard errors are presented in parentheses. To economize on space, we have excluded the estimation outcomes for city fixed effect and year dummy. The significance levels are denoted by ***, **, and *, which correspond to statistical significance at 1%, 5%, and 10%, respectively.

Table 8. Estimation results of the second stage of 2SLS.

Variables	(1)	(2)
Dis	0.971***	0.559*
	(0.327)	(0.326)
Observations	95,615	41,079
R-squared	0.180	0.129
Control variables (firm level)	Yes	Yes
Control variables (city level)	NO	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Kleibergen–Paap rk Wald F statistic	1447.31	994.86
Endogeneity test (p–value)	0.06	0.39

Note that: Robust standard errors are presented in parentheses. To economize on space, we have excluded the estimation outcomes for city fixed effect and year dummy. The significance levels are denoted by ***, **, and *, which correspond to statistical significance at 1%, 5%, and 10%, respectively.

Table 9. First-stage regression results of 2SLS.

	(1)	(2)
Variables	Dis	Dis
DisIV	0.741***	0.937***
	(0.019)	(0.030)
SOC	0.008***	0.005*
	(0.001)	(0.002)
FOC	0.003	0.006*
	(0.001)	(0.002)
TFP	0.027***	0.027***
	(0.002)	(0.003)
Age	0.005***	-0.005
	(0.001)	(0.003)
FCPC	0.025***	0.019***
	(0.001)	(0.001)
Size	-0.035***	-0.035***
	(0.001)	(0.002)
Profit	0.000	0.000
	(0.000)	(0.000)
Export	0.001	0.001
	(0.001)	(0.001)
ER_SO2		0.007*
		(0.003)
GI		-0.006
		(0.015)
GDP_P		-0.005
		(0.005)
PD		-0.075***
		(0.018)

Note: ***, **, and * represent significance levels at 10%, 5%, and 1%, respectively.

nonclean energy consumption, innovation activities, and pollution control.

To reveal the micro mechanisms between FDM and pollution intensity, we design the following three models:

$$Fossil_{it} = \alpha_1 + \beta_1 Dis_{it} + X_{ict}\varphi_1 + \rho_{1i} + \tau_{1t} + \varepsilon_{1it} \quad (7)$$

$$Patent_{it} = \alpha_2 + \beta_2 Dis_{it} + X_{ict}\varphi_1 + \rho_{2i} + \tau_{2t} + \varepsilon_{2it} \quad (8)$$

$$Removal_{it} = \alpha_3 + \beta_3 Dis_{it} + X_{ict}\varphi_1 + \rho_{3i} + \tau_{3t} + \varepsilon_{3it} \quad (9)$$

The purpose of Equation (7) is to test whether FDM increase the intensity of firms' consumption of nonclean energy. $Fossil_{it}$ is the firm's fossil energy consumption intensity (in logarithmic form). We convert firms' fuel coal consumption and fuel oil consumption into standard coal equivalents, which measures firms' fossil energy consumption, and use their ratio to output as the intensity of fossil energy consumption. We use $Fossil_{it}$ not only as a proxy variable for nonclean energy

Table 10. Regression results of mechanism analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Fossil	Fossil	Patent	Patent	Removal	Removal
Dis	0.394***	0.156**	–1.098***	–0.530***	–0.016	–0.057**
	(0.055)	(0.055)	(0.100)	(0.149)	(0.016)	(0.024)
Observations	99,825	69,519	35,397	14,513	96,651	42,618
R-squared	0.248	0.234	0.130	0.080	0.081	0.061
Control variables (firm)	Yes	Yes	Yes	Yes	Yes	Yes
Control variables (city)	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note that: Robust standard errors are presented in parentheses. To economize on space, we have excluded the estimation outcomes for city fixed effect and year dummy. The significance levels are denoted by ***, **, and *, which correspond to statistical significance at 1%, 5%, and 10%, respectively.

consumption intensity but also as the dependent variable in Equation (7).

The purpose of Equation (8) is to test whether FDM inhibits firms' willingness and ability to innovate. The dependent variable $Patent_{it}$ is the number of patent applications per employee (in logarithmic form). However, not all innovations are transformed into patents; moreover, not all patents can be introduced into productive activities [63]. However, the use of the number of patents as a valid variable to measure the level of knowledge innovation has been previously demonstrated [64]. Several studies have used the per capita patent applications as a measure of innovation capacity [63, 65]. In summary, we use $Patent_{it}$ to measure the innovation capacity of the firm.[8] In addition, given that Model (8) interprets the dependent variable as a firm's innovation output, we include economic factors that could affect innovation output, such as the degree of openness to foreign countries (*Open*) and the level of human capital (*HC*), in our city-level control variables along with *GI*, *GDP_P*, and *PD*.[9]

The purpose of Eq. (9) is to test whether FDM reduces firms' pollution control. $Removal_{it}$ is the pollution removal rate (the ratio of removal to generation) of the firm. A higher removal rate indicates that the firm has a higher pollution control investment. We take the SO_2 pollution removal rate of the enterprise as the dependent variable in Equation (9).

We focus on β_1, β_2, and β_3, which measure the effects of FDM on the intensity of nonclean energy consumption, innovation activities, and firms' pollution control, respectively. Based on the previous mechanistic analysis, we expect that β_2, and β_3 should be less than zero and that β_1 should be greater than zero. The regression outcomes are displayed in Table 10.

According to Table 10, when the dependent variable is *Fossil*, the coefficients of *Dis* are positive and pass the significance test. This indicates that FDM increases the intensity of their consumption of nonclean energy. When the dependent variable is *Patent*, the coefficients of *Dis* are all negative and pass the significance test. This indicates that FDM has a significantly negative effect on firms' innovation activities and reduces their willingness and ability to innovate. The coefficients of *Dis* are all negative when the dependent variable is *Removal* and pass the significance test when controlling for city-level control variables. This suggests that FDM inhibits the increase in the pollution removal rate by firms.

Furthermore, to address the endogeneity problem in Table 10, we utilized 2SLS with the instrumental variable *DisIV*, and the regression outcomes are presented in Table 11. The results show that the Kleibergen-Paap rk Wald F values are larger than the critical values of the Stock-Yogo weak ID test's 10% maximal IV size (16.38), indicating the absence of weak instrument issue. And the direction of the *Dis* coefficient in Table 11 is consistent with Table 10, in terms of its positive or negative sign. After considering endogeneity issues, the conclusions presented in Table 10 still hold.

8 China has three types of patents: invention patents, utility model patents, and appearance design patents. This study excludes appearance design patents, as they are not relevant to technical solutions and do not impact reducing enterprise pollution emission intensity. The data used is obtained through matching of ASIE and State Intellectual Property Office data and covers 1999-2013.

9 Open is measured by the ratio of total industrial output value of foreign-invested enterprises to total industrial output value. HC is the ratio of the number of students and faculty enrolled in general higher education institutions to the total population.

Table 11. Regression results of mechanism analysis (2SLS).

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Fossil	Fossil	Patent	Patent	Removal	Removal
Dis	0.774***	0.406*	–0.910***	–0.570*	–0.017	–0.269***
	(0.224)	(0.221)	(0.276)	(0.339)	(0.089)	(0.101)
Observations	88,396	59,925	34,104	11,126	86,544	33,057
R-squared	0.248	0.234	0.130	0.080	0.081	0.057
Control variables (firm)	Yes	Yes	Yes	Yes	Yes	Yes
Control variables (city)	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen–Paap rk Wald F statistic	1419.267	1206.583	785.613	446.502	683.025	426.664
Endogeneity test (p–value)	0.0704	0.2205	0.4672	0.8919	0.9891	0.0277

Note that: Robust standard errors are presented in parentheses. To economize on space, we have excluded the estimation outcomes for city fixed effect and year dummy. The significance levels are denoted by ***, **, and *, which correspond to statistical significance at 1%, 5%, and 10%, respectively.

Conclusions

Since the 1978 reform and opening, China's economy has experienced rapid growth and is now the second largest in the world. However, this growth has resulted in severe environmental problems. Moreover, due to China's gradual reform process, government intervention and regulation have been common phenomena, especially with respect to enterprises and banks, causing resource allocation to exhibit significant nonmarket characteristics [17]. Although some literature has argued for the effect of FDM on regional pollution emissions at the provincial level [10, 11], studies in this field lack microlevel evidence and mechanistic tests. This study finds evidence that FDM increases the intensity of firms' pollution emissions in the Chinese context and discusses and tests the mechanisms by which FDM affects firms' pollution intensity.

This study finds that FDM increases the intensity of SO_2 emissions by firms. This finding still holds after a series of tests with regression by groups, supplementing data, and instrumental variables regression. Further analysis shows that FDM increases the pollution intensity of firms through three channels: by increasing their consumption of fossil energy, by impeding their willingness and ability to innovate, and by diminishing their ability to control pollution.

This study confirms that FDM is detrimental to firms' pollution reduction, which suggests that effective pollution management requires accelerated reform of factor markets. This can be done in the following three ways.

First, the promotion appraisal standards of local government officials should be improved. A promotion contest with strong incentives based on GDP growth can lead governments to neglect environmental protection to achieve economic growth in the short term and provide lower environmental regulatory standards for some firms [38,39]. In recent years, the promotion of officials has begun to be linked to pollution reduction targets [38], which not only helps to reduce the improper intervention of local governments in factor markets under the influence of incorrect promotion appraisal standards but also urges enterprises to improve their own pollution control capacity.

Second, government intervention in the capital market should be reduced. The current free credit contract between banks and enterprises is seriously damaged by government intervention, local governments often interfere with the credit decisions of state-owned banks, and loan contracts between banks and enterprises are based more on government will and political ties than on the principle of maximizing market efficiency [17]. Therefore, it is necessary to improve the degree of freedom of the capital factor market and reduce the damage of local governments to the free credit contract between banks and enterprises to enhance the allocation efficiency of capital resources. The improvement of capital resource allocation efficiency will not only eliminate the channels and motives for enterprises to maintain corporate profits through cheap credit resources and activate their willingness to innovate but also provide financial support for enterprises with real innovation ability and willingness to innovate, thus providing technical support for pollution reduction.

Third, the reform of the factor market management system should be accelerated. Currently, government intervention in the factor market will undoubtedly lead to severe FDM (Qiao et al., 2022). FDM not only leads to the failure of enterprises to maximize factor utilization in production activities but also contributes to an extensive development model [11]. Therefore, it is necessary to improve the transparency, openness, and freedom of factor markets, clearly define the boundaries of the government's role, reduce the possible abuse of power in the administrative process, and truly return the allocation power to the market.

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Conflict of Interest

The author stated there is no conflict of interest.

Appendix

The Solution Procedure of *Dis*

According to Eq. (4), (5) and (6), the following three equations can be obtained:

$$\frac{(1+\tau_{ksi})R_{si}}{\alpha_s} = \frac{P_s Y_{si}}{K_{si}} \tag{A1}$$

$$\frac{(1+\tau_{lsi})W_{si}}{\beta_s} = \frac{P_s Y_{si}}{L_{si}} \tag{A2}$$

$$\frac{Z_{si}}{\mu_s} = \frac{P_s Y_{si}}{M_{si}} \tag{A3}$$

Based on Eq. (A1), (A2), and (A3), we can obtain Eq. (A4) as follows:

$$\left(\frac{(1+\tau_{ksi})R_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{(1+\tau_{lsi})W_{si}}{\beta_s}\right)^{\beta_s}\left(\frac{Z_{si}}{\mu_s}\right)^{\mu_s} = \frac{(P_s Y_{si})^{\alpha_s+\beta_s+\mu_s}}{K_{si}{}^{\alpha_s}L_{si}{}^{\beta_s}M_{si}{}^{\mu_s}} \tag{A4}$$

Combining Eq. (A4) with $A_{si} = \frac{Y_{si}}{K_{si}{}^{\alpha_s}L_{si}{}^{\beta_s}M_{si}{}^{\mu_s}}$, Eq. (A5) can be obtained as follows:

$$A_{si} = \frac{\left(\frac{(1+\tau_{ksi})R_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{(1+\tau_{lsi})W_{si}}{\beta_s}\right)^{\beta_s}\left(\frac{Z_{si}}{\mu_s}\right)^{\mu_s} * Y_{si}{}^{1-(\alpha_s+\beta_s+\mu_s)}}{P_s{}^{\alpha_s+\beta_s+\mu_s}} \tag{A5}$$

Combining Eq. (A5) with Eq. (2), Eq. (A6) can be obtained as follows:

$$A_{si} = \frac{\left[(1+\tau_{ski})^{\alpha_s}(1+\tau_{sli})^{\beta_s}\right]^{\frac{1}{\alpha_s+\beta_s+\mu_s}} * \left[\left(\frac{R_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{W_{si}}{\beta_s}\right)^{\beta_s}\left(\frac{Z_{si}}{\mu_s}\right)^{\mu_s} * \left(K_{si}{}^{\alpha_s}L_{si}{}^{\beta_s}M_{si}{}^{\mu_s}\right)^{1-(\alpha_s+\beta_s+\mu_s)}\right]^{\frac{1}{\alpha_s+\beta_s+\mu_s}}}{P_s} \tag{A6}$$

When there is no distortion in the factor market, τ_{ski} and τ_{sli} take the value of 0. At this time, $\left|\left[(1+\tau_{ski})^{\alpha_s}(1+\tau_{sli})^{\beta_s}\right]^{\frac{1}{\alpha_s+\beta_s+\mu_s}} - 1\right|$ in Eq. (A6) takes the value of 1, and Eq. (A6) becomes Eq. (A7):

$$A^*{}_{si} = \frac{\left[\left(\frac{R_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{W_{si}}{\beta_s}\right)^{\beta_s}\left(\frac{Z_{si}}{\mu_s}\right)^{\mu_s} * \left(K_{si}{}^{\alpha_s}L_{si}{}^{\beta_s}M_{si}{}^{\mu_s}\right)^{1-(\alpha_s+\beta_s+\mu_s)}\right]^{\frac{1}{\alpha_s+\beta_s+\mu_s}}}{P_s} \tag{A7}$$

A^*_{si} is the total factor productivity of the firm when there is no FDM.

Combining Equations (A6) and (A7), it can be found that $\left[(1+\tau_{ski})^{\alpha_s}(1+\tau_{sli})^{\beta_s}\right]^{\frac{1}{\alpha_s+\beta_s+\mu_s}}$ is the effect of FDM on the total factor productivity of the firm, which is actually also the effect of FDM on the total output of the firm. We use $\left[(1+\tau_{ski})^{\alpha_s}(1+\tau_{sli})^{\beta_s}\right]^{\frac{1}{\alpha_s+\beta_s+\mu_s}}$ to measure the degree of FDM (denoted as *Dis*) for the firm. When there is no FDM, $\left[(1+\tau_{ski})^{\alpha_s}(1+\tau_{sli})^{\beta_s}\right]^{\frac{1}{\alpha_s+\beta_s+\mu_s}}$ takes the value of 0; otherwise, *Dis* will deviate from 0. The farther *Mis* deviates from 0, the greater the degree of FDM is implied.

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