

Original Research

Labor Share in the Air: Who Bears More Production Efficiency Loss of Air Pollution?

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Received: 14 January 2022

Accepted: 4 March 2022

Abstract

This paper provides a nationwide casual estimation of air pollution on labor share for the manufacturing industry in China from 1998 to 2015. Using changes in the annual intensity of thermal inversion as an instrument, we find that a $1\mu\text{g}/\text{m}^3$ increase in PM2.5 increases labor share by 4.01%-6.50% (about 0.02-0.04 in absolute value). Results show that although both labor income and capital income decrease, capital income decreases more which results in a labor share increase. The results also reveal that labor income change is primarily driven by labor productivity loss and effective labor decline, and the drastic drop of capital income results from the complementary relationship between capital and labor which is indicated by the elasticity of substitution. By describing labor share as wage-productivity gap, we find that wage does not decline enough to match productivity loss when air pollution happens. Although stricter environmental regulations may lead to a reduced labor share and further income inequality, the study suggests that the overall economic benefit will be enhanced.

Keywords: labor share, PM2.5, labor productivity, elasticity of substitution, China

Introduction

How national income is distributed between capital and labor has always been of interest to policymakers and economists, since it measures the distribution of benefits from growth across the production factors. There has been a significant drop in the global labor share since the 1980s, with this decline occurring within the OECD countries and developing countries such as China [1-3]. The labor share is with vital

implications for the income distribution of a country. A lower labor share or higher capital share means a mounting trend in income inequality. This is because those who gain income mainly through labor are of the lower socioeconomic status in society and those who gain through capital are of the higher socioeconomic status. In addition, labor income is naturally dispersed, that is, a large fraction of the population works and receives wages, whereas capital income tends to be concentrated: relatively few people hold capital, and some hold a lot of it.

China has experienced exacerbated income inequality during the past four decades. As illustrated by inverted-U-shaped Kuznets Curve (KC), the overall

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economic inequality first increases then decreases as an economy develops [4] (Kuznets, 1955). In the meantime, energy consumption in economic development is linked to excessive air pollution emissions [5]. Similarly, Environmental Kuznets Curve (EKC) suggests that economic growth initially leads to environmental degradation, but after a certain level of economic development, the relationship between societies and the environment begins to improve and environmental degradation decrease [6]. Therefore, there may be an intrinsic connection between air pollution and income inequality.

In this paper, we investigated the relationship between air pollution on labor share. In 2020, air quality in 86% of Chinese cities improved compared to the previous year; despite this, Chinese residents are still exposed to PM_{2.5} levels (34.7 $\mu\text{g}/\text{m}^3$) that exceed three times the World Health Organization's annual guidelines (10 $\mu\text{g}/\text{m}^3$)¹. Numerous studies provide evidence for the negative effects of air pollution, such as threatening development of human well-being [7] and causing economic losses [8, 9]. In the field of environmental economics, a growing body of literature indicates that air pollution nearby greatly influences firm's production strategy. These studies on document the effect of air pollution on a firm's productivity [10], employee wages [11], investment levels [12], etc. However, few papers studied air pollution effects on firm's labor share. Liu and Wang (2020) found a positive correlation between China's environmental pollution and labor share based on rough analysis at the provincial level [13]. They also found an inverted-U-shaped relationship between labor income share and environmental pollution. Even so, the impact of air pollution on firm' factor income distribution remains largely unknown.

The goal of this paper is to estimate the causal relationship between air pollution and labor share for manufacturing firms in China. Using air pollution data retrieved from satellites, we can consider the pollution exposure of all firms in the manufacturing survey. Chinese manufacturing firm database surveys all non-SOEs (state-owned enterprise) with annual sales of over CNY 5 million and all SOEs, making the nationwide environmental policy assessment representative. For our estimation, this paper finds that air pollution increases firm's labor share. Holding other conditions constant, an exogenous 1 $\mu\text{g}/\text{m}^3$ increase in the particulate matter less than 2.5 μg in diameter (PM_{2.5}) decreases the average labor share of firms by 4.44%-6.51% (about 0.03-0.04 in absolute value). According to our analysis, firm's value-added drop significantly (-6.56%) under polluted air. Labor income decreases by 2.47% and capital income decreases by

8.09%. However, capital income decreases more than labor income, which is the reason why labor share increases.

Since the change in labor share may result from changes in wage rate, labor and capital inputs and other aspects of firm's decision, effects on labor share could not be seen directly. Using a theoretical model, we incorporate air pollution into firm's production function to understand the story behind it. Exposure to air pollutants can lead to employee absenteeism [14, 15] and reduced labor productivity [16-18], both of which decrease the firm's output. Even the loss of productivity can also be partially offset by firms hiring more workers, the number of effective workers still drops. Given the complementary relationship between labor and capital, firms invest less capital in production correspondingly. In addition, we describe labor share as wage-productivity gap and find that wage does not decline enough to match productivity loss when air pollution happens.

The primary challenge in estimating the effect of pollution on labor share is the bias caused by reverse causality and omitted-variable. Reverse causality bias in OLS estimates may result from the difference in the pollution emissions from labor income and capital income. Labor income is mainly used for living consumption and capital income for productive consumption. The higher proportion of income distributed to labor, the less air pollution emitted, biasing OLS estimates downwards. Omitted-variable bias may be due to time-varying, region-specific correlations between pollution and labor share caused by economic factors such as technological progress, international trade, and monopolies [19, 1]. Due to these factors, OLS estimates may be skewed either upwards or downwards because high labor share regions may adopt cleaner or dirtier technologies over time.

We use the annual intensity of thermal inversions to measure air pollution in counties to avoid reversal causality and omitted variable bias. Thermal inversion is an exogenous meteorological phenomenon that traps pollutants near the ground, increasing air pollution. In previous studies, thermal inversions were used as an instrument [20-23]. Thermal inversion is highly predictive for air pollution and reveals more positive labor share impacts than traditional OLS estimates in our analysis.

This article makes three main contributions. One is to provide new empirical evidence in the topics about labor share and pollution emission. Firstly, among factors affecting a firm's labor share, we find pollution as a new one except for the rise of "superstar firms" [24], economic globalization [25], technological progress [26], etc. Secondly, our findings also extend the growing body of literature on the negative outcomes of air pollution. High levels of PM_{2.5} can irritate the respiratory and cardiovascular systems, which can lead to severe asthma, lung disease, heart disease,

¹ AirVisual, IQAir. "2020 World air quality report." Region & City PM_{2.5} (2021).

and stroke. Like effects of air pollution on hospital use and mortality in the elderly and children [27], resident's health care expenditures [28], health insurance demand [29], the firm's labor share can be influenced by air pollution.

Secondly, we decompose the impact of pollution in multiple ways and come to a series of impacts on firm behaviors, such as output, factor income, wage rate, labor productivity, and labor employed. Previous papers avoided this complexity by considering only some particular aspects of firms and by using a relatively short logic chain. We also differ from Fu et al. (2021), who investigated impacts on productivity. In our paper, firm's labor productivity decline is one of the reasons for the labor share increase. Understanding the relationship between air pollution and labor share requires clarifying the influence mechanisms. We do so by decomposing the effect on labor share in three ways. The first way is to break down output into labor income and capital income. Pollution reduces labor income while making capital income fall evermore. The second way is to consider the decline in effective labor and the substitution or complementary relationship predicted by the theoretical model. The last way is to decompose the total effect into wage rate effect and productivity effect. The above three methods are general and can be applied to the analysis of labor share in any country.

Finally, our findings provide implications for income inequality and pollution-abatement policy. Our findings suggest pollution increases manufacturing firm's labor share. A higher labor share usually means less income equality. This result seems unreasonable. However, mechanism analysis tells us this "equality" is at the cost of reducing labor productivity and output, thereby hindering firm development, and increasing worker's health risks and lowering wage rate, thereby dampening employee welfare. Our analysis shows that environmental regulation is necessary to improve the productivity of enterprises and the welfare of employees. The rest of the paper is organized as follows. Section 2 provides a model of the links between air pollution and labor share. In section 3 we specify the econometric models and identification strategy. Section 4 describes the data. Section 5 reports our main results on firm's labor share and other responses. In Section 6 we discuss the potential welfare effect of air pollution and conclusions.

Conceptual Framework

Pollution Effects on Health and Productivity

How does air pollution affect manufacturing labor's health and productivity? Particular matters may enter the lungs and pass into the bloodstream. Human health is negatively impacted by exposure to air pollution, as demonstrated by a large body of literature in biomedicine, public health, and economics [30].

A growing body of economics literature has demonstrated that exposure to pollutants can also lead to reduced productivity and lost work. Short-term exposure to air pollution can increase the risk of diseases and morbidity of respiratory and cardiovascular systems [31, 14], leading to worker illness or absenteeism. Pollution can increase mortality and lead to the replacement of experienced workers by new, inexperienced ones after long-term exposure [32, 9].

Additionally, air pollution can affect mental health and cognition. Pollution may cause anxiety and depression, and even induce mental diseases [33]. A bad mental condition can deplete employees' self-control and organizational citizenship and increase damaging behaviors [34]. More importantly, these effects may be compounded by the spillover effect [9]. In the long run, PM_{2.5} exposure can reduce gray matter and white matter in the brain, which play an important role in thinking, decision-making and planning [35]. Pollution also reduces the cognitive performance and test scores of students [31] and the performance of manual and mental workers [9].

Papers have examined the effects of PM_{2.5} on farmer's productivity [36], manufacturing firm productivity in China and India [16, 17], the efficiency of call center workers [15], and the performance of football players and referees [37, 38]. As the majority of these studies focus on specific environments that minimize reverse causality effects, it is difficult to assess the effects of air pollution on workers more generally.

Pollution Effects on Labor Share

Aside from directly impacting human health and labor productivity, air pollution may also lead firms to take actions that influence labor share. For example, as air pollution reduces the productivity or marginal output of employees, firms are willing to pay fewer wages [39] and use more labor [9]. On the other hand, the wage rate also may rise to compensate for employee's health risk of pollution [12]. In addition, literature has proved the positive relationship between air pollution and firm's investment [40, 41].

Health effects and the substitution/complementary relationship between labor and capital may contribute to the effects of air pollution on labor share. A more significant effect on labor share occurs if impacts of pollution catalyze capital income change. Yet little is known about the distribution of output loss caused by air pollution shocks between labor and capital. The short-term health effects of air pollution may result in long-term productivity losses. It may take weeks or months for particulate matter to clear once it enters the body. Wages, labor use and capital inputs may respond to more serious illness due to endurance decline in worker's productivity. Although such responses to air pollution have not been documented, their importance

has been demonstrated in other contexts. For example, capital-labor substitution resulting from technological innovations replacing workers with machines displaces employment and reduces the labor share of value-added in the industries in which it originates [42].

Conceptual Model of Air Pollution and Labor Share

Factor Inputs and Labor Share

To illustrate the channels of effects implied by the combination of direct health effects, productivity effects, capital-labor substitution responses, we build a simple model of the firm production process to connect exposure to air pollution with labor share, our primary outcome measure.

According to Euler’s theorem, firm’s output is exactly the sum of capital income and labor income. Thus, labor share LS can be expressed as a function of output (Y), labor (L), capital (K) wage rate (w) and rent (r).

$$LS = \frac{wL}{Y} = \frac{wL}{wL + rK} = \frac{1}{1 + (r/w)(K/L)} \tag{1}$$

To clarify the reason why labor share change, consider a constant-returns-to-scale, constant-elasticity-of-substitution (CES) production function in capital (K) and labor (L) in which the air pollution level (Ω) affects labor productivity (A_L) and labor (L) (We assume here that pollution does not affect capital productivity (A_K) and capital (K)):

$$Y = \{ \alpha(A_K K)^{\frac{\varepsilon-1}{\varepsilon}} + (1 - \alpha)[A_L(\Omega)L(\Omega)]^{\frac{\varepsilon-1}{\varepsilon}} \}^{\varepsilon/(\varepsilon-1)} \tag{2}$$

Here, $\alpha \in (0,1)$, $\varepsilon \in [0, +\infty)$ which is the substitution elasticity between capital and labor. A representative firm maximizes profits by choosing the optimal level of output (Y), capital (K) and labor (L). We assume that the market is competitive.

$$\max_{K,L} \pi = Y - rK - wL \tag{3}$$

The first-order conditions for maximizing corporate profits satisfy that rent r will be equal to marginal product of capital Y_K, wage rate w equal to marginal product of labor, Y_L.

$$\frac{\partial \pi}{\partial K} = \alpha A_K \frac{\varepsilon-1}{\varepsilon} K^{-\frac{1}{\varepsilon}} \{ \alpha(A_K K)^{\frac{\varepsilon-1}{\varepsilon}} + (1 - \alpha)(A_L(\Omega)L(\Omega))^{\frac{\varepsilon-1}{\varepsilon}} \}^{\varepsilon/(\varepsilon-1)} - r = 0 \tag{4}$$

$$\frac{\partial \pi}{\partial L} = (1 - \alpha) A_L \frac{\varepsilon-1}{\varepsilon} L^{-\frac{1}{\varepsilon}} \{ \alpha(A_K K)^{\frac{\varepsilon-1}{\varepsilon}} + (1 - \alpha)(A_L(\Omega)L(\Omega))^{\frac{\varepsilon-1}{\varepsilon}} \}^{\varepsilon/(\varepsilon-1)} - w = 0 \tag{5}$$

Dividing (4) by (5) yields

$$\frac{r}{w} = \left(\frac{\alpha}{1 - \alpha} \right) \frac{A_K}{A_L(\Omega)} \frac{K^{\frac{\varepsilon-1}{\varepsilon}}}{L(\Omega)} \tag{6}$$

Substituting (6) into (1), so that

$$LS^* = \frac{1}{1 + \left(\frac{\alpha}{1 - \alpha} \right) \left(\frac{A_K K}{A_L(\Omega)L(\Omega)} \right)^{(\varepsilon-1)/\varepsilon}} \tag{7}$$

In equilibrium, firm’s labor income share depends on labor productivity (A_L), capital productivity (A_K), factor inputs (K, L(Ω)), the elasticity of substitution between labor and capital (ε) and parameter (α).

The Effect of Air Pollution

Taking derivatives and rearranging yields the effects of pollution on labor share:

$$\frac{d \ln(LS)}{d \Omega} = \frac{\varepsilon - 1}{\varepsilon} \cdot B \cdot \left[\frac{d A_L(\Omega)}{d \Omega} L(\Omega) + A_L(\Omega) \frac{d L(\Omega)}{d \Omega} \right] \tag{8}$$

Where $B = \frac{\alpha \left(\frac{A_K K}{A_L(\Omega)L(\Omega)} \right)^{\frac{1}{\varepsilon}} \frac{A_K K}{[A_L(\Omega)L(\Omega)]^2}}{1 + \left(\frac{\alpha}{1 - \alpha} \right) \left(\frac{A_K K}{A_L(\Omega)L(\Omega)} \right)^{(\varepsilon-1)/\varepsilon}} > 0$. The sign of

Eq. (8) depends on the sign of two parts: the effect on effective labor $\left[\frac{d A_L(\Omega)}{d \Omega} L(\Omega) + A_L(\Omega) \frac{d L(\Omega)}{d \Omega} \right]$ and the

magnitude of elasticity (ε). We estimate these two parts separately.

For effective labor, we estimate the effect on productivity $\frac{d A_L(\Omega)}{d \Omega}$ and on number of workers respectively $\frac{d L(\Omega)}{d \Omega}$. We use the approaches following Fu

et al. (2011) to estimate productivity effect and labor supply effect.

For the elasticity of substitution between labor and capital, we estimate the value range of ε. For 0 < ε < 1, labor and capital are complements; For ε > 1, labor and capital are substitutes; For ε = 1, labor and capital are neither complements nor substitutes and labor share will be constant over time. We also use method backing from Harrison (2005) to assess the ranges of elasticity.

Following our main estimates, we turn to the analysis above to deepen our understanding of the impact mechanisms.

Data

Pollution Data

By combining novel data on firm characteristics with air pollution data for highly-specific geographic areas across China from 1998-2015, we estimate the

effect of pollution on firm-level labor share. Compared with the study of Fu et al. (2021), our data has a longer period and is more updated. There have been several types of pollution studied, however, we focus on PM2.5 due to its serious impacts. The pollution data we use are the monthly levels of PM2.5 derived from the NASA-maintained aerosol optical depth (AOD) search system. They provide comprehensive measures of air pollution across China's geography over time. Even in areas where there are no ground monitoring stations, AOD can be used to measure the disappearance of sun rays due to dust and smoke to predict pollution [43]. Chinese ground station data were used to verify the AOD data and Chen et al. (2022) found that there was no systematic difference and no significance regarding the fixed effects of geography and year. The PM2.5 concentration is calculated based on Buchard et al. (2016) [44].

Compared to ground pollution data, satellite data offers several advantages. Firstly, the satellite data are from before the start of our firm sample in 1998, and the ground pollution data are from 2000, so we have more years of data to analyze. Secondly, satellite data covers the entire country, while ground pollution data only covered 42 cities in 2000 and 113 in 2010. Thirdly, pollutant data from the ground may be manipulated [45], but not satellite data. According to AOD data, 50 km by 60km grids are aggregated to the county level in China, the smallest administrative unit that reflects the location of firms. Then we get the annual mean concentration of PM2.5 in each year county.

Firm Data

Satellite pollution measures are countrywide, so we can include all manufacturing firms for which we have data. A survey of manufacturers conducted by the National Bureau of Statistics of China (NBS) provides data on labor share and characteristics at the firm level. Including SOEs of all sizes and non-SOEs with annual sales of over 5 million yuan (\$800,000), the survey contains detailed information on the firm's location, accounting standards, and characteristics. This captures above 90% of China's total manufacturing output in the later years [46].

Our unbalanced panel is formed by matching firms over time. The panel is very unbalanced, since China has experienced rapid growth during the sample period, and a large number of new firms have exceeded CNY 5 million in revenue each year. Using industry-level price indices, we first convert nominal values into real ones. Observations with missing or unreliable data are also dropped. Finally, to reduce the risk of data reporting errors, we winsorize the top and bottom 0.5% of data based on value-added, employment, and capital. The final data include 2,442,367 firm-year observations.

Measuring labor share is a challenge when trying to obtain a broad-based measure. According to the definition, labor share is the proportion of labor income

to total income. We use wages and welfare costs as the measure of firm's labor income. For total income or output, there are two commonly used indicators. One is the value-added of firms, which equals labor income (wages and welfare) plus capital income (operating profit and depreciation of fixed asset). Operating revenue, on the other hand, is reported directly in the data and is equal to the sales of company goods during the year.

Weather Data

We obtain daily station-level meteorological variables from China National Meteorological Information Centre (CNMIC). Weather conditions such as temperature, precipitation, relative humidity, wind speed, sunshine duration and pressure may affect air pollution and labor share. To allow that extreme weather events have different impacts compared to normal weather conditions, we follow Fu et al. (2021) and calculate the 20 quantiles of each meteorological variable based on the daily distribution and include the number of days in a year in each quantile. Then we match the weather conditions with firm-level data by county-year.

Thermal Inversion

Our instrument thermal inversion is obtained from NASA. This data reports the temperature of 42 vertical layers from 110 to 36,000 meters on a 50 km×60 km grid every 6 hours. The grid of each layer is aggregated to the county level every 6 hours. Following Arceo et al. (2016), we define thermal inversion as the temperature of the second layer (320 m), which is higher than the temperature of the first layer (110 m). Thermal inversion is short-lived compared to annual firm measurement (about a few weeks), so cumulative annual inversion measurements are used to maintain long-term consistency. Each county's annual average temperature difference (equal to or greater than zero) between the second layer and the first layer is used as a measure of inversion intensity.

City Data

We use city-level economic outcomes national in scope derived from China's prefecture-level Cities Yearbook. Regional economic activities can affect pollution and labor share. We use the city economic and demographic variables covering all manufacturing firms. The data are available for the entire sample period (1998-2015).

Table 1 shows summary statistics for the key variables. The firm's characteristics are at the firm's annual level, reflecting the high changes in labor share and productivity. Pollution and inversion are county-level data. High levels of pollution can affect physical and mental health and labor productivity. According to the World Health Organization (WHO), PM2.5 should

Table 1. Summary Statistics for Firm-Level Labor Share, County-level Pollution and Other Variables.

Notation	Variable	Definition	Unit	Mean	Std. dev.
<i>LS</i>	Labor share	$\frac{\text{wages} + \text{benefits}}{(\text{wages} + \text{benefits}) + (\text{profits} + \text{depreciation of fixed assets})}$	/	0.61	0.59
<i>LS2</i>	Labor share	$\frac{\text{wages} + \text{benefits}}{\text{operating revenue}}$	/	0.085	0.090
<i>Y/L</i>	Labor productivity	Operating revenue/number of employees	thousand yuan	480.77	763.27
<i>L</i>	Labor inputs	Number of employees	person	349.14	1452.31
<i>w</i>	Wage rate	(wages + benefits)/number of employees	thousand yuan	20.57	26.71
<i>PM2.5</i>	PM2.5 concentrations	County annual average PM2.5 concentrations calculated by bilinear interpolation	μg/m ³	37.88	10.40
<i>PM2.5b</i>	PM2.5 concentrations	County annual average PM2.5 concentrations calculated by nearest interpolation	μg/m ³	38.62	10.42
<i>IV</i>	Strength of thermal inversion	The temperature difference between 320 meters and 110 meters above the ground, the value less than 0 is recorded as 0	°C	0.26	0.18
<i>IV2</i>	Strength of thermal inversion	The temperature difference between 320 meters and 110 meters above the ground	°C	0.21	0.36
Firm characteristics	State-owned	Equals to 1 if the firm is „state-owned”, otherwise 0	/	0.075	0.26
	Foreign capital	The proportion of foreign capital in the paid-in capital of	/	0.064	0.23
	Ln (age)	Log value of firm’s duration years	/	2.04	0.80
	Asset-liability ratio	Liabilities/total assets	/	0.54	0.28
	Profit margin	Profit/revenue	/	0.05	0.087
	Size	Log value of total assets	/	10.17	1.51
City variables	Percentage of secondary industry	Secondary industry output /GDP	/	0.51	0.082
	ln (GDP per capita)	Log value of CPI-adjusted real GDP per capita	/	1.30	0.52
	Population density	Population/administrative area	/	0.072	0.071
	Fiscal self-sufficiency rate	Financial revenue/financial expenditure	/	0.79	2.64
	Tax burden	Financial revenue /GDP	/	0.066	0.025
Weather bins	Temperature bins	The annual number of days within every 20 quantiles for temperature	days	/	/
	Precipitation bins	The annual number of days within every 20 quantiles for precipitation	days	/	/
	Pressure bins	The annual number of days within every 20 quantiles for pressure	days	/	/
	Humidity bins	The annual number of days within every 20 quantiles for humidity	days	/	/
	Wind speed bins	The annual number of days within every 20 quantiles for wind speed	days	/	/
	Sunshine duration bins	The annual number of days within every 20 quantiles for sunshine duration	days	/	/

average no more than 10µg/m³ annually and no more than 20 µg/m³ within 24 hours (WHO, 2006) [47]. In our sample, the average annual pm2.5 level is 38 µg/m³. The annual intensity of thermal inversion is 0.26°C.

Research Strategy

We estimate the effects of pollution on labor share in two steps. We first estimate the impact of pollution on labor share by parameterizing the model in Section 2. Second, we conduct mechanism analysis in three ways. The first way is to divide firm’s output into labor income and capital income and compare changes in these two parts of income. The second is to estimate the effects of pollution on effective labor determined by labor productivity and labor inputs, which is predicted in the theoretical model of Section 2 and the elasticity of substitution between labor and capital. The last way is decomposing labor share change into wage rate effect and productivity effect and observing the two effects of pollution respectively. In this section, we discuss how to specify and identify estimates.

Effect of Pollution on Labor Share

Labor share is modeled in a log form to be consistent with previous literature that uses labor share as explained variables and for the convenience of composition analysis. We use the following regression equation to relate labor share to pollution concentrations:

$$\ln(LS)_{ijt} = \beta_0 + \beta_1 PM2.5_{jt} + \beta_2 X_{ijt} + \alpha_i + \rho_t + \varepsilon_{ijt} \quad (9)$$

We use two different measures for firm’s labor share (LS): labor income divides total value-added and labor income divides total revenue. Here *i* denotes the firm, *j* denotes the region firm located and *t* denotes the year. *PM2.5* is the mean PM2.5 across all regions and *X* contains the vector of firm characteristics, weather and city variables faced by firm *i* in year *t* and region *j*. Since most firms’ locations are known at the county level, the pollution and weather indicators are aggregated to the county level. Here β_1 captures the effect of pollution on labor share keeping other conditions constant.

Firm fixed effect (α_i) captures firm attributes that are time persistent. As no firms switch industries over the sample period, they also absorb time-invariant and industry-invariant factors that affect productivity. In addition, very few firms switch counties, so most time-invariant county-specific unobservables that affect labor share are observed by firm fixed effects. Annual shocks to labor share, such as business cycles, are captured by year-fixed effects (ρ_t). Firm-specific factors that affect labor share are captured by the error term (ε_{ijt}). We cluster SEs by firms to enable serial correlation within firms within a firm over time and examine

robustness by clustering SEs to county-level and prefecture-level.

Identification requires that pollution is independent of the error term in (9). A casual identification issue can lead to bias in OLS estimates of the effect of pollution on labor share due to reversal-causality bias and omitted-variable bias.

Causal Identification – Instrumental Variable (IV) Method

We use thermal inversion as the instrument of air pollution to obtain causal effects on labor share. An effective instrument is correlated to air pollution in the county and uncorrelated to firm’s labor share. Our instrument is the annual average intensity of thermal inversion in each county. Thermal (or temperature) inversion departs from this general rule when the temperature drops with height above the surface of the earth. This occurs when large amounts of warm, low-density air move over cooler, denser air masses that trap dust and contaminants near the ground and increase air pollution. The inversion layer is a good instrument since it is uncorrelated to labor share other than through pollution after adjusting for weather variables. This identification strategy has been used to estimate the impact of air pollution on a variety of outcomes [19-22].

With this as an instrument, we employ two-stage least square (2SLS) with the first stage equation

$$PM2.5_{ijt} = \gamma_0 + \gamma_1 IV_{jt} + \gamma_2 X_{ijt} + \alpha_i + \rho_t + \eta_{ijt} \quad (10)$$

where IV_{jt} is the intensity of thermal inversion in firm *i*’s county in year *t*. In order to ensure that the exclusion restriction in the second stage is met, the firm, weather, and region variables from the second stage are included.

Results

Effect of Pollution on Labor Share

Baseline Results

Our first estimates do not take into account the endogeneity bias between labor share and pollution. Table 2 presents OLS estimates of (9) using labor share as the explained variable. The results show that whether or not controlling firm, weather and region variables, PM2.5 pollution is negatively related to labor share.

A reverse causal effect and omitted variables cause the OLS to produce inconsistent estimates. Eq. (10) is used to produce instrumented pollution concentration values. The top panel of Table 3 shows the second-stage results. Compared with the OLS estimates, the coefficient moves to being significantly positive which means that OLS estimates generate downward biases. Labor share is positively affected

Table 2. OLS estimates of Effect of Air Pollution on Labor Share.

	(1)	(2)	(3)	(4)
Variables	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$
$PM_{2.5}$	-0.0112***	-0.0068***	-0.0067***	-0.0059***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Firm characteristics		Y	Y	Y
Weather Variables			Y	Y
City Variables				Y
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	2,442,367	2,442,367	2,442,367	2,442,367
Adjusted R ²	0.5468	0.7412	0.7415	0.7426

Note: ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively. The numbers in parentheses are the standard errors clustering to the firm level. The same setting applies below with no special instructions.

Table 3. 2SLS Estimates of Effect of Air Pollution on Labor Share.

The second stage of 2SLS estimates				
	(1)	(2)	(3)	(4)
Variables	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$
$PM_{2.5}$	0.0650***	0.0634***	0.0418***	0.0401***
	(0.0045)	(0.0035)	(0.0023)	(0.0023)
Firm characteristics		Y	Y	Y
Weather Variables			Y	Y
City Variables				Y
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	2,442,367	2,442,367	2,442,367	2,442,367
Adjusted R ²	-0.0469	0.3889	0.4122	0.4164
The first stage of 2SLS estimates				
	(1)	(2)	(3)	(4)
	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$
IV	3.1376***	3.1403***	4.7584***	4.7784***
	(0.0380)	(0.0380)	(0.0387)	(0.0384)
KP F-statistics	63.02	28.80	30.65	36.10

Note: ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively.

by instrumented $PM_{2.5}$ when there is no control. A $1 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$ increases labor share by 6.50%. Gradually controlling for firm, weather and region variables decreases the estimate slightly and the significance level does not change. A $1 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$ increases labor share by 4.01%. How large are these effects? Evaluating this at the mean labor share of the sample (0.61) yields an absolute value of 0.024.

Also, since controlling for all variables is preferred, we do so throughout the rest of the paper.

The lower panel of columns of Table 3 shows that the thermal inversion is an effective predictor of $PM_{2.5}$ concentration. With or without controls, the coefficient of annual thermal inversion is positive and highly significant, and the F-statistic for weak identification is much greater than the Stock-Yogo critical value.

Table 4. Effect of Air Pollution on Labor Share: Robustness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	<i>ln(LS2)</i>	<i>ln(LS2)</i>	<i>ln(LS)</i>	<i>ln(LS)</i>	<i>ln(LS)</i>	<i>ln(LS)</i>	<i>ln(LS)</i>	<i>ln(LS)</i>
<i>PM2.5</i>	0.0401***	0.0638***		0.0431***	0.0356***	0.0401***	0.0401***	
	(0.0023)	(0.0027)		(0.0032)	(0.0022)	(0.0088)	(0.0123)	
<i>PM2.5b</i>			0.0415***					
			(0.0024)					
<i>SO₂</i>								0.1018**
								(0.0399)
Firm characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Weather Variables	Y	Y	Y	Y	Y	Y	Y	Y
City Variables	Y	Y	Y	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
year×industry fix effects					Y			
Cluster level of standard errors	Firm	Firm	Firm	Firm	Firm	County	City	Firm
Observations	2,442,367	2,442,367	2,442,367	2,442,367	2,442,367	2,442,367	2,442,367	2,442,367
Adjusted R ²	0.4164	0.3024	0.4150	0.4142	0.4165	0.2616	0.4164	0.1693
KP F-statistics of the first stage	36.10	36.10	35.46	45.67	31.28	36.88	38.29	37.36

Note: ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively.

A 1-degree increase in thermal inversion raises PM2.5 by 4.78 µg/m³ controlling for all variables.

Robustness Checks

As shown in Table 4, we show robustness to different model settings compared to the baseline results shown in column (1). Firstly, we re-estimate our main specification, Eq. (9), for labor share calculated in another way, that is, labor income divided by operating revenue. The result in Column (2) is slightly bigger (6.38%) but similar to that based on the labor share measure for our baseline analysis. Secondly, we test whether changing air pollution measures affect our results. Column (3) changes the calculation method of PM2.5 concentration from bilinear interpolation to nearest interpolation, yielding the same estimate (4.15%). Thirdly, we use the annual average of the daily temperature difference between the third layer (the second layer in baseline analysis) and the first layer as the measurement of inversion intensity. As shown in column (4), the result is similar to baseline analysis. Fourthly, In the baseline results, year-fixed effects are used to control for national time trends and firm fixed effects are used to control for time-persistent firm characteristics. We test for robustness to industrial time trends by adding industry-by-year fixed effects in

column (5) and yield significant results. Fifthly, as some of our explanatory variables are grouped at the county-level and prefecture-level, we cluster the SEs at the county level in column (6) and at the city level in column (7), allowing for spatial and serial correlation within larger areas. The SEs in column (6) and column (7) increase slightly and the coefficient remains significant. Lastly, we verify that using the concentration of sulfur dioxide (SO₂) as an alternative measure of air pollution level would not change the baseline results. Like PM2.5, SO₂ is an air pollutant and can harm both health and the environment. SO₂ concentration data was also collected from NASA and its effect on labor share is shown in the last column of Table 4. It indicates that air pollution, as measured by other pollutants, also increased firm’s labor income share. Although the coefficient of SO₂ and is not directly comparable to the coefficient of PM2.5, its positive sign enhances our confidence in the benchmark results.

Labor Productivity and Firm’s Behavior

Effects on Output, Labor Income and Capital Income

Estimates so far capture the effect of air pollution on labor income. Since firm’s output is either allocated to labor in the form of wage and benefits or capital

Table 5. Effect of Air Pollution on Value-added, Labor Income and Capital Income.

	(1)	(2)	(3)
Variables	ln (Value added)	ln (Labor income)	ln (Capital income)
PM2.5	-0.0656***	-0.0247**	-0.0809***
	(0.0132)	(0.0116)	(0.0176)
Firm characteristics	Y	Y	Y
Weather Variables	Y	Y	Y
City Variables	Y	Y	Y
Firm fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Observations	2,442,367	2,442,367	2,442,367
Adjusted R ²	0.2697	0.0979	0.2532

Note: ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively. The results are all estimated using the IV method and from the second stage of 2SLS estimates. The K-P F statistics of the first stage of 2SLS are the same as column (5) of Table 2.

in the form of profit and depreciation, the increase in labor share may result from changes in output, labor income and capital income. To assess this, we estimate Eq. (9) with the above three parts as the dependent variable using the intensity of thermal inversion as the instrument.

The results are shown in Table 5. As shown in column (1), a 1 $\mu\text{g}/\text{m}^3$ increase in PM2.5 decreases firm's output by 6.56%. This production loss is caused by the productivity decline caused by air pollution. We can see the change of different parts of output in column (2) and column (3). A 1 $\mu\text{g}/\text{m}^3$ increase in PM2.5 decreases labor income by 2.47%, while a 1 $\mu\text{g}/\text{m}^3$ increase causes capital income decline by 8.09%. Observing the magnitude of the two estimates, we find that when air pollution occurs, capital bears more production loss compared with labor.

Effect on Effective Labor and Substitution Elasticity Between Labor and Capital

An important but previously most unanswered question is why air pollution decreases labor income more than capital income and hence increases the firm's labor share. As we point out in section 2, such effects can occur through two channels. In the first place, air pollution can cause health problems, like asthma or heart attacks, leading to chronic health issues. Workers may be less productive and less available for work if they have these chronic diseases. Firms may hire more labor to compensate for this productivity decline. Intuitively, the firm's total effective labor inputted in production will still decrease. Second, change in labor share depends on the substitution elasticity between capital and labor. A large literature in factor share documents the relationship between labor share and capital-labor elasticity. The correlation between the capital-labor ratio and labor share reflects the elasticity

since the derivative of labor share to $\ln(K/L)$ varies with the elasticity of substitution between labor and capital (Harrison, 2005). The coefficient on $\ln(K/L)$ could also be positive or negative, depending on whether the elasticity of substitution is high or low².

In column (1) of Table 6, we test for the elasticity of substitution between capital and labor. The coefficient on relative factor inputs (K/L) is negative and significant. This suggests that one important factor driving labor share is changes in factor inputs: increases in the labor endowment (or declines in the capital stock) led to an increase in labor share. This implies that the elasticity of substitution between labor and capital is relatively low, or that labor and capital are substitutes. For example, a fall in effective labor cannot be easily substituted with more capital, leading to a more than proportionate increase in return to labor relative to capital and increasing labor share.

As indicated in column (2) and column (3) in Table 6, the results suggest that air pollution led to the decrease in labor productivity and the increase in labor hired by firms. For every 1 $\mu\text{g}/\text{m}^3$ increase in PM2.5, the labor productivity decreased by 8.44%, and the labor hired increased by 1.85%. The effect of air pollution on effective labor can be calculated using $[\frac{dA_L(\Omega)}{d\Omega} L(\Omega) + A_L(\Omega) \frac{dL(\Omega)}{d\Omega}]$ in Eq. (8). Therefore, based on a mean L of 349.14 and a mean A_L of 480.77, the estimated effective labor decrease for every 1 $\mu\text{g}/\text{m}^3$ increase in PM2.5 is 20.57 in yuan.

² In previous studies, the coefficient of (K/L) can be used to judge the complementary or substitutional relationship between labor and capital. As shown in Eq. (7), $LS^* = \frac{1}{1 + \frac{\alpha}{1-\alpha} (\frac{AK}{A_L(\Omega)L(\Omega)})^{\epsilon-1}/\epsilon}$. It is easy to find that LS increases as (K/L) increases when $0 < \epsilon < 1$ and LS decreases as (K/L) increases when $\epsilon > 1$.

Table 6. Elasticity of Substitution and Effects on productivity, labor inputs and wage rate.

	(1)	(2)	(3)	(4)
Variables	ln(LS)	ln(Y/L)	ln(L)	ln(w)
PM2.5	0.0406***	-0.0844***	0.0185***	-0.0410***
	(0.0095)	(0.0151)	(0.0071)	(0.0115)
ln(K/L)	-0.0603***			
	(0.0019)			
Firm characteristics	Y	Y	Y	Y
Weather Variables	Y	Y	Y	Y
City Variables	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	2,442,367	2,442,367	2,442,367	2,442,367
Adjusted R ²	0.2439	0.3037	0.1467	0.0938

Note: ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively. The results are all estimated using the IV method and from the second stage of 2SLS estimates. The K-P F statistics of the first stage of 2SLS are the same as column (5) of Table 2.

The firm’s total effective labor decreased as a result of this productivity loss, even though firms hired more labor to compensate for some of it. Furthermore, due to the complementary relationship between labor and capital, capital income decreases more than labor income. The reduction of the effective labor means a reduction in the ability to operate machines, and accordingly, the firm reduces its capital stock. Therefore, air pollution reduces labor productivity and firm’s total output and through the complementary effect between labor and capital, the income allocated to capital has decreased more than the income allocated to labor.

Labor Share as Wage-Productivity Gap

As shown above, firm’s labor share increase stems from the reduced productivity caused by air pollution and the firm hires more labor to compensate for this efficiency loss. Likewise, firm’s wage-productivity gap can provide a new explanation for labor share change. To further explain this point, we decompose the labor share decline (or increase) into wage rate change and labor productivity change. By comparing the relative magnitude of the two effects of air pollution, we can further explain the impact of air pollution on labor share.

Dividing the numerator and denominator of Eq. (1) by L, we have

$$LS = \frac{wL}{Y} \tag{11}$$

Taking the logarithm of both sides of the equation, we get

$$\ln(LS) = \ln(w) - \ln(Y/L) \tag{12}$$

Further, we can express the change in labor share as the gap between change in wage rate and labor productivity

$$\Delta \ln(LS) = \Delta \ln(w) - \Delta \ln(Y/L) \tag{13}$$

The sign and magnitude of $\Delta \ln(w)$ can influence labor share. As shown in Eq. (13), if $\Delta \ln(w) > \Delta \ln(Y/L)$, the wage rate effect is bigger than the productivity effect, labor share increases; otherwise, labor share decreases. As the results have shown, pollution cause a decrease in labor productivity and thus $\Delta \ln(Y/L) < 0$. To estimate the wage rate effect, we use the logarithm of wage per capita as explained variable to test for pollution effects. As reported in column (4) of Table 6, a $1 \mu\text{g}/\text{m}^3$ increase in PM2.5 decreases the wage rate by 4.1% over the sample period. By comparison, a $1 \mu\text{g}/\text{m}^3$ increase in PM2.5 decreases labor productivity by 8.44%. Labor share change caused by $1 \mu\text{g}/\text{m}^3$ increase in PM2.5 concentration can be calculated using Eq. (13) is $\Delta \ln(LS) = (-0.0410) - (-0.0844) = 0.0434$, which is consistent with our baseline estimates for the effect of pollution on labor share (0.0401).

In a perfectly competitive labor market, wage and productivity change simultaneously and the gap between these two is constant. As workers’ productivity is reduced by air pollution, the firm is willing to pay less for one more unit of employees. Although workers tend to move to good air quality areas, the expected cost of migration in one year is too high compared to the expected benefit and thus the labor supply is inelastic. The firm has incentives to pay a lower wage rate. In the short run, the wage does not decline enough to match

productivity loss. Since productivity is more responsive to pollution, there is a larger wage-productivity gap and larger labor share.

Heterogeneity by Factor Inputs Intensity, Property Type and Environmental Regulation

In the previous section, we find a robust and significant effect of air pollution on manufacturing firm's labor share in China. We argue that the effect we identify reflects the labor productivity loss and complementary relationship between labor and capital. However, different firm types may have different responses.

To understand the conditions under which labor share is most sensitive to pollution shocks, we explore how pollution effects vary with firm characteristics. To do so, we categorize each firm as labor-intensive, capital-intensive and technology-intensive according to their factor inputs proportion. Column (1)-(3) in Table 7 reports the results of this heterogeneity analysis. We find that air pollution causes larger labor share increases in capital-intensive and technology-intensive firms. A 1 $\mu\text{g}/\text{m}^3$ increase in PM2.5 concentration increased labor share of capital-intensive and technology-intensive firms by 5.25% and 5.20% respectively. In contrast, a 1 $\mu\text{g}/\text{m}^3$ increase in PM2.5 level increases labor-intensive firm's labor share by only 2.78%.

Air pollution has greater effects on capital-intensive and technology-intensive firms for two reasons. First, these two types of firms have high proportions of high-skilled or high-educated workers and high firm productivity. The heterogeneity could stem from differences in vulnerability to air pollution. Individuals with higher levels of education are more likely to

understand the harmful effects of air pollution [23], which would increase their avoidance or defensive actions like spending more time indoors and missing work that may hamper productivity. Second, capital and labor may be more complementary in capital-intensive and technology-intensive firms since high skilled workers master important production technologies such as operating complex machines and developing new patents, making them more difficult to be replaced by machines(capital) in labor-intensive industries. When air pollution hampers their productivity, the capital stock would decline more to match the firm's effective labor reduction and hence labor share increases.

To explore heterogeneity in labor share effects of air pollution by property rights, we estimated Eq. (9) samples into privately-owned enterprises (POEs), state-owned enterprises(SOEs) and foreign-funded enterprises(FFEs). Results are reported in columns (4)-(6) of Table 7. We find a relatively bigger effect in POEs and a smaller effect in FFEs. A 1 $\mu\text{g}/\text{m}^3$ increase in PM2.5 level increases POEs' and FFEs' labor share by 4.62% and 2.57% respectively. It is known as the "knowledge spillover effect" that For FFEs can bring technical expertise, marketing and management skills to host countries from home countries [48]. This effect is likely to slow the impact of air pollution on productivity and labor share. In comparison, SOEs' labor share is not significantly affected by pollution. This result could derive from the stricter job protection in SOEs. In China, employees in SOEs have more access to medical insurance and job protection when working in polluted environments. As a result, their productivity is more likely to be immune to air pollution.

Column (7) and (8) of Table 7 shows how our estimates of the effect on labor share vary by the implementation of New Ambient Air Quality Standards

Table 7. Heterogeneous Labor Share Effects of Air Pollution.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Labor-intensive	Capital-intensive	Technology-intensive	POEs	SOEs	FFEs	1998-2011	2012-2015
	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$	$\ln(LS)$
<i>PM2.5</i>	0.0278*** (0.0105)	0.0525*** (0.0115)	0.0520*** (0.0109)	0.0462*** (0.0095)	-0.0045 (0.0111)	0.0257** (0.0119)	0.0474*** (0.0087)	-0.0144 (0.0247)
Firm characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Weather Variables	Y	Y	Y	Y	Y	Y	Y	Y
City Variables	Y	Y	Y	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	873,565	737,577	807,753	2,079,486	133,779	187,763	1,601,784	692,131
Adjusted R ²	0.1739	0.4193	0.4377	0.4291	0.2472	0.4359	0.3381	0.3331

Note: ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively. The results are all estimated using the IV method and from the second stage of 2SLS estimates. The K-P F statistics of the first stage of 2SLS are the same as column (5) of Table 2.

in China in 2012. In this year, China revised its national ambient air quality standards (NAAQS) (GB3095-2012) for particular matters (PM) to protect public health. We expect that the new NAAQS would mitigate the health risk from exposure to ambient PM_{2.5} and hence the effect on labor productivity and labor share. Column (7) and column (8) of Table 7 show the estimates using samples before and after 2012. As we expected, the effect become insignificant after the act of NAAQS. A recent study finds that the new NAAQS has a certain positive effect on health and that PM₁₀ and PM_{2.5} become less harmful to human health due to the new standard [49] (Bai et al., 2021). In addition, there is a possibility that the sample after NAAQS is relatively short and our data frequency is annual. Using only 4 time periods in itself could skew the result towards zero. However, longer samples are needed to rule out this possibility in future research.

Discussion and Conclusion

Our study estimates the effect of air pollution on labor share using Chinese manufacturing enterprises database with the largest sample size. To deal with potential endogeneity issues that may cause biased estimates, we apply the instrumental variable method. We use exogenous and meteorologically determined thermal inversions to measure the impact of pollution on labor share. The method weakens the endogeneity bias and demonstrates that air pollution has a positive effect on labor share.

Our results provide the first evidence of the causal effect of air pollution on firm's labor share at a national scale. The implications of these results are broad for income distribution. On the one hand, our study shows a labor share increase in air pollution. It is consistent with the previous study by Liu and Wang (2020) who find an inverted-U-shaped relationship between air pollution and labor share and China is currently on the left side of the inverted-U-shaped curve. This result also indicates that stricter environmental regulations may exacerbate income inequality. On the other hand, air pollution brings economic losses by decreasing labor productivity, output, labor income, capital income and wage rate. This suggests potential economic benefits of improving air quality.

By providing comprehensive empirical evidence on how pollution can affect labor share, our study contributes to the emerging literature on the substitution elasticity between capital and labor. Our findings indicate that air pollution decreases labor productivity significantly. Although firms make up for this efficiency loss by hiring more labor, the downward trend in total effective labor cannot be offset. Due to the complementary relationship between labor and capital, effective labor per unit can only operate a fixed amount of machinery, and the capital stock is reduced correspondingly.

Our findings shed new light on the debate over whether environmental regulations positively or negatively affect workers' wages. There has been much discussion of the cost-saving benefits of a better living environment due to improved air quality, which reduces wage compensation and labor costs. Another channel influencing this debate is confirmed by our results. By reducing pollution, environmental regulations will increase wages through an increase in labor productivity, and as a result, improve workers' welfare.

Since our identification relies on yearly variation, the results in this paper are short-run effects of air pollution on labor share. However, long-run effects can be different from short-run impacts. To boost productivity, firms may respond to pollution in the long term by reducing indoor pollution or moving to less-polluted areas. Pollution will have a smaller effect on labor share in the long run if workers, especially those with a greater willingness to pay for better air quality, migrate in the long run.

Although we capture channels by which pollution can influence labor share and find the reason behind is the decline in labor productivity, we are unable to explain how exactly pollution influences labor productivity. For example, effects on hours worked would indicate that in addition to worker's pollution exposure at work, they need to take care of family members who are sick due to air pollution, while effects on productivity per hour might indicate that there are large necessities from preventing pollution exposure at the workplace.

Estimations of the effect of environmental regulations on labor share are what we hope will receive more attention in future research. Since environmental regulations would bring extra complying costs to firms, the results might be asymmetric to our findings due to different strategies firms can use when maximizing profits.

Acknowledgment

This research is supported by the National Natural Science Foundation of China (Grant No. 71903008).

Conflicts of Interests

The authors declare no competing interest.

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