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# Earning reduction caused by air pollution: Evidence from China

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ABSTRACT

This paper investigates the effect of air pollution on employees' earnings in China. Using both instrument variable (IV) and regression discontinuity design (RDD), we find that air pollution reduces employees' yearly earnings. A one μg/m$^3$ increase in yearly $PM_{2.5}$ decreases employees' yearly earnings by 175.4 CNY. The total loss in earnings for all employees working for our sample firms amounts to about 268.59 million CNY. Our estimations are not sensitive to a battery of different robustness checks. We also find that the effect of air pollution differs based on several factors including labor intensity, ownership types and firm size. Our mechanism tests indicate that air pollution can reduce employees' earnings by lowering their unit wage and reducing their working time. The resulting increase in firms' labor costs further undermines their operating status. Notably, air pollution exerts a non-linear negative effect on employees' earnings. Overall, our findings suggest that air pollution can significantly lower employees' benefits by reducing their earnings. Our paper also provides powerful support for formulating environmental regulations in the future.

## 1. Introduction

Citizens' welfare, such as health status, subjective well-being, consumption, and income, has been a topic of concern in both developed and developing countries. In this paper, we focus on people's income, which directly affects their welfare. The determinants of workers' earnings have been widely discussed in the literature on labor and political economics, exploring topics such as firm size (El Badaoui, Strobl, & Walsh, 2010; Oi & Idson, 1999), ownership types (Cronqvist, Heyman, Nilsson, Svaleryd, & Vlachos, 2009; Girma & Görg, 2007; Heyman, Sjöholm, & Tingvall, 2007), and management system such as employee stock ownership (Harbaugh, 2005), employees' individual characteristics such as skilled and education level (Chen, Fan, Gu, & Zhou, 2020; Heckman, Humphries, & Veramendi, 2018; Lemieux, 2006), health status (Chirikos & Nestel, 1985; Lee, 1982), cognitive ability (Heckman, Stixrud, & Urzua, 2006; Lindqvist & Vestman, 2011), marriage and childbearing age (Blackburn, Bloom, & Neumark, 1993; Loughran & Zissimopoulos, 2009), and gender (Blau & Kahn, 2017; Card, Cardoso, & Kline, 2016), international market environment such as trade shock (Artuç & McLaren, 2015; Friedrich, 2020) and exchange-rate shock (Araújo & Paz, 2014; Verhoogen, 2008), labor market force such as labor supply (Clemens, Kahn, & Meer, 2021) and labor spatial misallocation (Hsieh & Moretti, 2019), national macroeconomic cycle such as social unemployment rate (Blanchard & Katz, 1999; Hall & Milgrom, 2008), social and economic force such as minimum wage (Lemos, 2009; MaCurdy, 2015), and the household registration system in China (Démurger, Gurgand, Li, & Yue, 2009; Meng & Zhang, 2001).

However, little is known about how much air pollution, a non-economic factor that employees encounter during work, can

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influence their earnings. Therefore, we conduct a causality investigation of the relationship between air pollution and workers' yearly earnings to address this research gap. In the context of heightened climate risks and severely rising air pollution in several developing countries (Greenstone & Hanna, 2014), policymakers and researchers are giving increasing attention to air quality since it can significantly affect citizens' well-being. Thus numerous studies have sought to investigate the causal effect of air pollution on citizens' welfare level indicators, including people's physical health (Guan, Zheng, Chung, & Zhong, 2016; Schlenker & Walker, 2016; Xu, Chen, & Ye, 2013), mental health (Chen, Oliva, & Zhang, 2018; Xue, Zhu, Zheng, & Zhang, 2019), infants and adults mortality (Chay & Greenstone, 2003; Cheung, He, & Pan, 2020; Ebenstein et al., 2015; Fan, He, & Zhou, 2020; He, Liu, & Zhou, 2020), subjective well-being (Li et al., 2019; Zhang, Zhang, & Chen, 2017; Zheng, Wang, Sun, Zhang, & Kahn, 2019), avoidance behaviors (Ito & Zhang, 2020; Zhang & Mu, 2018), and long-run earnings (Heblich, Trew, & Zylberberg, 2021; Isen, Rossin-Slater, & Walker, 2017).

China provides an ideal background for our research for two reasons. First, China has experienced severe environmental pollution problems. Statistical data compiled by the World Health Organization (WHO) in 2016 demonstrates that air pollution is a major risk for people with non-communicable diseases and leads to a significant increase in morbidity and mortality.[1] In our sample, the annual average $PM_{2.5}$ rose from 46.02 μg/m$^3$ in 1998 to 67.29 μg/m$^3$ in 2007 for nearly 46%. Second, according to gross domestic product (GDP) data reported by the National Bureau of Statistic (NBS) in China, China's GDP increased from 7.96 trillion CNY in 1998 to 24.66 trillion CNY in 2007, a threefold increase for 10 years, suggesting that people in China experienced a rapid earning increase from 1998 to 2007.[2] Thus, China's significant differences in air pollution combined with the huge changes in income levels contributes to our understanding of the relationship between air pollution and employees' earnings.

Because we focus on employees' total labor income, we infer that air pollution can affect employees' earnings by lowering their unit wage (defined as labor productivity) (Chang, Graff Zivin, Gross, & Neidell, 2016, 2019; Fu, Viard, & Zhang, 2021; Graff Zivin & Neidell, 2012; He, Liu, & Salvo, 2019) and reducing their labor supply (e.g., by taking leave for health reasons) because previous studies have found that air pollution can cause great harm to human physical and mental health. The increase in firms' labor costs caused by the resulting decline in employees' labor productivity and work time can further undermine firms' operating status. Therefore, we consider that the earnings reduction caused by air pollution may be even larger in the long term if firms encounter operating problems.

However, several issues arise when estimating the causal effect of air pollution on employees' annual earnings because of the natural endogeneity of air pollution. First, air pollution is the coproduct of local economic activities which are highly likely to be determinants of local citizens' earnings. Second, measurement error problems exist because we use the air pollution of the county in which the firm is located to proxy the real air pollution that the firm faces. Finally, the omitted variables problem cannot be neglected in empirical studies. To deal with these endogeneity problems, we use an instrumental variable (IV) approach as our preferred specification by instrumenting air pollution with the number of days in a year on which thermal inversion occurs at least once. Thermal inversion, as a meteorological phenomenon, is independent of economic activities, thus separating the exogenous parts of air pollution to ensure our validity of specification. And thermal inversion can increase the air pollution level because this meteorological phenomenon hinders the diffusion of smoke, pollutants, and water vapor since it dampens the vertical convection of the air. Additionally, thermal inversion has been used as an instrument variable for air pollution in several studies (for example, Chen, Oliva, & Zhang, 2022; Deschênes, Wang, Wang, & Zhang, 2020; Fu et al., 2021; Jans, Johansson, & Nilsson, 2018). In our preferred IV specification, we find that a one μg/m$^3$ increase in yearly average $PM_{2.5}$ decreases employees' annual earnings by around 175.4 CNY (14.6 CNY monthly), corresponding to 1.4% of the mean value, a strong negative influence. Based on this estimator, we further reveal that the total loss in earnings for all employees working for our sample firms amounts to about 268.59 million CNY. To strengthen our estimators' reliability, we conduct several robustness tests. Our baseline results remain intact.

We also implement a regression discontinuity design using the air pollution difference caused by China's Qinling-Huai River heating system, a policy determined by geographical elements to reinforce our casual estimations. We then implement a battery of heterogeneity analyses of firms' labor intensity, ownership types, pollution level and size to further demonstrate our underlying mechanisms.

Given the fact that the impact of air pollution on economic activities has been shown to be non-linear (He et al., 2019; Schlenker & Walker, 2016; Zhang, Ren, Zhang, & Zhang, 2020), we explore whether the non-linear effect exists in our paper. Not surprisingly, our paper also shows that air pollution has a negative impact on employees' annual earnings until it surpasses a specific threshold.

Our paper makes four primary contributions. First, this paper adds to the strand of literature studying the socioeconomic effect of air pollution, especially the stream investigating how air pollution affects human welfare. Previous studies investigating people's welfare give greater attention to health status (including physical and mental health), subjective well-being, mortality, and additional living expenditure for avoidance behaviors. Little is known about workers' earnings, the indicator most directly related to welfare level. Recently Heblich et al. (2021) finds that historical industrial pollution exerts a significant impact on the income distribution of residents in neighboring communities caused by high-skill workers' migration behaviors from poor air quality regions to better ones. Isen et al. (2017) investigates whether being exposed to severe air pollution early in life can reduce income in adulthood, a potential long-run effect of air pollution. This paper differs from theirs by focusing on the immediate response of earnings to poor air quality, a relatively short-run response. Our paper also differs from Fu et al. (2021) in that it estimates air pollution's effect on short-run productivity for China's manufacturing sector, but our paper focuses on the causal effect of air pollution on the employee's earnings reduction, an economic variable of the aggregate concept, which is determined with two parts: unit wage which can be regarded as the

[1] Information source: http://www.who.int/gho/publications/world_health_statistics/2016/en/

[2] Information source: http://www.stats.gov.cn/sj/tjgb/ndtjgb/ (in Chinese).

labor productivity and working time per year which can be regarded as labor supply. In addition, our paper explores the negative effect of air pollution on people's welfare level from the perspective of income since the employee's total earning is related to their welfare level much more directly compared to labor productivity.

Second, our paper also relates to previous studies investigating the economic cost of air pollution for individuals. In economic theory, one important and commonly used approach is to calculate the impact of air pollution on defensive expenditures or living costs (Bartik, 1988; Courant & Porter, 1981) if we lack a market price for air quality. Several studies have provided empirical estimators for the economic cost of air pollution from the viewpoints of reducing outdoor activities (Graff Zivin & Neidell, 2009; Neidell, 2009), purchasing more health insurance (Chang, Huang, & Wang, 2018), buying more facemasks (Zhang & Mu, 2018) and air purifiers (Ito & Zhang, 2020) and even migrating to clean air regions (Chen, Chen, Lei, & Tan-Soo, 2021; Freeman, Liang, Song, & Timmins, 2019). However, they can be considered from the perspective of living expenditure to study the economic cost of air pollution. There is relatively little evidence for quantitative analysis concerning people's earning loss, a perspective of income, suggesting that our paper provides an estimate of the direct economic costs of air pollution.

Third, our study also complements and extends the stream of research investigating the theory of determinants of employees' earnings. As noted above, previous studies have focused on economic perspectives such as firm characteristics, employees' characteristics, international market factors, and labor market forces. In this study, we show that air quality is also salient and is under-investigated when considering what factors affect employees' income.

Finally, our paper delivers strong policy implications and provides policymakers with an effective basis for cost-benefit analyses when drafting environmental regulations in the future.

The remainder of the paper is structured as follows. Section 2 describes the data and sample. Section 3 introduces the empirical strategy. Section 4 presents our empirical results along with robustness checks and heterogeneity analyses. Section 5 shows the mechanism analyses. Section 6 presents a further study on firm performance and the non-linear effects of air pollution. Section 7 offers our conclusion.

## 2. Data

### 2.1. Firm level

We obtain firm-level data including annual average regular wage and data on other characteristics from the annual surveys of industrial enterprises (ASIE) conducted by the NBS in China. The ASIE includes all state-owned enterprises and all non-state-owned enterprises whose annual sales exceed CNY 5 million.[3] Following the matching algorithm described in Brandt, Van Biesebroeck, and Zhang (2012) and further cleaning processes and standards for the ASIE database presented in Fu et al. (2021), we convert the nominal values of variables into real values using industry level prices indices, match firms over time, and construct unbalanced panel data. We drop firm-year observations with negative or missing values for industrial output value, value-added, capital, and employment following the cleaning standards used in the literature. Moreover, firms with fewer than eight employees and firms violating accounting identities are also excluded.

We measure a firm's average earning level by using employees' yearly average regular wage (total regular wage payable to employees divided by the total number of employees). The other firm characteristics include total assets, value-added, output value, total profits, main business income, interest expense, location, and industry affiliation.

### 2.2. Individual level

We obtain two indicators representing the labor supply from the 2002 Chinese Household Income Project (CHIP) Survey, which was carried out by the Chinese Academy of Social Science and Beijing Normal University, with assistance from the NBS in China.[4] In the 2002 CHIP survey questionnaire, the following questions (No.147a and No.147b) were given to both urban and rural residents:

- How many working days per month on average? (Excluding weekend)
- How many hours per working day on average?

Respondents need to fill the blank for the specific number of working days and the number of hours worked in a day.

The CHIP dataset has been extensively used by economic researchers around the world across a broad range of economic fields (see, e.g., Jiang, Lu, & Sato, 2012; Piketty, Yang, & Zucman, 2019). We focus on the 2002 survey for identification in the mechanism analyses for two reasons. First, our sample period is from 1998 to 2007. Second, the information of working hours per day and working days per year is not reported in the 1999 survey and is largely missing in the 2007 survey. We obtain the *Working Hours per Year* by interacting *Working Hours per Day* with *Working Days per Year*. We further winsorize *Working Hours per Year* and *Working Days per Year* at the 1–99% level and obtain the natural logarithm of one plus *Working Hours per Year* and *Working Days per Year*, respectively.

Moreover, we also obtain a vector of individual characteristic variables that may be related to the labor supply including years of

[3] According to Brandt et al. (2012), the ASIE covers 90.7% of total manufacturing output from 1998 to 2007.

[4] The CHIP project conducted household surveys in 1989, 1996, 2003, 2008, and 2014. They collected income and expenditure information in 1988, 1995, 2002, 2007, and 2013, as well as other family and personal information on both urban and rural residents.

education, age, marital status, gender, and health condition from the 2002 CHIP survey.

### *2.3. Air pollution*

The primary air pollution measure is $PM_{2.5}$ because of its pernicious effect on air quality and its severe effects on people compared to other air pollutants. Fine particulate matter can remain suspended in the air for a long time. As a result, the higher its concentration in the air, the more severe the air pollution. Moreover, $PM_{2.5}$ has a smaller particle size and a larger area, making it easier to carry harmful substances (for example, heavy metals and microorganisms), and has a longer transportation distance than coarser atmospheric particulate matter. Therefore, it is more hazardous for human health and atmospheric environmental quality. We obtain air pollution data from satellite-based Aerosol Optical Depth (AOD) retrieval techniques maintained by National Aeronautics and Space Administration (NASA). And we also obtain $SO_2$ and $PM_{10}$ concentration data from NASA for robustness tests.[5] This air pollution data has been widely used in several previous studies (Chen et al., 2018; Deschênes et al., 2020; Fu et al., 2021). This data has several advantages over ground-based pollution data. First, ground-based data begins in 2000 while our sample period is 1998–2007, which means that satellite-based data captures the air pollution level information throughout our sample period. Second, several studies observe that ground-based air pollution data can be potentially affected by government manipulation (Andrews, 2008; Ghanem & Zhang, 2014), which will undermine the validity of using ground-based air pollution. We aggregate the monthly grid-level air pollution to the county level and compute its annual average as our measure of air pollution according to Buchard et al. (2016). We then match this county-level data with firm characteristics mentioned above based on firm location.

### *2.4. Thermal inversion*

Thermal inversion, the instrument for air pollution, is also obtained from the MERRA-2 database maintained by NASA. We aggregated air temperature data from the 50*60-km grid to the county level by every six hours within each layer (a total of 42 vertical layers within the range from 110 to 36,000 m). Following the definition of Arceo, Hanna, and Oliva (2016), a thermal inversion is defined as the air temperature of the second layer (320 m) being higher than that of the first layer (110 m) within a six-hour period of each day. We define the instrument variable as the total yearly number of days with a least one thermal inversion at the county level for baseline regression.

### *2.5. Meteorological factors*

Data for the meteorological variables, which may affect both air quality and employees' annual earnings, are taken from the China Meteorological Data Service Centre (CMDC). They include temperature, relative humidity, wind speed, sunshine duration, air pressure and precipitation. Following the inverse distance weighting method presented by Deschênes and Greenstone (2011), we convert the station level weather data to the county level for each day within a radius of 200 km. Then we use the county-daily level weather data to calculate annual average relative humidity, wind speed, sunshine duration, pressure, and annual cumulative precipitation. Following an approach used in previous studies (Deschênes et al., 2020; Fu et al., 2021), we construct 20 temperature bins (1 below 5° Fahrenheit, 1 above 100° Fahrenheit, and 18 in between) to capture the potential non-linear effect of temperature. The temperature bin is defined as the number of days in which the average daily temperature falls in the temperature range corresponding to that bin. The weather data at the county level is matched with all firm characteristic variables by firms' locations. The final data is firm-year level.

### *2.6. Descriptive statistics*

We matched the data as mentioned above to form an unbalanced panel data at the firm-year level. Our final sample contains 348,281 unique manufacturing firms covering 1998 to 2007, with 1,540,368 firm-year observations. Table 1 shows the detailed definitions of our main variables. Their summary statistics are reported in Table 2.

Panel A of Table 2 is the descriptive statistics of firm-level characteristics. The earning per employee is our primary dependent variable with a mean value of 12.284 corresponding to 12,284 CNY annually. An average firm has logged total assets of 9.65 (40.2 million CNY in terms of raw value) and a return on total assets ratio of 0.12, implying that 1 unit of total assets creates 0.12 units of total profit, an asset turnover rate of 2.07, and a yearly sale growth rate of 0.30, suggesting that the mean yearly sales revenue growth of firms reach 30%. Additionally, we calculate labor productivity measured by the natural logarithm of one plus value-added and the output value of manufacturing firms with a mean value of 3.9 and 5.2, respectively.

Panel B presents the individual-level variables including working hours per year and working days in 2002. Our sample for investigating the effect of air pollution on the labor supply of people across urban and rural areas contains 9497 unique individuals for *Working Hours per Year* and *Working Days per Year*. Additionally, Panel B suggests that people in the CHIP survey worked for nearly

[5] We collected $PM_{10}$ data covering as much of our baseline sample as possible since there is no readily available $PM_{10}$ diagnostic in the MERRA-2, and we need to calculate the $PM_{10}$ concentrations from the aerosol mixing ratios in the aer_Nv collection. And the calculation method of $PM_{10}$ is given in frequently asked questions for the MERRA-2. Information Source for calculation method is: https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/FAQ/ and the aer_Nv data can be downloaded in: https://disc.gsfc.nasa.gov/datasets/M2I3NVAER_5.12.4/summary?keywords=aer_Nv.

**Table 1**
Variables' Definition.

| Variable | Definition |
|---|---|
| Firm Level | |
| Earning *per* Employee | Annual average earnings per employee (Unit:1000 CNY) |
| Size | Natural logarithm of the total assets (Unit:1000 CNY) |
| Return on Assets | Total profit plus interest expense divided by total assets |
| Asset Turnover | Main business income divided by total assets |
| Sale Growth Rate | Main business income for the current year minus main business income for the previous year divided by main business income for the previous year |
| Ln (1 + Labor Productivity measured by value-added) | Natural logarithm of the total value-added divided by total employee plus one |
| Ln (1 + Labor Productivity measured by output value) | Natural logarithm of the total output values divided by total employee plus one |
| Individual Level | |
| Working Hours *per* Year | Natural logarithm of number of hours worked plus one in 2002 (Unit: hour) |
| Working Days *per* Year | Natural logarithm of the number of days worked plus one in 2002 (Unit: day) |
| Years of Education | The number of years that the individual has received education (Unit: year) |
| Marriage | One if the individual is married; Zero otherwise |
| Gender | One if the individual is female; Zero otherwise |
| Age | The age of the individual (Unit: year) |
| Health Condition | One if the individual's health is "Very Good"; Two if the individual's health is "Good"; Three if the individual's health is "Just so-so"; Four if the individual's health is "Worse"; Five if the individual's health is "Worst" |
| County Level | |
| $PM_{2.5}$ | Annual average $PM_{2.5}$ in a county (Unit: μg/m$^3$) |
| $PM_{10}$ | Annual average $PM_{10}$ in a county (Unit: μg/m$^3$) |
| $SO_2$ | Annual average $SO_2$ in a county (Unit: μg/m$^3$) |
| Thermal Inversion | The Number of thermal inversions within a year (Unit: times) |
| Relative Humidity | Annual average relative humidity in a county (%) |
| Wind Speed | Annual average wind speed in a county (Unit: km/h) |
| Sunshine Duration | Annual average sunshine duration in a county (Unit: hour) |
| Air Pressure | Annual average air pressure in a county (Unit: Pa) |
| Cumulative Precipitation | Annual cumulative precipitation in a county (Unit: cm) |
| Temperature Bin | 20 temperature bins are constructed 1 below 5° Fahrenheit, 1 above 100° Fahrenheit, and 18 in between with a 5° Fahrenheit interval. |

*Notes*: This table presents the detailed variables' definitions.

1894 h per year on average in 2002. Another important labor supply indicator is the number of working days per year, with a mean value of 224 (corresponding to 224 days within a year). For the remaining individual characteristics, taking *Years of Education* as an example, it means that individuals in the 2002 CHIP survey receive approximately 8.9 years of education on average with a max value of 23 years and no education.

Panel C of Table 2 presents the meteorological variables at the county level. For example, our primary measure of air pollution is $PM_{2.5}$ with a mean value of 53.61 and a standard deviation of 25.44 during the sample period. Another important variable is thermal inversion, our instrument for $PM_{2.5}$, ranging from 0 to 333. The mean value of thermal inversion suggests that there are approximately 157 days with a thermal inversion during a year in the counties covered in our sample from 1998 to 2007.

## 3. Econometric model

To evaluate the impact of air pollution on employees' yearly earnings, our primary econometric model is as follows:

$$Earning_{ict} = \beta_0 + \beta_1 Air\ Pollution_{ict} + \beta_2 f(W_{ict}) + \beta_3 Size_{ict} + \theta_i + \mu_t + \varepsilon_{ict} \quad (1)$$

Where $Earning_{ict}$ denotes annual average earnings per employee of firm $i$ in county $c$ in year $t$. $Air\ Pollution_{ict}$ refers to the annual average $PM_{2.5}$ of year $t$ in county $c$ where firm $i$ was located during our sample period. $W_{ict}$ denotes a vector of weather variables, including relative humidity, wind speed, sunshine duration, atmospheric pressure, cumulative precipitation and temperature. These are the key meteorological factors that affect the economic outcomes. We add linear and quadratic terms of these meteorological factors to capture the nonlinear effects following previous studies (Deschênes et al., 2020; Fu et al., 2021). Moreover, we construct 20 temperature bins (1 below 5° Fahrenheit, 1 above 100° Fahrenheit, and 18 in between) to control for the nonlinear effect of temperature. To capture the impact of the pre-determined firm factor on yearly average earning per employee, we introduce firm size (defined as logged total assets). $\theta_i$ refers to firm fixed effects to control for any firm-specific time-invariant characteristics. We also use $\mu_t$ as year fixed effects controlling any economic shocks that have the same effects across all counties in each different year of our sample period. $\varepsilon_{ict}$ are classical error terms at the firm level. $\beta_1$ is our coefficient of interest.

However, the endogeneity problems originating from the feature of air pollution can bias our OLS estimation in Eq. (1). Air pollution is frequently related to economic activities, especially production in manufacturing firms. More developed (affluent) regions

**Table 2**
Summary Statistics.

| | Obs. | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Panel A: Firm Level | | | | | |
| Earning *per* Employee | 1,540,368 | 12.2844 | 8.7433 | 1.1497 | 55.4198 |
| Size | 1,540,368 | 9.6500 | 1.3002 | 0 | 16.5108 |
| Return on Assets | 1,306,808 | 0.1179 | 0.1603 | 0 | 0.9121 |
| Asset Turnover | 1,539,965 | 2.0687 | 2.2424 | 0.1069 | 13.7390 |
| Sale Growth Rate | 1,034,915 | 0.2958 | 0.7755 | −0.7601 | 5.1812 |
| Ln (1 + Labor Productivity Measured by Value-added) | 1,539,967 | 3.9011 | 1.0049 | 0.0004 | 9.6957 |
| Ln (1 + Labor Productivity Measured by Output Value) | 1,540,347 | 5.2421 | 0.9997 | 0.0134 | 11.4519 |
| Panel B: Individual Level | | | | | |
| Working Hours *per* Year | 9497 | 1893.5170 | 919.6142 | 180 | 4320 |
| Working Days *per* Year | 9497 | 223.9435 | 94.7389 | 30 | 360 |
| Years of Education | 9497 | 8.9214 | 3.0298 | 0 | 23 |
| Marriage | 9497 | 0.4270 | 0.4947 | 0 | 1 |
| Gender | 9497 | 0.3204 | 0.4667 | 0 | 1 |
| Age | 9497 | 37.3421 | 11.3008 | 16 | 65 |
| Health Condition | 9497 | 1.9478 | 0.7214 | 1 | 5 |
| Panel C: County Level | | | | | |
| $PM_{2.5}$ | 25,266 | 53.6086 | 25.4438 | 2.6159 | 134.8417 |
| $PM_{10}$ | 20,943 | 49.1569 | 23.8954 | 5.0046 | 316.8029 |
| $SO_2$ | 25,266 | 15.1004 | 10.7006 | 0.0428 | 54.6783 |
| Thermal Inversion | 25,266 | 157.0380 | 78.6821 | 0 | 333 |
| Relative Humidity | 25,266 | 68.9249 | 9.1450 | 27.2384 | 89.0945 |
| Wind Speed | 25,266 | 2.1272 | 0.6911 | 0.3375 | 7.2780 |
| Sunshine Duration | 25,266 | 5.5259 | 1.4030 | 1.8073 | 10.0907 |
| Cumulative Precipitation | 25,266 | 959.6154 | 69.2275 | 580.9397 | 1017.2330 |
| Air Pressure | 25,266 | 93.8074 | 50.7554 | 1.7157 | 355.0737 |
| Temperature | 25,266 | 14.2088 | 5.0718 | −4.3414 | 26.7585 |

*Notes*: See Table 1 for detailed variables' definitions. The sample period is from 1998 to 2007.

tend to generate more air pollution while providing higher average income at the same time, suggesting that our empirical strategy can be biased upward or even above zero due to the reverse causation problem. Furthermore, despite controlling for meteorological factors and firm-level variables, we cannot solve the missing variable problem completely, biasing $\beta_1$ upward or downward. Finally, measurement errors originate from using the annual average $PM_{2.5}$ at county level to represent the real air pollution faced by firms located in a given county.

The strategy we used to manage the endogeneity problems is as follows. First, we adopt an IV approach by exploiting the thermal inversion. We use the number of days in which a thermal inversion occurs in a year. The selection of IV needs to satisfy both relevance and exogeneity. The exogeneity of thermal inversion is as follows. As a meteorological phenomenon, the occurrence of a thermal inversion is independent of economic outcomes such as employees' performance. However, an underlying threat to the exogeneity problems may be that thermal inversions are likely to be related to other meteorological factors that influence employees' earnings or that thermal inversions occur more frequently in regions with specific weather patterns. Based on Sager (2019), a vector of weather variables that we control for are indeed helpful to satisfy the independence principle while implementing the IV approach. Thermal inversion and air pollution are related (relevant) because in an inversion, temperature rises with the increase in altitude. This impairs the vertical convection of the air, hindering the diffusion of smoke, pollutants, and water vapor. An inversion layer tens or even hundreds of meters high traps air pollutants underneath it, preventing them from circulating out. The more they accumulate, the thicker the smoke and the dust will be, inevitably increasing the air pollution.

We introduce the 2SLS approach to implement the causality investigation on how air pollution influences employees' annual earnings with the first stage regression equation as follows:

$$Air\ Pollution_{ict} = \delta_0 + \delta_1 Thermal\ Inversion_{ict} + \delta_2 f(W_{ict}) + \delta_3 Size_{ict} + \theta_i + \mu_t + \eta_{ict} \tag{2}$$

Where $Thermal\ Inversion_{ict}$ is the number of days that thermal inversions occur in county $c$ where firm $i$ is located in year $t$. The weather control variables and the firm-level control are the same as those in the second stage. Firm fixed effects and year fixed effects are also included in Eq. (2).

## 4. Results

### 4.1. Baseline results

We first present the OLS estimates before reporting the 2SLS estimates in Table 3 for testing the validity of OLS results in the context of endogeneity problems. Without including firm size and weather controls (column 1), the coefficient of $PM_{2.5}$ is negative (−0.0057) and statistically significant at the 1% level. After including firm size and weather controls (column 2), the coefficient decreases to −0.0063 and remains statistically significant at the 1% level. The OLS estimates of column 2 suggest that $PM_{2.5}$ (air pollution) can negatively affect employees' income level, which is consistent with our expectation.

However, the reliability of OLS estimates can be undermined by the endogeneity problems of air pollution. We identify the bias from the second-stage results in Table 4. We first show the first-stage estimates of how the thermal inversion affects air pollution ($PM_{2.5}$) in Table 4. In column 1, we exclude firm size and weather control variables but include firm fixed effects and year fixed effects. In column 2, we add firm size and weather control variables into the regression model conditional on firm fixed effects and year fixed effects. Overall, we find a strongly positive relationship between thermal inversion and $PM_{2.5}$ in the first-stage estimates in two columns, as evidenced by the coefficients of thermal inversion, statistically significant at the 1% level. Additionally, the KP F-statistic in column 2 is significantly above the Stock-Yogo critical value of 16.38 (Stock & Yogo, 2005), which eliminated a weak instrument for air pollution in our paper.

In column 3, we exclude all controls and the coefficient of $PM_{2.5}$ remains negative and statistically significant at the 1% level. In column 4, our preferred specification includes a battery of meteorological factors to relieve the potential threat to the independence of the instrument as much as possible, the coefficient of $PM_{2.5}$ is −0.1754 and statistically significant at the 1% level.[6] The baseline result means that a one $\mu g/m^3$ increase in yearly average $PM_{2.5}$ decreases employees' annual earnings by 175.4 CNY corresponding to a 14.6 CNY (175.4/12 = 14.6) reduction in each month's earnings. If we focus on the impact as measured by standard deviation, to exclude the influence of the variables' unit, a one standard deviation increase in $PM_{2.5}$ decreases employees' yearly average earnings by 0.51 standard deviation. That is, air pollution can exert an obvious and, more importantly, greater impact on employees' annual income than previously thought. In monetary terms, the 21.27 $\mu g/m^3$ increase in average $PM_{2.5}$ during our sample period (from 46.02 $\mu g/m^3$ in 1998 to 67.29 $\mu g/m^3$ in 2007) means that the total loss in earnings for all employees working for our sample firms amounts to about 268.59 million CNY.[7]

We also argue that the actual loss of all Chinese employees' earnings is even much larger than this back-of-the-envelope calculation.

## 4.2. Robustness check

### 4.2.1. Robustness check I: Alternative FE, clustered S.E., dependent Variable's form, and air pollutants

We first present the results of several robustness checks of our baseline regression results in Table 5 to test the validity of our preferred specification by altering fixed effects, standard errors level, dependent variables, and the functional form of $PM_{2.5}$. In column 1–3, we examine whether region and industry time-variant factors can affect our baseline result. In columns 1 and 2, we include the region-by-year fixed effects and industry-by-year fixed effects respectively to examine whether region and industry time-variant factors can bias our baseline results. The coefficients of columns 1 and 2 remain negatively and highly significant (1% level), and nearly intact in magnitude. We replace the vector of fixed effects with firm fixed effects and region-by-year fixed effects and industry-by-year fixed effects in column 3, which is the most rigorous set of fixed effects. The coefficient of $PM_{2.5}$ is robust to the combination of different fixed effects and statistically significant at the 1% level, suggesting that our baseline results are not sensitive to region and industry time-variant factors. In sum, the results in columns 1–3 suggest that our baseline estimates are not sensitive to different combinations of fixed effects.

One concern is that our coefficient of interest may be biased downward since our main explanatory variable ($PM_{2.5}$) is county-specific (Moulton, 1986). To allow for serial correlation within each country or country-year and further alleviate the concern mentioned above, we replace firm-level clustered standard error with county and county-by-year level respectively allowing for serial correlation within each country or county-year. The results in columns 4 and 5 show that our concern mentioned above is reasonable (standard errors in columns 4 and 5 increase around 6 times), but does not exert a significant impact on our baseline result.

Additionally, to alleviate the concern that our results can be biased by the measurement of $PM_{2.5}$, we use the logged annual average $PM_{2.5}$ as our independent variable to re-estimate in column 6 and find no such impact. Finally, we provide the effects of different pollutants on earning reductions for robustness since there are other air pollutants that are also important factors to influence people's health, especially $SO_2$ and $PM_{10}$ (Ebenstein et al., 2015; Gehrsitz, 2017). The coefficients of interest reported in column 7–8 are also negative and significant at the 1% level.

### 4.2.2. Robustness check II: RDD estimates of the Qinling-Huai River policy

We further test the validity of our coefficient of interest by exploiting the regression discontinuity design estimates of China's Qinling-Huai River Policy. According to Chen, Ebenstein, Greenstone, and Li (2013), Ebenstein, Fan, Greenstone, He, and Zhou (2017) and Fan et al. (2020), the central government implemented the winter heating system in the 1950s and expanded the winter heating policy across the regions which are located in northern China during the planned economy period (1950s–1980s) since the average air temperature north of the line formed by the Qinling-Huai River in January is around 0C. No such heating system was installed south of the Qinling-Huai River even if the cities are located just south of the line. The winter heating system is maintained by burning coal, thus generating massive air pollutants due to the incomplete combustion of coal and the inefficient and underdeveloped combustion

[6] The difference between OLS and IV estimators is similar to the finding of the causal effect estimation of air pollution on labor productivity in by Fu et al. (2021) using OLS and IV specifications. Moreover, it exactly highlights the importance of dealing with the endogeneity when evaluating the causal effect of air pollution on economic outcomes.

[7] The mean of employment of an enterprise during sample period is 206.71. Thus, the total loss is: 0.1754 × 206.71 × 21.27 × 348,281.

**Table 3**
Ordinary Least Squares (OLS) Regression Results.

| | (1) | (2) |
|---|---|---|
| | Annual Earnings per Employee | |
| $PM_{2.5}$ | −0.0057*** | −0.0063*** |
| | (0.002) | (0.002) |
| Weather Controls | No | Yes |
| Firm Control | No | Yes |
| Firm FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 1,540,368 | 1,540,368 |

*Notes*: Standard errors are clustered at the firm level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**Table 4**
The Impact of Air Pollution on Earnings per Employee (2SLS).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $PM_{2.5}$ | | Annual Earnings per Employee | |
| | First Stage Regression Results | | Second Stage Regression Results | |
| Thermal Inversion | 0.0295*** | 0.0369*** | | |
| | (0.000) | (0.000) | | |
| $PM_{2.5}$ | | | −0.2065*** | −0.1754*** |
| | | | (0.015) | (0.012) |
| Weather Controls | No | Yes | No | Yes |
| Firm Control | No | Yes | No | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| KP F-statistics | 5507.04 | 9054.18 | \ | \ |
| Observations | 1,540,368 | 1,540,368 | 1,540,368 | 1,540,368 |

*Notes*: The IV for $PM_{2.5}$ is the number of days with at least one thermal inversion in each county year. Standard errors are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**Table 5**
Robustness Check I: Alternative FE, Clustered S.E., Dependent Variable's Form, and Air Pollutants.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Annual Earnings per Employee | | | | | | | |
| | Different FE | | | County S.E. | County Year S.E. | Functional form(log) | Alter. Pollutant | |
| $PM_{2.5}$ | −0.1942*** | −0.1786*** | −0.1977*** | −0.1754** | −0.1754*** | | | |
| | (0.017) | (0.013) | (0.017) | (0.077) | (0.066) | | | |
| Ln $(1 + PM_{2.5})$ | | | | | | −10.5588*** | | |
| | | | | | | (0.746) | | |
| $PM_{10}$ | | | | | | | −0.3520*** | |
| | | | | | | | (0.022) | |
| $SO_2$ | | | | | | | | −0.5669*** |
| | | | | | | | | (0.041) |
| Weather Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Region-Year FE | Yes | No | Yes | No | No | No | No | No |
| Industry-Year FE | No | Yes | Yes | No | No | No | No | No |
| Observations | 1,540,368 | 1,540,368 | 1,540,368 | 1,540,368 | 1,540,368 | 1,540,368 | 1,300,957 | 1,540,368 |

*Notes*: In Columns 1–3, we add region-by-year fixed effects, industry-by-year fixed effects, and region-by-year and industry-by-year fixed effects, respectively. In column 4 and 5, we cluster standard errors at the county and county-year level, respectively. Column 6 uses the natural logarithm of one plus the annual average $PM_{2.5}$ as independent variable. In Columns 7–8, we replace $PM_{2.5}$ with $PM_{10}$ and $SO_2$, respectively. Standard errors are clustered at the firm level in the parentheses except for Columns 5 and 6. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

technology. Not surprisingly, an air pollution discontinuity around the Qinling-Huai River's north-south boundary results (Almond, Chen, Greenstone, & Li, 2009; Chen et al., 2013; Ebenstein et al., 2017; Ito & Zhang, 2020), which provides an opportunity to investigate its impact using regression discontinuity strategy as an additional robustness check. We first estimate the following parametric equation by introducing polynomial terms of the distance between the firm location and the Qinglin-Huai River Line:

$$Earning_{ijt} = \alpha_0 + \alpha_t + \alpha_j + \eta_1 I\left(Distance_{ijt} > 0\right) + \eta_2 f\left(Distance_{ijt}\right) + \eta_3 I\left(Distance_{ijt} > 0\right) \times f\left(Distance_{it}\right) + \beta X_{ijt} + \varepsilon_{ijt} \quad (3)$$

where *i*, *j*, *t* denotes firm, industry, and year, respectively. $Earning_{ijt}$ is the annual mean earning per employee of firm *i* of industry *j* in year *t*. $I(Distance_{ijt} > 0)$ is an indicator variable that equals one if the firm is located north of the Qinglin-Huai River boundary, and zero otherwise. $f(Distance_{ijt})$ includes polynomial (linear, quadratic, cubic and biquadratic) terms of distance to the Qinglin-Huai River boundary. To reflect the possibility that the functional forms are different on the two sides of the threshold (Qinglin-Huai River boundary), we interacted polynomial terms of distance with $I(Distance_{ijt} > 0)$ respectively. $X_{ijt}$ is a vector of firm and weather variables including firm size, temperature, wind speed, sunshine duration, relative humidity, air pressure, and cumulative precipitation. We expect that $\eta_1$, the coefficient of interest, will be negative, indicating that employees' yearly mean earnings are lower for firms located in the winter heating regions which suffer from severe air pollution. Standard errors are clustered at the county-by-year level since we use pooled panel data RDD.

We start with parametric RDD. We then conduct a non-parametric local linear regression (LLR) analysis and emphasize the LLR approach since parametric RDD has several assumptions about the functional form in Eq. (3) and will face the contradiction of selecting enough observations to provide a reliable estimation and focusing on the firms located near both sides of Qinling-Huai River line, where the identification assumption of RDD is the strongest. Moreover, given the fact that a few cities north of the Qinling-Huai River boundary were not given the heating system (for instance, Suqian, Lianyungang and Yancheng in Jiangsu province, and Huaibei and Bozhou in Anhui province), it appears that the Qinling-Huai River boundary is not the only determinant. Thus, we prefer fuzzy RDD. We choose an optimal bandwidth following the selection criteria of Imbens and Kalyanaraman (2012) and a triangular kernel, the most commonly selected kernel for RDD estimation, indicating that we give larger weight to firm observations located near the Qinling-Huai River boundary. The results are shown in columns 3 to 5. Standard errors are also clustered at the county-by-year level.

All coefficients using fuzzy RDD are negative and statistically significant, from at least the 10% (See Table 6). Taking the preferred specification as an example, the coefficient in column 5 shows that people working for firms located in the heated (north) side of the Qinling-Huai River boundary will have yearly earnings lowered about 414 CNY compared to those in the non-heated regions (south). Moreover, we calculate the annual mean $PM_{2.5}$ of counties located on either side of the Qinling-Huai River boundary within the range of optimal bandwidth in column 5 (116.72 km) on average. The yearly average $PM_{2.5}$ of targeted counties located in the north side is 65.25 $\mu g/m^3$ compared to 63.18 $\mu g/m^3$ in the south side in our sample period, suggesting that annual earnings reduction of employees living in high air pollution regions achieves 200 CNY [414/(65.25 − 63.18)], an estimator similar to the baseline, if yearly average $PM_{2.5}$ increases one $\mu g/m^3$.

Moreover, to visualize the employees' yearly earnings difference for firms across the Qinling-Huai River boundary, we also plot the local linear regression results in Fig. 1. We construct 10 distance bins on each side based on the distance between firms' location and the Qinling-Huai River line, where each dot represents the annual earnings per employee in each distance bin. We also plot a fitted line on either side of the line (blue in the left of zero line and red in the right of zero line). We can observe a clear discontinuous drop in employees' yearly earnings in Fig. 1.

In addition, we also implement a sharp regression discontinuity design. The empirical results are shown in Table A1.

#### 4.2.3. Robustness check III: Firm's exit and entry, sorting, and minimum wage regulations

First, previous studies show that we can only observe the effect of air pollution on existing firms in our database (Fu et al., 2021; Liu, Tan, & Zhang, 2021). However, some firms are compelled to shut down and exit, and new firms will encounter restrictions or difficulties with entry if the negative impact of air pollution or other unobservable disadvantages in the macroeconomic environment are large enough that firms are unable to survive, which can lead to an underlying underestimation of the negative impact of air pollution. Thus, we calculate the natural logarithm of one plus the total number of firms, total industrial output value, and total employment at the county level (final county-year level observations) to examine whether our paper is affected by firm exit and entry caused by severe air pollution based on Liu et al. (2021). Columns 1 to 3 of Table A2 in the appendix show that air pollution has no significant impact on firm exit and entry. We then construct balanced panel data from 1998 to 2007 to ensure that we use all firms existing throughout the sample period, and then re-estimate our coefficient of interest. The results shown in column 4 of Table A2 are negative and statistically significant at the 1% level. In sum, these findings show that our main finding is not sensitive to firms' exit and entry.

Second, another concern is that some firms are likely to relocate (though it is a rare behavior) because of the poor local air quality, although manufacturing firms find it difficult to relocate because of a large amount of fixed assets and production equipment. If this is the case, our significantly negative estimators in the baseline regression will be biased by firms' relocation behaviors. Thus, we treat firms that relocate their registered addresses to other cities as firms that have undergone relocation since the Chinese government implemented a policy of moving industrial enterprises away from the central urban area to the suburbs in the Tenth Five-Year Plan in 2001 called "*TuiErJinSan*".[8] However, most of the relocations caused by this policy were moves inside the prefecture instead of intercity because of the administrative barriers between different cities, suggesting that firms' relocations at the county level were more likely to be affected by the "*TuiErJinSan*" policy instead of air pollution. Hence, we mainly focus on firm relocation behaviors happening across cities. The coefficient shown in column 5 of Table A2 is similar to that in our baseline results, suggesting that our findings are not sensitive to firms' relocation behaviors. Moreover, after excluding all firms that implemented relocation, we find that

[8] Source: http://www.gov.cn/zhengce/content/2016-10/11/content_5117403.htm (in Chinese).

**Table 6**
Robustness Check II: RDD Estimates of the Qinling-Huai River Policy.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Annual Earnings per Employee | | | | |
| $I(Distance_{ijt} > 0)$ | −1.3900*** | −1.4040*** | −1.1911* | −0.8682*** | −0.4143* |
| | (0.226) | (0.314) | (0.478) | (0.226) | (0.197) |
| Weather Controls | No | No | No | No | Yes |
| Firm Control | No | No | No | No | Yes |
| Year FE | Yes | Yes | No | Yes | Yes |
| Industry FE | Yes | Yes | No | Yes | Yes |
| RD type | Polynomial RD | Polynomial RD | LLR (FRD) | LLR (FRD) | LLR (FRD) |
| Polynomial of Degree | 4 | 4 | / | / | / |
| Kernel | / | / | Triangular | Triangular | Triangular |
| Optimal Bandwidth (Kilometer) | / | / | 103.55 | 120.13 | 116.72 |
| Only cities within 4°latitude | No | Yes | No | No | No |
| Observations | 1,540,368 | 852,143 | 147,820 | 178,497 | 171,449 |

*Notes:* Columns 1 to 2 use the Polynomial RDD. In Column 2, we limited our samples to the observations within four degrees of latitude on either side of the Qingling-Huai River Line. In Columns 3 to 5, we use a local linear fuzzy RD design. Standard errors are clustered at the county-by-year level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

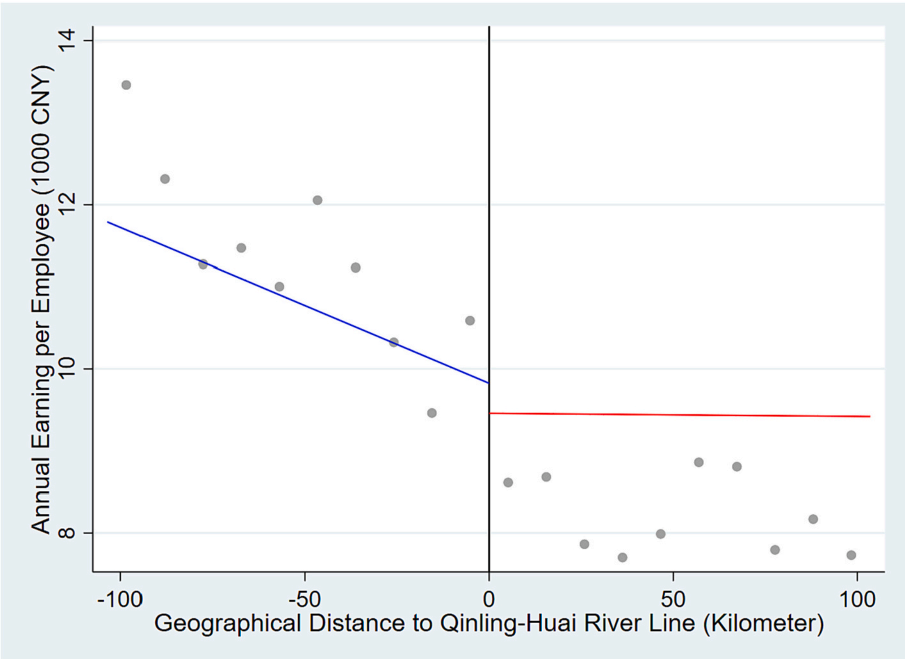


**Fig. 1.** RDD Plot of Annual Earnings per Employee across the Qinling-Huai River Line (Local Linear Regression).
*Notes*: This figure shows the estimator of annual earnings per employee across the Qinling-Huai River line based on local linear regression.

only 0.17% of them moved to other cities, which is consistent with our argument above.[9]

Third, there is also a concern that people who are sensitive to air pollution may leave for someplace with better air quality, and it may lead to the sorting issue of worker skill levels across counties. If the sorting issue of worker skill level is true, the population migration will enter the empirical model of our paper as an omitted variable. It also suggests that our baseline result is biased since we capture the impact of sorting of worker skill level instead of the causal effect of air pollution. Therefore, it is important to test whether population migration leads to the sorting issue of workers' skill levels across counties during our sample period. The only channel that air pollution can lead to the sorting issues of workers' skill level in our paper is to influence the fraction of employment with high skilled (education) level of firms, given the fact that air pollution has no significant effects on the total number of firms and total employment since the total number of workers with high skilled level at the county level consists of three parts: the total number of

[9] Nearly 9% of total firms relocated across counties within one city. The result of excluding them remains close to what we find in the baseline regression (unreported and available upon request)

firms, the number of total employment of firms and the fraction of employment with high skilled (education) level of firms.[10] Therefore, we investigate whether yearly air pollution (instrumented with thermal inversion) affects the fraction of workers in high technological intensity firms and low technological intensity firms at the county level following Fu et al. (2021). We split our sample into high-technology industries and low-technology industries according to the classification standard presented by OECD (2011).[11] Then we calculate the fraction of workers employed in high-technology industries and low-technology industries at the county level. And then, we regress the fraction of workers employed in high-technology industries and low-technology industries at the county level on instrumented air pollution ($PM_{2.5}$) respectively, and we include the weather controls (the same as baseline regression), county fixed effects and year fixed effects to capture any time-invariant factors across counties and macroeconomic shock over time. We cluster the standard error at the county level. The result is reported in column 6 in Table A2. The coefficient of interest in column 6 lacks significance in statistics. In addition, we also investigate the effect of air pollution on the sorting issue of worker education level at the county level during our sample period in China to further support that the sorting issue of workers is not a problem in our paper. ASIE database reports the number of employees with different education levels (master's or above degree, bachelor's degree, college degree, high school degree, and junior high school degree or below) in 2004 because the Chinese government took the first national economic census in that year. Thus, we obtain the high education employment fraction at the county level by calculating the fraction of workers with a college degree or above (including the master's or above degree, bachelor's degree, and college degree). We also obtain the low education employment fraction at the county level by calculating the fraction of workers with a high school degree or below (including the high school degree and junior high school degree or below). Then we regress the high (low) education level fraction on instrumented air pollution at the county level, including the same weather controls and province fixed effects. We cluster standard error at the county level. The regression results are reported in column 7 in Table A2 with no statistical significance, which also suggests that air pollution does not lead to the sorting issue of worker education level. Even if we refer to economic significance, air pollution causes little impact on the sorting issue of workers' education level in our paper since for instance, the coefficient of interest in column 7 shows that a one $\mu g/m^3$ increase in $PM_{2.5}$ decreases the average fraction of employment with high education level by 0.0001 (equivalent to only 0.09% of the mean value of the fraction of employment fraction with high education level). Finally, we refer to 1% sample data from China's 2005 census collected from NBS since the database provides detailed information on individuals' education levels and whether the individual is a migrant or not. We only keep the migrants in this database and calculate the fraction of high education level with a college degree or above (including the master's or above degree, bachelor's degree, and college degree) at the city level. We also obtain the low education level fraction at the city level by calculating the fraction of people with a high school degree or below (including the high school degree and junior high school degree or below). Then we regress the fraction of high (low) education level on instrumented air pollution at the city level, including the same weather controls and province fixed effects. We cluster standard error at the city level. The regression results are reported in column 8 in Table A2 with no statistical significance, which also suggests that air pollution does not lead to the sorting issue of worker education level.

Therefore, the results shown in column 6–8 in Table A2 indicates that air pollution does not lead to the significant sorting issue of worker skill level across counties, which also suggests that our baseline results remain intact. The conclusion is also similar to the findings of Fu et al. (2021) which also find no significant sorting issue of worker skill level during the same period as ours.

Finally, we learn from the relevant regulations and documents regarding labor wages in China during the sample period that the Chinese government announced the minimum wage policy in 2004. Thus, it is necessary to eliminate the potential impact of the minimum wage policy. The policy allowed different administrative regions within a province, autonomous regions, and municipalities to formulate different minimum wage standards. In addition, this policy required local governments to upgrade the minimum wage standard every 2–3 years. Thus, we exploit the prefecture-by-year fixed effects to absorb the effect originating from minimum wage policy. The results are shown in column 9 in Table A2: our coefficient of interest is similar to the coefficient in the baseline regression for both significance level and magnitude, suggesting that the effect of minimum wage policy is slight and limited.

### 4.3. *Heterogeneous effects*

Our sample covers firms of labor intensity, ownership types, industry information, and size. Given these variations, it is interesting to examine the heterogeneity across different types of enterprises. Such an analysis permits us to infer underlying channels about how air pollution affects employees' earnings.

#### 4.3.1. *Effects by labor intensity*

We start with an investigation of heterogeneous effects across firms with different labor intensity. To do this, we first calculate the capital-labor ratio at the industry level by dividing the total amount of capital in a given industry by the total amount of labor. We then split all industries in our sample into two subsamples based on the capital-labor ratio as follows: an industry is placed in the capital (labor) intensive subsample if its capital-labor ratio is larger (smaller) than the median of all industries. After that, we classify all firms into capital-intensive and labor-intensive based on the attribute of the industry that they belong to. The results of our analysis of the

[10] The Number of Workers with High Skill(Education) Level at the County Level = The Number of Firms at the County Level × The Number of Total Employment of Firms × The High Skilled (Education) level Fraction of Firms

[11] There are four categories of different technology levels in OECD (2011): low-technology level, median-low technology level, median-high technology level and high technology level. We classify low (high)-technology level, median-low (high) technology level into low (high)-technology level industries.

heterogeneous effects by labor intensity are shown in columns 1 and 2 of Table 7. It is not surprising that although air pollution has a negative impact on both capital-intensive firms and labor-intensive firms, the magnitude of the coefficient of $PM_{2.5}$ for labor-intensive firms is nearly 1.5 times as large as that of capital-intensive firms. A one μg/$m^3$ increase in annual average $PM_{2.5}$ lowers the yearly earning of employees working for labor-intensive firms by 212.3 CNY.

This finding that employees working in labor-intensive firms are the primary sufferers from air pollution indicates that it decreases annual earnings by lowering people's labor productivity and reducing the labor supply. To further corroborate our inference, we also regress the labor productivity and total employment on $PM_{2.5}$ (instrumented with thermal inversion) in capital-intensive firms and labor-intensive firms. The results of heterogeneous effects by labor intensity reported in Table A3 confirm our above inference. A one μg/$m^3$ increase in annual average $PM_{2.5}$ weakens the labor productivity of employees working for labor-intensive firms by around 0.011%, a significantly larger effect than for capital-intensive firms. We also observe that labor-intensive corporations hire additional workers to compensate for the labor loss caused by air pollution in columns 3 and 4, indicating that their employees suffer more from poor air quality and generate greater losses of productivity and labor supply.

#### 4.3.2. *Effects by ownership types*

The ASIE database contains the information of ownership types of each firm, thus providing us with a useful opportunity to examine the effects of firms' ownership types on our baseline results. More importantly, studying the heterogeneous effects of ownership type matters as state-owned enterprises (SOEs) can obtain more government support, and maintain both human capital and financial advantage over their non-SOE counterparts. We classify each firm in our sample into one of two ownership types: SOEs and non-SOEs. Non-SOEs consist of domestic private firms, foreign firms and collective firms. The results of effects by ownership types are reported in columns 3 and 4 of Table 7. Air pollution has a negative impact on both SOEs and non-SOEs. However, the magnitude of the coefficient of $PM_{2.5}$ for non-SOEs is four times larger than that of SOEs. Additionally, the significance level of the estimated coefficient falls to the 10% level for SOEs, compared to the 1% level for non-SOEs. Our findings show that a one μg/$m^3$ increase in yearly $PM_{2.5}$ reduces employees' annual earnings by around 195 CNY for non-SOEs, suggesting non-SOEs are the main victims of air pollution.

This finding is consistent with previous literature and our expectations: SOEs are able and even forced to offer their employees higher job security with stricter labor contracts than non-SOEs (Wong, Wong, Ngo, & Lui, 2005) since they are under the direct supervision of the local government, which partly offsets the negative effect of air pollution on employees' yearly earnings. SOEs also benefit from the soft budget constraint problem (especially during our sample period) and suffer less from financing problems (Cull, Li, Sun, & Xu, 2015; Guariglia, Liu, & Song, 2011).

#### 4.3.3. *Effects by pollution level*

We also wonder whether air pollution causes a different negative impact on people working in firms with different pollution levels. We collect the classification standard of heavily polluting industries and lightly polluting industries based on He, Wang, and Zhang (2020).[12] Thus, we are able to investigate whether the negative impact of air pollution on earning reduction is different from heavily and lightly polluting industries. However, we are unable to find a significantly different impact based on our estimators. In column 5–6, we estimate the coefficients of interest in the two subsamples (heavily polluting group and lightly polluting group). The impact of air pollution on both the heavily polluting group and the lightly polluting group is negative and significant at the 1% level, and the magnitude of the two coefficients shows no significant difference in the impact of air pollution between the two subsamples. We think that there are two primary reasons to explain it. First, heavily polluting industries include many types of pollution such as water pollution, soil pollution and air pollution, which suggests that the classification standard of polluting industries does not necessarily represent the difference in employees' net exposure to air pollution. Second, we consider that the magnitude of the negative impact of air pollution on earning reductions mainly depends on the workers' net exposure to air pollution, which is equivalent to the total exposure to air pollution minus avoidance behavior such as air purification and emission reduction equipment in the workplace. In other words, it suggests that the actual net exposure of workers to air pollution is not entirely determined by the polluting characteristics of the industry.

#### 4.3.4. *Effects by firm size*

The negative impact of air pollution on earning reductions is mainly determined by the workers' net exposure to air pollution as mentioned above. It is a pity that we are unable to collect the data on the net exposure of workers in the workplace. However, we would like to provide some suggestive evidence of the heterogeneous effect of air pollution on firm size. We consider that workers in larger firms are much more likely to have lower net exposure to air pollution because of three reasons: (1) workers in larger firms are more likely to work with a better workplace (2) larger firms are more capable of installing air purification and emission reduction equipment (3) larger firms are more likely to have a cleaner production process. Thus, if we find that air pollution leads to a slighter impact on earning reductions in larger firms, we can provide effective evidence to support our consideration mentioned above. The results of effects by firm size are reported in columns 7 and 8 in Table 7. Columns 7–8 reveal that although air pollution causes a significantly negative impact on people working in both large firms and small firms, workers in the smaller firms suffer more since they take a greater earning reduction caused by air pollution. The magnitude of the coefficient of $PM_{2.5}$ for smaller firms is nearly 2.5 times as large as that of larger firms. A one μg/$m^3$ increase in annual average $PM_{2.5}$ concentration lowers the yearly earnings of employees

[12] The division between polluting industries and non-polluting industries in He et al. (2020b) is according to the Ministry of Ecology and Environment of the People's Republic of China:http://wfs.mep.gov.cn/gywrfz/hbhc/zcfg/201009/t20100914_194483.htm (in Chinese).

**Table 7**
Heterogeneous Impact of Air Pollution across Firms.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Annual Earnings per Employee | | | | | | | |
| | Capital Intensive | Labor Intensive | SOE | Non-SOE | Heavily Polluted | Lightly Polluted | Large | Small |
| $PM_{2.5}$ | −0.1417*** | −0.2123*** | −0.0493* | −0.1951*** | −0.1711*** | −0.1781*** | −0.1061*** | −0.2494*** |
| | (0.017) | (0.019) | (0.028) | (0.014) | (0.021) | (0.015) | (0.018) | (0.017) |
| Weather Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 748,896 | 791,472 | 152,374 | 1,376,947 | 475,839 | 1,064,529 | 770,180 | 770,188 |

*Notes*: In Column 1–2, we divide the capital-intensive and labor-intensive subsamples based on the capital-labor ratio of each industry. In Column 3–4, we divide the state-owned enterprise and non-state-owned enterprise subsamples. In Column 5–6, we divide the heavily polluting and lightly polluting subsamples based on He et al. (2020b). In Column 7–8, we divide the sample into large and small firms based on the total assets of firms. The IV for $PM_{2.5}$ is the number of days with at least one thermal inversion in each county year. Standard errors are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

working for smaller firms by 249.4 CNY. Therefore, the results in column 7–8 in Table 7 further support our inference that air pollution results in less earning reductions to workers with lower net exposure to air pollution.

## 5. Mechanism analyses

Employee's total earnings consist of two parts: unit wage and work time. We discuss these two underlying mechanisms by which air pollution lowers employees' annual earnings. The first channel is that air pollution can reduce the unit wage. Second, poor air quality can decrease the total labor supply by hurting their physical and mental health, thus decreasing the annual income they can receive.

### *5.1. Employees' unit wage*

We start by investigating the impact of air pollution on employees' unit wage by investigating their labor productivity in columns 1 and 2 of Table 8. The ASIE database provides detailed information on the firm characteristics needed to calculate the labor productivity such as value-added, industrial output value and employment. We construct two measures of employees' labor productivity following Fu et al. (2021): the first is the logarithm of value-added divided by total employment while the second is the logarithm of output value divided by total employment. All nominal values of these variables are converted into real values using industry-level prices indices. We believe that labor productivity, as a measurement of unit wage, matters because it is a highly important and positive determinant of employees' wage (Caselli, 1999; He et al., 2019; Hellerstein, Neumark, & Troske, 1999; Lazear, 2000; Zhang & Huang, 2010). To verify whether our argument is true, we regress each firm's employees' labor productivity on $PM_{2.5}$ (instrumented by thermal inversion) and other control variables. The second stage results in columns 1 and 2 show that air pollution can significantly lower employees' labor productivity, whether measured by value-added or output value. Specifically, taking the coefficient of interest in column 1 as an example, a one $\mu g/m^3$ increase in annual mean $PM_{2.5}$ decreases employees' labor productivity by around 0.01% (significant at the 1% level). Thus, employees' unit wage level falls because of poor air quality.

**Table 8**
Underlying Mechanisms Analysis.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Labor Productivity (VA) | Labor Productivity (Output) | Working Hours per Year | Working Days per Year | Employment |
| $PM_{2.5}$ | −0.0087*** | −0.0113*** | −0.0191*** | −0.0174*** | 0.0058*** |
| | (0.001) | (0.001) | (0.007) | (0.006) | (0.001) |
| Weather Controls | Yes | Yes | Yes | Yes | Yes |
| Individual Controls | No | No | Yes | Yes | No |
| Firm Control | Yes | Yes | No | No | Yes |
| Province FE | No | No | Yes | Yes | No |
| Firm FE | Yes | Yes | No | No | Yes |
| Year FE | Yes | Yes | No | No | Yes |
| Observations | 1,539,967 | 1,540,347 | 9497 | 9497 | 1,540,368 |

*Notes*: In Columns 1 and 2, we examine the impact of air pollution on employees' labor productivity measured by value-added and total output divided by the total number of employees, respectively. In Columns 3 and 4, we test the effect of air pollution on the labor supply by working hours per year and working days per year. In Column 5, we investigate the effect of air pollution on firm's employment. The IV for $PM_{2.5}$ is the number of days with at least one thermal inversion in each county year. Standard errors are clustered at the individual level in Column 3 and 4, and at the firm level in the remaining columns. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

### 5.2. Employees' labor supply

Additionally, employees' labor supply is also a vital factor that can be affected by poor air quality since air pollution can do great harm to mental health such and physical health. However, the ASIE is unable to provide us with the data we need to investigate this. Therefore, we draw on the 2002 CHIP survey and employ the two variables reported in this survey indicating employees' total labor supply: *Working Hours per Year* and *Working Days per Year* (the natural logarithm form). We match our air pollution, thermal inversion and meteorological factors data at county-by-year level with the 2002 CHIP survey data, obtaining a cross-section data at the individual level. We remove samples that were not working and then replace the dependent variable in the baseline regression with *Working Hours per Year* and *Working Days per Year* and implement 2SLS regression. To control for elements that may influence people's working time, we include the workers' years of education, gender, marital status, age, and health condition instead of firm characteristics. We include province fixed effects to take local economic, social, and political factors across provinces into consideration. The results of regressing *Working Hours per Year* on yearly average $PM_{2.5}$ are shown in column 3 of Table 8: the coefficient of interest is −0.0191, statistically significant at the 1% level, meaning that a one μg/m$^3$ increase in yearly average $PM_{2.5}$ reduces average working hours per year around 0.02%. We next investigate whether air pollution causes reductions in working days. We replace the dependent variable with the logged number of working days in 2002 and retain the same controls and fixed effects. It is not surprising that air pollution decreases employees' working days as well. The coefficient of interest presented in column 4 shows that a one-unit increase in yearly mean $PM_{2.5}$ reduces the total average working days in a year by 0.017% because workers may seek medical help for some illnesses caused by severe air pollution.

Overall, we find that workers reduce their labor supply when confronted with poor air quality by decreasing both working hours per year and total working days per year.

### 5.3. Firm employment

Finally, firms are likely to hire additional workers to compensate for productivity and labor supply loss of existing workers caused by air pollution, as we discuss in section 4.3.1. In other words, we should observe an increase in firms' total employment if our findings in sections 5.1 and 5.2 are valid. To verify our argument, we regress the logged employment of each firm plus one on yearly average $PM_{2.5}$ (instrumented with thermal inversion) and the same controls as those in the baseline regression. The coefficient of interest reported in column 5 reveals what happens inside firms when faced with severe air pollution, supporting our argument. Firms are apt to hire more workers to offset existing employees' productivity and work time losses, increasing total employment by around 0.01% with a one-unit increase in yearly mean $PM_{2.5}$. Moreover, coupled with the findings in section 6.1 below showing decreases in firms' total wage expenditures with the increasing trend in firms' employment, we can conclude that the average annual income of employees is falling. This finding also suggests that air pollution reduces existing employees' labor productivity and work time.

## 6. Further study

### 6.1. Further study on firm operating status

We further investigate the effect of air pollution on firms' total wage expenditure and study how the labor cost of firm changes. We find that a one-unit increase in yearly mean $PM_{2.5}$ reduces firms' total wage expenditure by around 0.004%. Although the total wage expenditure decreases nominally, we can know that the employee labor productivity loss is nearly 2 to 3 times as great that of the firms' total wage expenditure reduction based on the findings in the mechanism analysis, suggesting that firms' actual labor cost rises dramatically. Therefore, we infer that poor air quality can also undermine firms' operating status because of the dramatic increase in labor costs.

To test this assumption, we select three indicators representing firms' operating status. First, we examine how air pollution affects the return on assets measured by the ratio between enterprises' total profit plus interest expense and total assets, a basic index used to investigate corporate profitability. The higher the indicator, the better the input-output level and the more effective asset operation of the enterprises. The second stage results of regressing *Return on Assets* on yearly average $PM_{2.5}$ and other control variables are reported in column 2 in Table 9: the coefficient of interest is −0.002. It is statistically significant at the 1% level, indicating that regions with severe air pollution have lower average *Return on Assets* of enterprises.

After that, we focus on the operating status by calculating the asset turnover of each firm as it is an important financial ratio in measuring the efficiency of corporate asset management and reflects the transfer speed of all assets from input to output. The second stage result of regressing firms' *Asset Turnover* (measured by main business income divided by total assets) on $PM_{2.5}$ and other control variables confirms our assumption: the coefficient of $PM_{2.5}$ is negative (−0.0108) and statistically significant at the 1% level, suggesting that a one μg/m$^3$ increase in annual mean $PM_{2.5}$ reduces firms' asset turnover by 0.52%, indicating that air pollution may lead to underutilize existing assets or redundant or idle assets in firms because of the dramatic increase in labor costs.

Additionally, we investigate whether firms' long-term development ability is also affected by the sharply rising labor costs. To do this, we first construct an indicator: *Sale Growth Rate*, calculated as main business income for the current year minus main business income for the previous year divided by main business income for the previous year, as an indicator to show a firm's ability of the long-term growth. A higher value of for *Sale Growth Rate* means a stronger ability to develop in the long run. The second stage results of regressing *Sale Growth Rate* on annual average $PM_{2.5}$ in column 4 show that air pollution has significantly negative impact (corresponding to 2.5% decrease of the mean value with one μg/m$^3$ increase in annual mean $PM_{2.5}$) on the *Sale Growth Rate* value and

**Table 9**
Further Study on Firm Performance.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Total Wage Expenditure | Return on Assets | Assets Turnover | Sales Growth Rate |
| $PM_{2.5}$ | −0.0038*** | −0.0020*** | −0.0108*** | −0.0075*** |
| | (0.001) | (0.000) | (0.003) | (0.002) |
| Weather Controls | Yes | Yes | Yes | Yes |
| Firm Control | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 1,540,368 | 1,306,808 | 1,539,965 | 1,034,915 |

*Notes*: In Column 1, we investigate the effect of air pollution on firms' total wage expenditure. From Column 2 to 4, we investigate the impact of air pollution on indicators of business status: return on total assets, assets turnover and sales growth rate. The IV for $PM_{2.5}$ is the number of days with at least one thermal inversion in each county year. Standard errors are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

statistical significance is at the 1% level, suggesting that air pollution can undermine the firms' long-term development ability.

To sum up, these results indicate that air pollution indeed degrades firms' operating status because of the sharp increase in labor costs. Therefore, we infer that the earning loss caused by poor air quality may be even larger in the long term if firms remain trapped in operating troubles in the future.

### 6.2. *Further study on the non-linear effects of air pollution*

Given the fact that several studies have found that the effects of air pollution on economic outcomes are non-linear, we examine whether employees' earnings are more sensitive to regions where air quality is worse than regions with better air quality in our paper. We first define three pollution dummies based on annual mean $PM_{2.5}$ according to the Ministry of Ecology and Environment of the People's Republic of China (MEEPRC): *Low Pollution* (annual mean $PM_{2.5}$ lower than 35 $\mu g/m^3$) (the omitted group), *Intermediate Pollution* (annual mean $PM_{2.5}$ higher than 35 $\mu g/m^3$ and lower than 75 $\mu g/m^3$), and *High Pollution* (annual mean $PM_{2.5}$ higher than 75 $\mu g/m^3$).[13] Each dummy takes the value of one if the local annual mean $PM_{2.5}$ falls into the corresponding range, and zero otherwise. However, since the number of dummy variables exceeds that of the instrument variables, we are unable to implement an IV approach. Instead, we replace the $PM_{2.5}$ in Eq. (1) with *Intermediate Pollution* and *High Pollution* to estimate the non-linear model using OLS with adding various control variables and fixed effects. Column 1 of Table 10 shows the results: the coefficient of *Intermediate Pollution* remains negative but lacks significance, and the coefficient of *High Pollution* is positive and insignificant, suggesting that there is no non-linearity in the impact of severe air pollution. However, as noted in section 3, the endogeneity problems between air pollution and economic outcomes can bias the coefficient of interest severely. Thus, we focus on the effect of different levels of thermal inversion, the exogenous meteorological phenomenon, on employees' yearly earnings. First, we divide thermal inversion into three groups and generate three dummy variables based on the one-third threshold with the max value 333 of our instrument: *Low Pollution* (thermal inversion falls in 0–111) (the omitted group); *Intermediate Pollution* (thermal inversion falls in 111–222); *High Pollution* (thermal inversion falls in 222–333). Then we replace the annual mean $PM_{2.5}$ in Eq. (1) with *Intermediate Pollution* and *High Pollution* and conduct the OLS estimation again. The results are presented in column 2. There is an obvious non-linear pattern of coefficients in column 2: air pollution has no significant effect on employees' income as thermal inversion falls in the *Low Pollution* group but remains negative. When thermal inversion turns to the *High Pollution* group, the effect of air pollution is significantly negative at the 1% level and the magnitude of the coefficient is nearly 20 times as large as much that of the *Low Pollution* group.

These results, taken together, suggest that air pollution has a negative effect on employees' yearly earnings until a specific threshold is exceeded, again demonstrating that employing the IV approach can address the endogeneity problems of air pollution, enabling reliable estimations.

## 7. Conclusion

Using a database on nationwide industrial enterprises, our research estimates the effect of air pollution on employees' annual earnings from 1998 to 2007. We find that air pollution can significantly lower employees' yearly earnings using an IV approach. These results remain intact after implementing a battery of robustness checks including altering fixed effects and standard error level, using different samples (excluding relocating firms) and dependent variables, functional forms of $PM_{2.5}$ (logged) and other air pollutants. And we exclude the sorting issues of firms and population migration after serious discussions. Additionally, a series of RDD estimations based on the Qinling-Huai River line also support our baseline finding. Our paper reveals that the yearly average earnings loss of employees living in high air pollution regions is 175.4 CNY with every one $\mu g/m^3$ increase in annual average $PM_{2.5}$.

Moreover, the total employees' earnings loss for our sample firms amounts to about 268.59 million CNY. Heterogeneous effects analysis demonstrates that air pollution does greater harm to labor-intensive firms, non-state-owned firms and smaller firms. In addition, mechanism analyses indicate that air pollution hurts employees' yearly earnings by weakening their unit wage and reducing

[13] Information source: http://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201203/t20120302_224166.shtml (in Chinese)

**Table 10**
Further Study on the Non-Linear Effect of Air Pollution.

| | (1) | (2) |
|---|---|---|
| | Annual Earnings per Employee | |
| | $PM_{2.5}$ | Thermal Inversion |
| Intermediate Pollution Level | −0.0237 | −0.0136 |
| | (0.044) | (0.028) |
| High Pollution Level | 0.0193 | -0.2773*** |
| | (0.052) | (0.045) |
| Weather Controls | Yes | Yes |
| Firm Control | Yes | Yes |
| Firm FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 1,540,368 | 1,540,368 |

*Notes*: In Column 1, we divide $PM_{2.5}$ across counties into three groups: 0–35 (Low Pollution (Omitted Group)), 35–75 (Intermediate Pollution), and 75 and above (High Pollution), according to the thresholds provided by the MEEPRC. In Column 2, we divide our IV, thermal inversion, equally into three groups based on its distribution. Standard errors are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

working time. Further study reveals that air pollution can also undermine enterprises' operating status due to the rising firms' labor costs. We also reveal a monotonically increasing pattern of the effect of air pollution on employees' annual earnings through non-linear effect analyses of air pollution.

Finally, the earnings loss of employees caused by air pollution evaluated by this paper facilitates a direct economic cost of air pollution and more accurate cost-benefit analyses for fashioning environmental regulations in China or even in other developing countries.

## Declaration of Competing Interest

We declare that we have no relevant or material financial interests that relate to the research described in this paper.

## Data availability

The authors do not have permission to share data.

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## Appendix A. Appendix

**Table A1**
Sharp RDD Estimates of the Qinling-Huai River Policy.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Annual Earnings per Employee | | |
| $I(Distance_{ijt} > 0)$ | −1.1265* | −0.8175*** | −0.3834** |
| | (0.447) | (0.210) | (0.182) |
| Weather Controls | No | No | Yes |
| Firm Control | No | No | Yes |
| Year FE | No | Yes | Yes |
| Industry FE | No | Yes | Yes |

(*continued on next page*)

**Table A1** (*continued*)

| | (1) | (2) | (3) |
|---|---|---|---|
| | Annual Earnings per Employee | | |
| RD type | LLR (SRD) | LLR (SRD) | LLR (SRD) |
| Kernel | Triangular | Triangular | Triangular |
| Optimal Bandwidth (Kilometer) | 103.55 | 120.13 | 116.72 |
| Observations | 147,820 | 178,497 | 171,449 |

*Notes:* Columns 1 to 3 use the local linear regression for sharp RD design. Standard errors are clustered at the county-by-year level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**Table A2**
Robustness Check III: firm exit and entry, sorting, and minimum wage regulations.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Ln (1 + Number of Firms) | Ln (1 + Industrial Output) | Ln (1 + Employment) | Annual Earnings per Employee | Annual Earnings per Employee | High Technology Employment Fraction | High Education Employment Fraction Based on ASIE | High Education Employment Fraction Based on 1% Sample from 2005 China Census | Annual Earning per Employee |
| $PM_{2.5}$ | −0.0075 | −0.0017 | 0.0093 | −0.1294*** | −0.1843*** | 0.0010 | −0.0001 | −0.0018 | −0.1641*** |
| | (0.006) | (0.008) | (0.008) | (0.039) | (0.013) | (0.002) | (0.001) | (0.002) | (0.033) |
| Weather Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Control | No | No | No | Yes | Yes | No | No | No | Yes |
| Firm FE | No | No | No | Yes | Yes | No | No | No | Yes |
| Province FE | No | No | No | No | No | No | Yes | Yes | No |
| County FE | Yes | Yes | Yes | No | No | Yes | No | No | No |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| Prefecture-Year FE | No | No | No | No | No | No | No | No | Yes |
| Observations | 25,118 | 25,118 | 25,118 | 174,600 | 1,537,049 | 25,118 | 2676 | 305 | 1,540,348 |

*Notes*: We calculate the natural logarithm of one plus the total number of firms at county level in Column 1. In Column 2, we calculate the natural logarithm of one plus the total industrial output value at the county level. In Column 3, we calculate the natural logarithm of one plus the total employment at the county level. Column 4 uses balanced panel data from 1998 to 2007. Column 5 excludes the firms whose locations were changed during our sample period at prefecture level. In Column 6, we calculate the high-technology industries employment fraction based on OECD (2011). In Column 7, we calculate the high education level fraction based on ASIE. In Column 8, we calculate the high education level fraction based on 1% Sample from 2005 China Census. We include prefecture-by-year fixed effects in Column 9. Standard errors are clustered at the county level in Columns 1, 2, 3, 6 and 7, and at the firm level in Columns 4, 5 and 9, and at the city level in Column 8. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**Table A3**
Heterogeneous Impact across Capital-intensive and Labor-intensive Industry.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Labor Productivity (VA) | | Employment | |
| | Capital Intensive | Labor Intensive | Capital Intensive | Labor Intensive |
| $PM_{2.5}$ | -0.0060*** | -0.0109*** | 0.0044*** | 0.0070*** |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| Weather Controls | Yes | Yes | Yes | Yes |
| Firm Control | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 748,686 | 791,281 | 748,896 | 791,472 |

*Notes*: We divide the capital-intensive and labor-intensive subsamples based on the capital-labor ratio of each industry. The IV for $PM_{2.5}$ is the number of days with at least one thermal inversion in each county-year. Standard errors are clustered at the firm level. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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