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# Job destruction and creation: Labor reallocation entailed by the clean air action in China

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ABSTRACT

Understanding the mechanism of labor reallocation during the implementation of environmental regulations is important for countries to stabilize employment. Using city-level data and listed firm-level data from 2005 to 2019, we investigated the labor reallocation entailed by the Clean Air Action (CAA) from 2013 to 2017 in China, and found that the CAA substantially reduced labor demand in regulated cities and listed firms. Notably, the CAA has entailed different levels of job destruction and job creation across time, industries, and firm types, boosting labor reallocation. Firstly, the effect of the CAA on labor demand was time-varying, as labor demand first decreased and then recovered from 2013 to 2019. Secondly, the CAA generated a greater job destruction in polluting industries and their downstream industries, and job creation in clean industries. Lastly, thanks to the CAA firms have increased the hiring of highly skilled workers, although equipment upgrades have reduced labor demand, especially in polluting firms.

## 1. Introduction

Over the past few decades, air pollution has caused considerable economic losses and done harm to human health in China (Deryugina, Heutel, Miller, Molitor and Reif, 2019; Feng, Cheng, Shen and Sun, 2019; Fu, Viard and Zhang, 2021). To reduce the huge costs of air pollution, in September 2013, the Chinese government released the Air Pollution Prevention and Control Action Plan (APPCAP) (2013–2017). The Clean Air Action (CAA) established a system of centrally-planned, regionally-decomposed, politically-incentivized, and multifaceted air regulations (Li, Wang, Zhou and Shi, 2020). However, it has also increased production costs in most industrial enterprises, forcing several enterprises to downsize or close, and the associated declines in employment.

Maintaining employment stability is key to reducing the negative impact of environmental regulation on economic growth and social stability (Huang and Lanz, 2018). Recent studies have all revealed that China's environmental regulation on pollution emissions led to a significant decline in employment levels (Li and Lin, 2022; Liu, Shadbegian and Zhang, 2017; Liu, Tan and Zhang, 2021). The CAA is the largest, most stringent, and highest-stake air regulation in China's history (Sheehan, Cheng, English and Sun, 2014) and, thus, more likely to have a negative impact on employment. Therefore, several politicians are currently wondering how to reduce the job destruction and increase the job creation entailed by environmental regulation.

Existing empirical research decomposed the impact of environmental regulation on labor demand into two components: the output effect and the substitution effect. The output effect means that environmental regulation increases the production cost of enterprises

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(Féres and Reynaud, 2012; Zhang, Zhou, Zhou and Zhao, 2022), entailing a reduction of their output and of their demand for inputs, including labor demand. As such, the output effect is generally negative (Gray, Shadbegian, Wang and Meral, 2014). The substitution effect refers to the impact of enterprise equipment installation and upgrading on labor demand. Bauer and King (2018) argued that equipment upgrade will reduce employment. When "end-of-pipe" equipment is installed, it is necessary to have corresponding types of labor, which often increases labor demand. In addition, Yip (2018) claimed that if pollution and labor are substitutes in production, firms may hire more labor when the marginal cost of pollution increases. These considerations suggest that job destruction and job creation exist simultaneously within firms.

The scientific findings on the effect of environmental regulation on labor demand are mixed, as this depends on the net value of both job destruction and job creation. For example, Walker (2011) found that the 1990 U.S. Clean Air Action caused a 15% decline in manufacturing labor demand. Berman and Bui (2001) discovered that the sharp increase in air quality regulation in Los Angeles since 1979 substantially reduced $NO_X$ emissions, while at the same time it did not cause a substantially reduction in employment. However, it is generally agreed that the labor demand of pollution-intensive, energy-intensive, and labor-intensive industries is more vulnerable to the negative impacts of environmental regulation (Hille and Möbius, 2019; Liu et al., 2021), while capital-intensive and clean industries are less affected (Berman and Bui, 2001).

In addition, the effects of environmental regulations on polluting industries may be transmitted to other industries through capital markets and energy-intensive products, leading to labor reallocation across industries (Wang and Zhu, 2021). Vona, Marin, Consoli and Popp (2018) found that, although in the short term strict environmental regulations cause some workers to leave regulated firms or industries, in the medium and long term laid-off workers will eventually find a job again, especially in the services sector. Since the stringency of environmental regulations varies across industries, in addition to the negative effect on polluting industries, a positive effect will take place benefiting those industries that support the implementation of environmental regulations, including environmental management and green finance (Du, Cheng and Yao, 2021; Pipkin and Fuentes, 2017). As a result, there will be varying degrees of job creation and job destruction across industries, and labor flows will drive labor reallocation across industries.

In this study, we examined the dynamic impact of the CAA on labor demand and delved into the mechanisms of labor reallocation. The difference-in-differences (DID) method was used to perform analysis, as it is a relatively mature policy effects evaluation method. In order to ensure the accuracy of the evaluation results, the propensity score matching (PSM) method was used to eliminate the bias between the treatment group and the control group, and a longer window before policy implementation was considered to test the common trend assumption. We used both city-level and listed firm-level data for analysis, and combined these two levels of data to increase the robustness and representativeness. This study analyzed the effect of dynamic changes over time; unlike existing studies, we executed a dynamic placebo test to fully demonstrate the robustness of the dynamic analysis results.

Our findings contribute to the literature on the topic of environmental regulation and labor reallocation in three ways. Firstly, while existing studies have paid more attention to the aggregate effect, this study analyzed the dynamic impact of environmental regulation on labor demand over time (Li et al., 2020; Li and Lin, 2022). It is widely known that the government will continuously adjust their strategies and efforts according to the actual situation. In addition, enterprises and workforce will also make adjustments in the medium and long term. As a result, the effect of the CAA on labor demand will change with the passage of time; hence, it is more meaningful to estimate the dynamics of labor demand. Our findings suggest that the effect of the CAA on labor demand is time-varying. Focusing only on the aggregate effect of the CAA does mask the time-varying effect of policy development.

Secondly, as few researches have been conducted on the labor reallocation effect of environmental regulation, this study analyzed the labor reallocation effect of the CAA at two levels: inter-industry and intra-firm. Walker (2011) argued that environmental regulation typically affects the distribution of labor, rather than the level of employment. Therefore, the estimation of the regulatory costs should focus more on the transitional costs of labor. By performing a comprehensive review of the existing literature, this paper analyzes the labor reallocation entailed by environmental regulations at both inter-industry and intra-firm level. We found that the CAA reduced labor demand in polluting industries and their downstream industries, and increased labor demand in clean industries. Moreover, the number of highly skilled workers within firms increased, although equipment upgrades reduced labor demand.

Finally, while existing studies focused more on developed countries such as the United States and the European Union (Bauer and King, 2018; Raff and Earnhart, 2020), this study provided evidence from China, i.e., the largest developing country. Driven by the demographic dividend, China has grown rapidly to become the second largest economy in the world. However, unlike developed countries, the majority of Chinese firms are currently labor-intensive and energy-intensive; therefore, the implementation of the CAA is expected to lead to structural changes in the Chinese labor market. The results of the present study can provide support to stabilize employment during the implementation of environmental regulations, and inform other countries in similar situations around the world about the experience of China.

This paper is structured as follows. In Section 2, the background, goals, and content of the CAA are introduced. Section 3 presents the theoretical framework and provides support for the empirical analysis. Section 4 introduces the research methods, data, and descriptive statistics. In Section 5, we present the main results and the results of the robustness checks. In Section 6, labor reallocation across industries is further analyzed. Section 7 presents the labor reallocation effects within firms. Finally, Section 8 provides the research conclusions and policy recommendations.

## 2. The CAA in China

### 2.1. Background of the CAA

The APPCAP was issued by the State Council, the highest administrative organ in China. Under its umbrella, local governments at all levels are required to formulate specific implementation strategies for their regions and disclose them to the public. In order to strengthen the constraints on local governments, the central government requires them to take the overall responsibility for the air quality within their jurisdictions; accordingly, they are required to sign responsibility letters with higher governments, and use the results of environmental assessments as an important basis for the promotion of government officials at all levels. This vertical management model represents a major institutional innovation in China's environmental governance, under which environmental regulation can be implemented more quickly and effectively (Li, Lu and Wang, 2016). In fact, existing studies have shown that the CAA has effectively improved air quality in China (Huang, Pan, Guo and Li, 2018; Song, Li, Yang and Xia, 2020).

While previous environmental policies used total emission reduction as an assessment indicator, the CAA is the first environmental program in China to use air quality to this purpose. In relation to total emission reduction, air quality can be easily detected through appropriate equipment, thus reducing the possibility of cheating. The CAA set the goal that by 2017, the inhalable particulate matter ($PM_{10}$) in prefecture-level cities across the country would be reduced by >10% compared with 2012, and the fine particulate matter ($PM_{2.5}$) in key areas of Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta region would drop by 25%, 20%, and 10%, respectively. The mid-term assessment and the final assessment were planned to be conducted in 2015 and 2017, respectively.

Apart from regulating polluting industries, the CAA also promotes the development of green industries. This law focuses on the treatment of the following pollution sources: winter heating; industrial emissions; and automobile exhaust emissions. The measures taken include: the elimination of small coal-fired boilers; coal-to-gas and coal-to-electricity; the requirement for industrial enterprises to carry out desulfurization, denitrification, and dust removal; the improvement of fuel quality; and the control of the number of motor vehicles. These regulations were expected to have a direct impact on power, heating, and gas supply, manufacturing, and transportation industries. In addition, the CAA also adopted sustainable development measures such as the strengthening of scientific and technological innovation capabilities and the development of green finance, which were expected to promote the development of the science and technology industry and of the financial industry. A large number of sanitation workers were expected to be necessary for the implementation of the CAA, leading to the development of the environmental management industry.

### 2.2. *The most regulated region*

The Beijing-Tianjin-Hebei region is the most regulated region by the CAA. Beijing is the capital and the political, economic, and cultural center of China. Tianjin is the gateway to northern China, as well as the shipping center, logistics center, and manufacturing base of northern China, and like Beijing, is one of the four major municipalities in China. Hebei is a major manufacturing province in China, famous for its steel industry. The Beijing-Tianjin-Hebei region is the largest and most dynamic economy in northern China; it is the only winter heating region among the three key regions, and also one of the worst regions in terms of air quality.

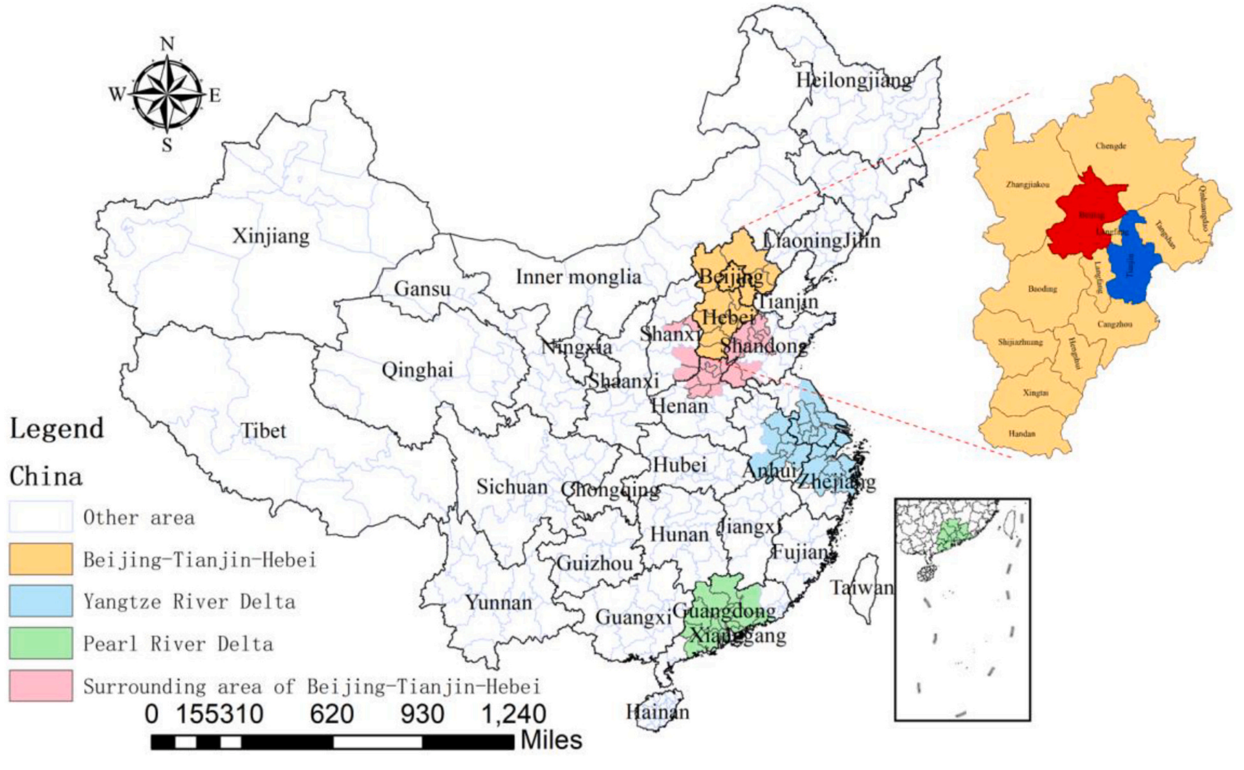



**Fig. 1.** The key regions of implementation of the CAA.

After the issuance of the APPCAP, the Beijing-Tianjin-Hebei's APPCAP implementation strategy was quickly developed. At the beginning, Beijing, Tianjin, and four prefecture-level cities in Hebei Province were considered as included in the core treatment areas, which in 2017 were expanded to include other 28 cities (Song et al., 2020), as shown in Fig. 1. The agreed implementation strategies and efforts are planned to be adjusted each year based on the effect of policy implementation. With the aim to keep the achievements obtained in air quality, the Beijing-Tianjin-Hebei region continued to enact annual regulations after 2017.

## 3. Conceptual framework

### 3.1. Framework for changes in labor demand

The CAA requires firms to adopt measures such as to use clean energy and install and upgrade equipment to reduce pollution emissions, which increases production costs. Therefore, in addition to capital and labor inputs, firms need to consider pollution while making their production decisions. Drawing on Smulders and Gradus (1996) and Cole, Elliott and Wu (2008) we took pollution as the non-production input factor of the production function. The price of the pollution factor can be used to represent environmental regulation, where the stronger the intensity of environmental regulation, the higher the price of the pollution factor. After introducing environmental regulation into the production function, we could analyze the economic decisions of firms under environmental regulation. Suppose there exists a polluting firm A with a production function satisfying the Cobb-Douglas formula:

$$Y_A = TE_A^{\alpha} L_A^{\beta} K_A^{\theta}, 0 < \alpha, \beta, \theta < 1 \tag{1}$$

Where $Y_A$ represents the outputs of firm A; $T$ denotes the technology; $E$,$L$,and $K$ indicate pollution, labor, and capital, respectively; and $\alpha$,$\beta$,and $\theta$ are the factor output elasticity coefficients of pollution, labor, and capital, respectively. Assume that firm A is in a perfectly competitive market and its product price is $P$, while the prices of pollution, labor, and capital are $R$, $W$, and $G$ respectively. The profit function for firm A is as follows:

$$\pi_A = PTE_A^{\alpha} L_A^{\beta} K_A^{\theta} - (RE_A + WL_A + GK_A) \tag{2}$$

The firm A maximizes its profits by adjusting the inputs of $E$, $L$, and $K$. According to the profit maximization principle, the relationship between labor and pollution can be obtained by calculating the derivative of the profit function with respect to $E$, $L$, and $K$, as follows:

$$L_A = \frac{\beta}{\alpha W_A} RE_A \tag{3}$$

Where $R_A$ denotes the intensity of environmental regulation of firm A. By deriving Eq. (3) to environmental regulation ($R_A$), we can calculate the marginal impact of environmental regulation on labor, as follows:

$$\frac{dL_A}{dR_A} = \frac{\beta}{\alpha W_A} E_A (1 - \delta_{ER}) \tag{4}$$

Where $\delta_{ER} = -\frac{R_A}{E_A}\frac{dE}{dR}$ indicates the demand price elasticity of the pollution factor. When the intensity of environmental regulation increases, firms will reduce the input of pollution, and $\frac{R_A}{E_A}\frac{dE}{dR}$ will be negative. In order to ensure that $\delta_{ER}$ is positive, a negative sign was added before $\frac{R_A}{E_A}\frac{dE}{dR}$.

According to Eq. (4), the impact of environmental regulation on labor demand can be divided into two parts. The first part is $\frac{\beta}{\alpha W_A} E_A$, because pollution and labor are substitutes in the production function, the price of labor ($W_A$) is relatively low as the price of pollution factors ($R_A$) increases, and firms choose to input more labor to replace pollution factors. Thus, the first part reflects the substitution effect of labor for the pollution factor. The second part is $\frac{\beta}{\alpha W_A} E_A \delta_{ER}$, whereby environmental regulation increases the marginal cost of pollution and firms have to reduce their output, resulting in a corresponding reduction in labor input. Therefore, this part reflects the output effect.

In addition, changes in capital factors will also affect labor demand. When firms face environmental regulation, they may choose to invest more capital in replacing pollution factors, such as retrofitting and upgrading equipment, which can squeeze out the substitution of the labor factor for the pollution factor. The capital investment of firms in the processes of change of production and end-of-pipe treatment will also have a different impact on labor demand (Zhao and Fang, 2022).

These results suggest that both job destruction and job creation will take place within firms after the implementation of environmental regulation. The changing direction of labor demand depends on the net value of three components, namely the output effect, the substitution effect of labor for pollution, and the substitution effect of capital for labor. Since Eq. (4) cannot express the substitution effect of capital for labor and is relatively complex, we transformed the formula of the effect of environmental regulation on labor into the following form:

$$\frac{dL_A}{dR_A} = \gamma_1 \frac{dY_A}{dR} + \gamma_2 \frac{dK_A}{dR} + \gamma_3 \frac{dW_A}{dR} \tag{5}$$

Where $\frac{dY_A}{dR}$ represents the output effect; $\frac{dK_A}{dR}$ denotes the substitution effect of capital for labor; and $\frac{dW_A}{dR}$ is the substitution effect of labor for the pollution factor.

### 3.2. Framework for inter-industry labor reallocation

The regulatory differences between industries will promote inter-industry labor reallocation. While imposing constraints on polluting enterprises, it also promotes the development of clean industries. Assuming the existence of firm B, which has a relatively small pollution reduction constraint than firm A, the impact of CAA on firm B's labor demand can be expressed as follows:

$$\frac{dL_B}{dR} = \gamma_1 \frac{dY_B}{dR} + \gamma_2 \frac{dK_B}{dR} + \gamma_3 \frac{dW_B}{dR} \tag{6}$$

We compared the changes in labor demand for firms A and B along three components, namely the output effect, the substitution effect of labor for pollution, and the substitution effect of capital for labor.

Firstly, we adopted the typical assumption that environmental regulation will lead to lower output in polluting firms (Liu et al., 2021). As the environmental regulation of Firm B is less stringent than that of Firm A, the output reduction of Firm B will be lower than that of Firm A. In addition, the government will be more inclined to support the development of clean industries, thus stabilizing the economy. Therefore, we assumed that $\frac{dY_B}{dR} > \frac{dY_A}{dR}$. Secondly, above in Section 3.1, the capital investment in the processes of "change of production" will reduce the labor demand, while the "end-of-pipe" treatment will have the opposite effect; thus, the direction of $\frac{dK}{dR}$ will be uncertain. However, if firm B is a clean firm that has achieved scale growth with government support, then $\frac{dK_B}{dR}$ will be positive. Lastly, since the price per unit of polluting emissions increases with environmental regulation, firm A will hire more workers to replace polluting factors relative to firm B, that is, $\frac{dW_A}{dR} > \frac{dW_B}{dR}$.

Therefore, the impact of the CAA on labor demand varies across industries, due to the different levels of environmental regulation. When $\frac{dL_B}{dR} > \frac{dL_A}{dR}$, workers will move from firm A to firm B, and more towards the cleaner firms.

## 4. Empirical framework and data

We used city-level and listed firm-level data to improve the robustness and representativeness of the results. In the vertical management system of the Chinese government, prefecture-level cities are regional administrative subjects, and the smallest administrative unit appearing in the APPCAP document. Hence, we used city-level data to analyze macro changes in the city's labor demand. Listed firm-level data were used to analyze the micro changes in labor demand within firms. The robustness of the results can be largely enhanced when the two levels of data results are generally consistent. We could also further explore the reasons for the subtle differences between the results derived from the two data levels to discover the uniqueness of listed firms when facing environmental regulations.

### 4.1. DID estimation strategy

In this study, the DID model was used to estimate the effect of the CAA on labor demand. The DID model allowed to compare the differences between the treatment and control groups before and after the implementation of the CAA, so as to effectively mitigate endogenous problems and obtain a more accurate picture of the impact of this policy.

The DID model is a quasi-natural experiment method, where the affected area is considered as the treatment group and the unaffected or slightly impacted area as the control group. The fact that the treatment group experienced significantly stronger policy shocks than the control group is fundamental to determine the policy effects.

Although the CAA is a national policy, the environmental regulation implemented by the CAA varies across different regions of China. In particular, the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions are required to reduce their $PM_{2.5}$ by 25%, 20%, and 10% respectively, while the other non-key regions are required to reduce their $PM_{10}$ by 10%. We took advantage of the differences in the environmental regulatory intensity across cities to select the treatment and control groups (Li, Qiao and Shi, 2019). Because the Beijing-Tianjin-Hebei region has the highest level of regulatory target among all Chinese regions, it was included in the treatment group; the non-key regions were included in the control group because of their lowest regulatory targets.

The regulatory differences between the other two key regions (i.e., the Yangtze River Delta and the Pearl River Delta) and the non-key regions are relatively small, compared to those with the Beijing-Tianjin-Hebei region. Therefore, the Yangtze River Delta and the Pearl River Delta region were excluded from the scope of the study.[1] In addition, those cities that joined the Beijing-Tianjin-Hebei core regulation area in 2017 were also excluded, because they may experience the same level of regulation as the Beijing-Tianjin-Hebei region after 2017.

The key assumption for the establishment of the DID model was that the level of environmental regulation of the Beijing-Tianjin-Hebei region is stricter than that of the non-key cities. Since it was not determined whether the actual air quality improvement in the Beijing-Tianjin-Hebei region was higher than in other cities, it was necessary to first test the effectiveness of the CAA. To capture the effect of the CAA on $PM_{2.5}$, we used the following DID model:

[1] We analyzed the Yangtze River Delta and the Pearl River Delta regions. Firstly, the results for the Yangtze River Delta could not meet the common trend assumption; hence, they were biased and had no reference value. Secondly, we found that the labor demand in the Pearl River Delta region was not significantly affected by the CAA. An important reason for this result is that the regulatory differences between the Pearl River Delta and the non-key areas are relatively small, which erroneously led to insignificant estimation results.

$$Ln(PM_{2.5})_{it} = \alpha_0 + \beta_1(CAA_i \times Post_t) + \gamma C_{it} + \xi W_{it} + \varphi_i + \phi_t + \varepsilon_{it} \tag{7}$$

Where *i* represents the city; *t* denotes the year; and $Ln(PM_{2.5})_{it}$ is the log of $PM_{2.5}$ concentration. $CAA_i$ is a grouping variable, equal to 1 if the city belongs to the Beijing-Tianjin-Hebei region, and 0 otherwise. $Post_t$ is a policy shock variable, equal to 1 for the years after 2013, and equal to 0 otherwise. $\varphi_i$ indicates the city fixed effects, which were used to eliminate inter-city differences that do not vary with time, while $\phi_t$ indicates the year fixed effects, which were used to eliminate macro factors that do not vary across cities. $\varepsilon_{it}$ is the error term.

$PM_{2.5}$ is affected not only by city factors, but also by meteorological factors. Therefore, referring to the research of Cao, Wang and Zhou (2022), we added the following city-level control variables ($C_{it}$) to the model: (i) Economic development level (*Ln(pgdp)*); (ii) Share of secondary production (*Secondary*); (iii) Infrastructure level (*Infrastructure*); (iv) Population density (*PD*); (v) Foreign capital (*FDI*); and (vi) Average wage (*Ln(wage)*). Following the theory of the environmental Kuznets curve (Sephton and Mann, 2016), we added (vii) a squared term of the economic development level. We also added control variables to reflect weather ($W_{it}$), including (viii) Mean annual temperature (*Temperature*); (ix) Mean annual wind speed (*Wind*); (x) Mean annual rainfall (*MRain*); (xi) Total annual rainfall (*TRain*); (xii) Cloud thickness (*Cloud*); and (xiii) Sea level pressure (*Pressure*).

We then estimated the policy effect on labor demand using the similar DID model, which was the focus of our investigation. The DID model for labor demand was built as follows:

$$Ln(Labor)_{it} = \alpha_0 + \beta_1(CAA_i \times Post_t) + \gamma X_{it} + \varphi_i + \phi_t + \varepsilon_{it} \tag{8}$$

When *it* indicates city-level data, *i* represents the city and *t* denotes the year. $Ln(Labor)_{it}$ is the log of the labor demand of city *i* in year *t*. $X_{it}$ is a vector of control variables, including: (i) *Ln(pgdp)*; (ii) *Secondary*; (iii) *Ln(wage)*; (iv) *Infrastructure*; (v) *FDI*; (vi) Population density (*PD*); (vii) Share of triple production (*Tertiary*); and (vii) Technology level (*TI*). $\varphi_i$ indicates the city fixed effects, the definitions of $CAA_i$, $Post_t$, $\phi_t$, and $\varepsilon_{it}$ remain unchanged.

When *it* indicates listed firm-level data. *i* represents the firm, and *t* denotes the year. $Ln(Labor)_{it}$ is the log of the labor demand of firm *i* in year *t*. $CAA_i$ is equal to 1 if a firm is located in the Beijing-Tianjin-Hebei region, and 0 otherwise (Liu et al., 2017). Listed firms are not only affected by city factors, but also by market factors. Therefore, for listed firm-level data, $X_{it}$ included the following city macro variables: (i) *Ln(pgdp)*; (ii) *Secondary*; and (iii) PD, and the following firm micro variables: (iv) Company size (*Size*); (v) Return on assets (*Roa*); (vi) Tobin's Q (*Tobin*); (vii) Financial debt ratio (*Finlev*); and (viii) Market-to-Book ratio (*Mbratio*). $\varphi_i$ indicates the firm fixed effects. The definitions of $Post_t$, $\phi_t$, and $\varepsilon_{it}$ remain unchanged.

In Eqs. (7) and (8), $CAA_i \times Post_t$ indicates the interaction term between $CAA_i$ and $Post_t$. Its coefficient $\beta_1$ was used to capture the aggregate effect of the policy, for the reasons shown in Fig. 2.

The gap between the treatment group and the control group before the implementation of the policy was used to estimate the original difference. The post-policy difference between the two groups consists of the original difference plus the effect of the policy. It was assumed that the original difference did not change over time; therefore, $\beta_1$ represents the effect of the CAA.

### 4.2. Dynamic analysis model

The government continuously adjusts their strategies and efforts according to the actual implementation effectiveness. In addition, as the mobilization and allocation of manpower and capital required by the policy will require a certain amount of time, the effect of the CAA is expected to change over time. Studying the dynamics of the policy effects over time is important to further help us gain insights into the CAA. The dynamic analysis of policy effectiveness was set up as follows:

$$Ln(PM_{2.5})_{it} = \alpha_0 + \sum\nolimits_{t=2005}^{2019} \beta_t(CAA_i \times Year_t) + \gamma C_{it} + \gamma W_{it} + \varphi_i + \phi_t + \varepsilon_{it} \tag{9}$$

Where $Year_t$ is the year dummy variable, equal to 1 when the year is *t* and 0 otherwise. The other variables are consistent with those in Eq. (7). As the air quality improvement effect in 2017 relative to 2012 was set as the final evaluation indicator, in the model expressed by Eq. (9) the year 2012 was considered as the baseline (Walker, 2013).

We then estimated the time-varying effect of the CAA on our main outcome variable, using the similar dynamic analysis model as follows:

$$Ln(Labor)_{it} = \alpha_0 + \sum\nolimits_{t=2005}^{2019} \beta_t(CAA_i \times Year_t) + \gamma X_{it} + \varphi_i + \phi_t + \varepsilon_{it} \tag{10}$$

Where $\beta_t$ in Eqs. (9) and (10) could be used to capture the change for the treatment group in year *t* relative to 2012. The relative change before policy implementation is due to stochastic factors such as natural disasters, while the relative change after policy implementation is generated by both policy and stochastic factors, for the reasons shown in Fig. 3.

Unlike the DID Estimation Strategy, the Dynamic Analysis Model used the baseline to identify the original differences between the treatment group and the control group.

Before the CAA, the t-year difference between the two groups was composed of the original difference and stochastic factors. The original difference did not change over time; therefore, an insignificant value of $\beta_t$ in the majority of the years before policy implementation indicated that the common trend assumption was satisfied. That is, the treatment group and the control group were not confounded by stochastic factors before policy implementation.

After the launch of the CAA, the difference between the two groups represented the policy effect and the original difference in year *t*. The original difference remained unchanged; hence, $\beta_t$, $t \geq 2013$, which captures the effect of the CAA in year t.

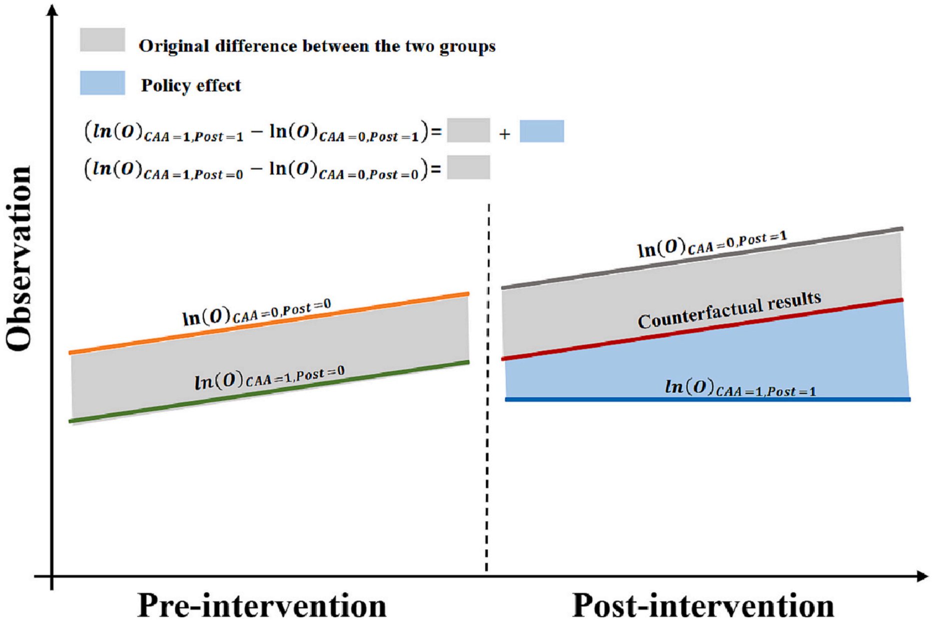



**Fig. 2.** Schematic of the DID estimation strategy.

### 4.3. Data

This study merged three types of datasets from 2005 to 2019, namely city-level data, firm-level data, and weather data. The city-level data were mainly obtained from the China City Statistical Yearbook. For cities with missing data, these were firstly taken from the provincial statistical yearbooks, and secondly added by interpolation method. After removing the cities with several missing data, a total of 225 prefecture-level cities were retained. The firm-level data were collected from the China Stock Market and Accounting Research (CSMAR) database, excluding financial industries. The original weather data were obtained from the U.S. National Oceanic and Atmospheric Administration (NOAA). We extracted data from >400 weather stations in China, and then converted the hourly station measures into yearly city measures. In addition, the data on $PM_{2.5}$ were taken from the surface $PM_{2.5}$ concentration map raster data provided by the Atmospheric Composition Analysis Group of the Dalhousie University. The vector data were separated using ArcGIS, and the average value of the prefecture-level city was used as the annual average value of $PM_{2.5}$ in that city.

The CAA was issued in 2013, we considered a period of 8 years before that date, i.e., a longer window, to examine whether there was a common trend in the treatment and control groups. In fact, the longer the window that satisfies the common trend, the more reliable the results obtained by using the DID model (Abadie, Diamond and Hainmueller, 2010). Moreover, since 2020 China was affected by the COVID-19 pandemic, which had an impact on labor employment (Fang, Ge, Huang and Li, 2020). Therefore, in order to exclude this impact on the results of this study, we limited the data to the year 2019. The variable definitions and summary statistics are shown in Table 1.

### 4.4. PSM strategy

The designation of the Beijing-Tianjin-Hebei region as the area with the highest level of regulation in the CAA was not made by chance. In fact, this region has the highest air pollution among all Chinese regions. Therefore, this study may be affected by a selection bias (Du and Takeuchi, 2019). In addition, a good control group needs to have the same trends with the treatment group. However, China is a vast country, with wide variations in natural resource endowments and economic development patterns across cities; hence, not all cities can be included in the control group. We used the PSM to pair cities in the treatment group with those in the control group that had similar characteristics, so as to eliminate the selection bias and meet the common trend assumption.

The PSM holds that cities with similar characteristics ($x_i$) have a similar probability of entering the treatment group. The PSM uses the individual characteristics ($x_i$) to calculate the propensity score $p(x_i) = P(D_i = 1 \mid x_i)$, and then combines units with similar propensity scores to the treatment units into a new control group. We used control variables to reflect individual characteristics, as well as the nearest neighbor 1:4 matching, and only retained paired data; in this way, a value would only retain the most similar 4 values. Fig. 4 shows the bias between the treatment group and the control group before and after matching. The results suggest that the bias of most indicators decreased significantly after matching for both city-level and firm-level data. This indicates that the PSM effectively reduces the potential bias between the treatment group and the control group. Fig. 5. illustrates the geographical distribution of the treatment and control cities, as well as the coordinates of the treatment and control firms.

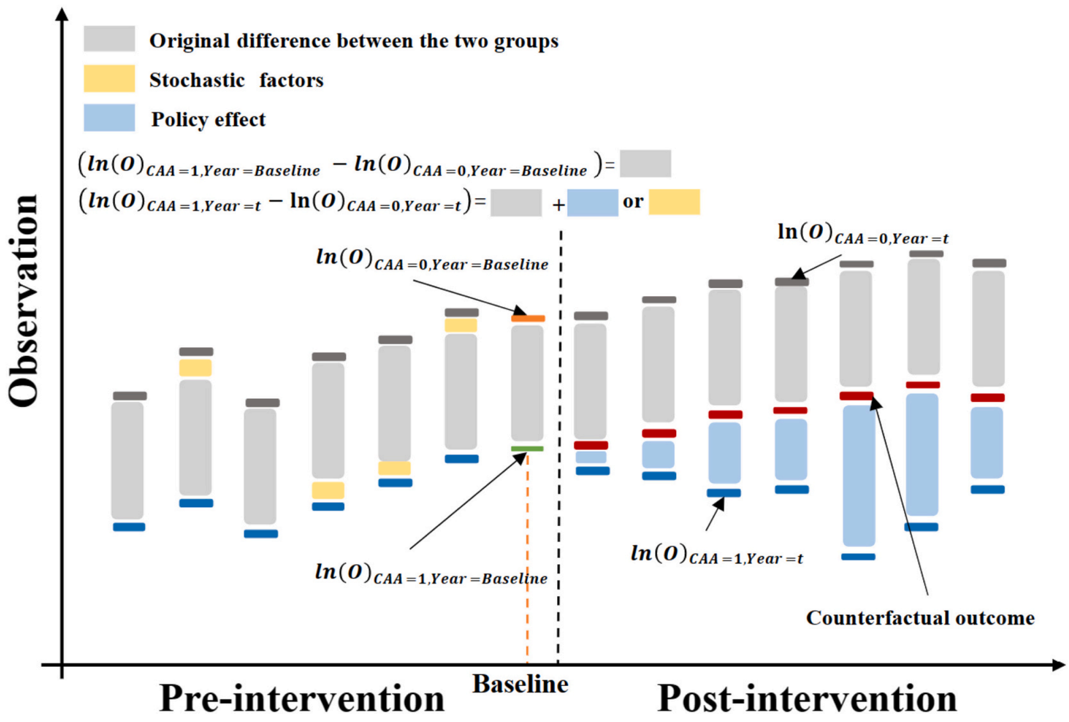



**Fig. 3.** Schematic of the dynamic analysis model.

**Table 1**
Summary statistics.

| Data | Variable | Definition | Obs | Mean | Std. Dev. |
|---|---|---|---|---|---|
| *City-level* | *Ln(Labor$_{city}$)* | Ln(Number of workers in the city (Persons)) | 3375 | 12.617 | 0.778 |
| | *Ln(PM$_{2.5}$)* | Ln(Particulate matter (μg/$m^3$)) | 3375 | 3.710 | 0.341 |
| | *Ln(pgdp)* | Ln(GDP per capita (CNY/Persons)) | 3375 | 10.245 | 0.732 |
| | *Lnwage* | Ln(Average wage of employees (CNY)) | 3374 | 10.481 | 0.545 |
| | *Secondary* | (Secondary Industry Output (CNY)) / GDP (CNY)) * 100 | 3375 | 46.798 | 11.507 |
| | *Tertiary* | (Tertiary Industry Output (CNY) / GDP (CNY)) * 100 | 3375 | 38.476 | 9.706 |
| | *TI* | Science spending (CNY) / year-end population (Persons) | 3375 | 86.1 | 182.2 |
| | *Infrastructure* | Highway mileage (Km) / Year-end population ($10^4$*Persons) | 3375 | 32.751 | 19.56 |
| | *PD* | (Year-end population ($10^4$*Persons) / City size ($Km^2$)) * 100 | 3375 | 3.692 | 3.004 |
| | *FDI* | (Foreign Investment (CNY) / GDP (CNY)) * 100 | 3375 | 1.551 | 1.824 |
| *Firm-level* | *Ln(Labor$_{firm}$)* | Ln(Number of employees in the firm (Persons)) | 9849 | 7.163 | 1.321 |
| | *Size* | Ln(Total firm assets (CNY)) | 9882 | 21.568 | 1.296 |
| | *Roa* | Net profit after tax (CNY) / Total assets (CNY) | 9882 | 2.251 | 237.606 |
| | *Tobin* | Market value (CNY) / Total assets (CNY) | 9350 | 4.579 | 155.685 |
| | *Finlev* | Financial debt ratio (%) | 9882 | 0.418 | 0.261 |
| | *Mbratio* | Market-to-book ratio (%) | 9350 | 0.589 | 0.247 |
| *Weather* | *Temperature* | Average yearly temperature (0.1°C) | 3375 | 140.11 | 54.976 |
| | *Wind* | Average yearly wind speed (0.1 m/s) | 3375 | 23.873 | 8.441 |
| | *MRain* | Average yearly rainfall (Millimeters) | 3375 | 30.619 | 12.256 |
| | *TRain* | Total yearly rainfall (Millimeters) | 3374 | 9243.459 | 5484.664 |
| | *Cloud* | Average yearly cloud thickness (0.1 mm) | 3375 | 5.149 | 1.263 |
| | *Pressure* | Average yearly sea level pressure (0.1 hPa) | 3375 | 10,162.283 | 30.961 |

## 5. Results

### 5.1. *Test of policy effectiveness*

Fig. 6 shows the effect of the CAA on $PM_{2.5}$. Three important observations can be made from this figure. First, the aggregate effect of the CAA on $PM_{2.5}$ was equal to −0.050 and statistically significant at the 5% level, which suggests that the air regulation of the treated cities was greater than that of the control cities, that is, the choice of the treatment and control groups was reasonable. Second, the effectiveness of the CAA grew in terms of the dynamics of $PM_{2.5}$, especially in 2017 when the $PM_{2.5}$ dropped by 16.6%[2]. Last, the trends in $PM_{2.5}$ between the treatment and the control group were largely parallel before the policy, apart from 2008 when they were significantly negative. In that year, China successfully hosted the Beijing Olympic Games, and implemented strict pollution reduction measures in Beijing and surrounding cities to meet the $PM_{2.5}$ requirements to host this event. Therefore, the air quality in that year was significantly better than in other years. These results show that the common trend assumption was satisfied.

### 5.2. The impacts on labor demand

We then tested the impacts of the CAA on labor demand. Fig. 7a illustrates the estimation results of the city-level data, presenting three important pieces of information. First, the aggregate effect of the CAA on city's labor demand was equal to −0.107 and statistically significant at the 1% level, which suggests that the CAA decreased the labor demand in regulated cities. Second, the latter part of this Figure indicates that the effect of the CAA on labor demand was time-varying, whereby the labor demand in the Beijing-Tianjin-Hebei region first decreased and then recovered. In 2017, the labor demand had the largest decrease by 25.6%, recovering to −4.8% in 2019. This result shows that the effect of the CAA on city employment from 2013 to 2017 consisted mainly in job destruction, while job creation only started to emerge gradually in 2018. Last, the coefficients for all years before the CAA were not significant, indicating that the treatment group and the control group satisfied the common trend assumption.

Fig. 7b shows the results of the firm-level data, also presenting three important pieces of information. Firstly, the aggregate effect of the CAA on firm's labor demand was equal to −0.159 and statistically significant at the 1% level, suggesting that the CAA significantly reduced employment in regulated firms. Notably, the negative impact on listed firms was greater than that measured at city level. Second, the latter part of this Figure shows that the labor demand of listed firms first decreased and then increased. In 2014, it decreased by 31.9%, recovering to −6.8% in 2019. However, the recovery started in 2015 and started earlier than at city level. The dynamics of labor demand for both data levels were largely consistent, enhancing the robustness of the results of this study. Last, the trends in firm's labor demand between the treatment and the control group were largely parallel before the policy change, the results suggest that the common trend assumption was satisfied in the firm-level data.

Listed firms are generally the leading firms in a region or industry; they have greater environmental responsibility and were more likely to be the first to face remediation imposed by the CAA. Listed firms are larger than small firms, and their actions will have a greater impact. In particular, compared to small firms, listed firms have abundant capital, long-term development goals, higher sensitivity to market changes, and will make timely adjustments when they encounter operational problems (Liu, Woodward and Zhang, 2021); therefore, the labor demand of listed enterprises will recover earlier.

### 5.3. The relationship between haze removal and labor demand

While improving air quality, the CAA has also caused a reduction in labor demand. However, based on the results shown in Figs. 6 and 7a, we can infer that this situation has been gradually improving from 2018. We divided the post-policy period into three stages according to the changes in $PM_{2.5}$. In the first stage, covering the period 2013–2014, no significant changes in $PM_{2.5}$ were observed, indicating that the CAA did not actually improve air quality. The second stage, from 2015 to 2016, includes the first wave of great improvements in $PM_{2.5}$, which occurred in 2015. The third stage covers the period 2017–2019, including the second wave of great improvements in $PM_{2.5}$, which took place in 2017. These three stages are consistent with the CAA implementation strategies, whereby the mid-term assessment of the CAA was conducted in 2015 and the final assessment in 2017; therefore, a wave of large improvements in $PM_{2.5}$ occurred in both 2015 and 2017.

During the first stage, the city-level labor demand in the Beijing-Tianjin-Hebei region gradually decreased in both 2013 and 2014; especially in 2014, labor demand decreased by 9.3%. During the second stage, labor demand decreased by 10.5% in 2015, while $PM_{2.5}$ decreased by 5.4%, indicating that a 1% reduction in $PM_{2.5}$ led to a 1.94% decrease in labor demand. During the third stage, $PM_{2.5}$ decreased by 16.6% in 2017, marking the highest improvement across the whole study period, while labor demand fell by 25.6%, marking the largest decline. This indicates that for every 1% drop in $PM_{2.5}$, labor demand dropped by 1.54%. Labor demand began to recover from 2018, while $PM_{2.5}$ continued to record relatively large improvements. By 2019, labor demand raised to −4.8% and $PM_{2.5}$ continued to decrease (−15.1%), indicating that labor demand decreased by 0.32% for every 1% decrease in $PM_{2.5}$. These observations suggests that the Beijing-Tianjin-Hebei region has achieved simultaneous air quality improvements and labor demand recovery in 2018 and 2019.

### 5.4. Robustness checks

#### 5.4.1. Changing the matching strategy of the PSM

The PSM can help find the appropriate control group for the selected treatment group and reduce the selection bias. However, two problems may exist in the matched sample of this study. First, if the matching accuracy of 1:4 is not enough, there may be some control

[2] Since we use the semilog model, the elasticity of all models can be calculated by the formula: $(e^{\beta} - 1) \times 100\%$.

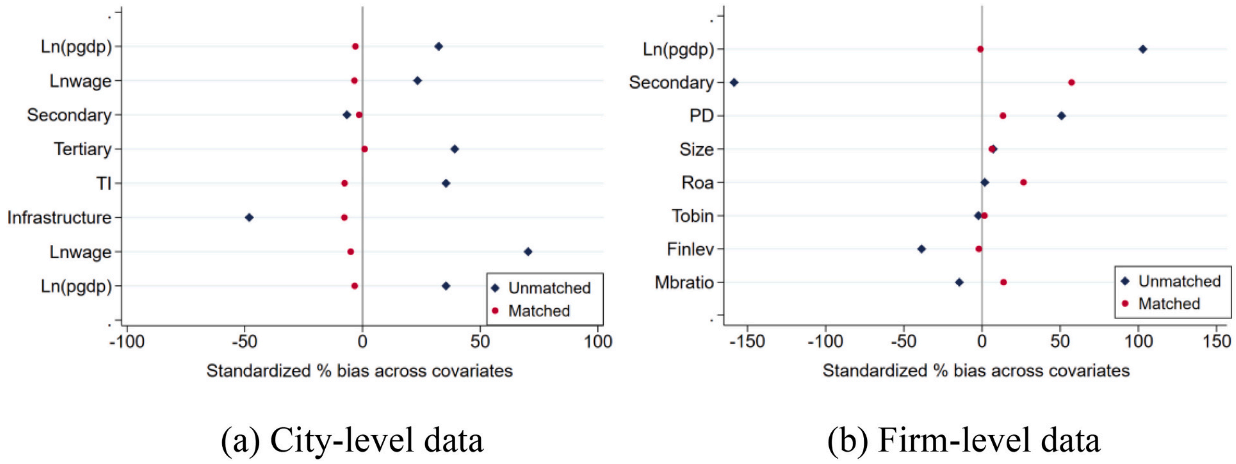



**Fig. 4.** Characteristic bias before and after matching.
(a) City-level data (b) Firm-level data.

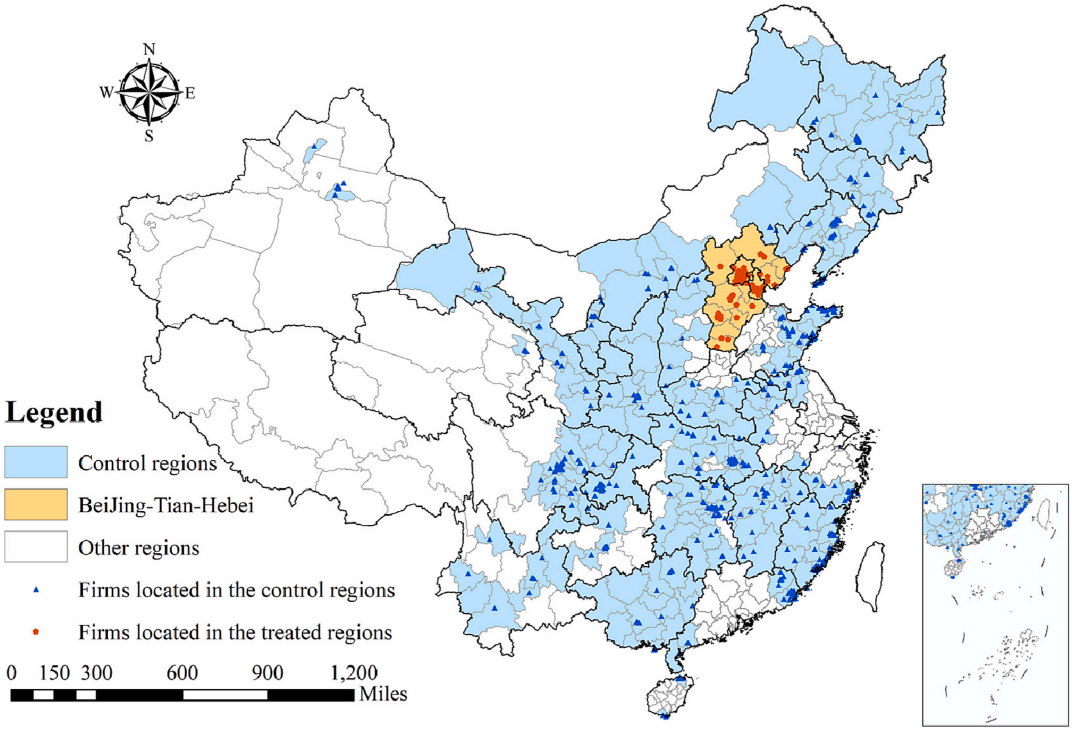



**Fig. 5.** Geographical distribution of the treatment and control cities and firms.

units in the matched samples that deviate significantly from the treatment group, resulting in biased results. Second, a higher matching accuracy is accompanied by a lower number of control units that will be retained, a reduced representativeness of the control group, and an increase in the possibility that the results are influenced by chance.

To address the first problem, we used the nearest neighbor 1:3 matching to increase the matching accuracy. The sample sizes of city-level data and firm-level data after using the nearest neighbor 1:4 matching were 687 and 2393, respectively, while those using the nearest neighbor 1:3 matching were 413 and 1923, respectively. This reduction in the sample size indicates that the bias between the treatment and control group was narrowed. We performed a dynamic analysis of labor demand using the nearest neighbor 1:3 matched sample; the results are shown in Fig. 8a and b. Labor demand at the city level continued to decline from 2013 to 2017, fell off a cliff in 2017, and recovered in 2018 and 2019. The firm-level labor demand was most negatively impacted in 2014, and began to recover in

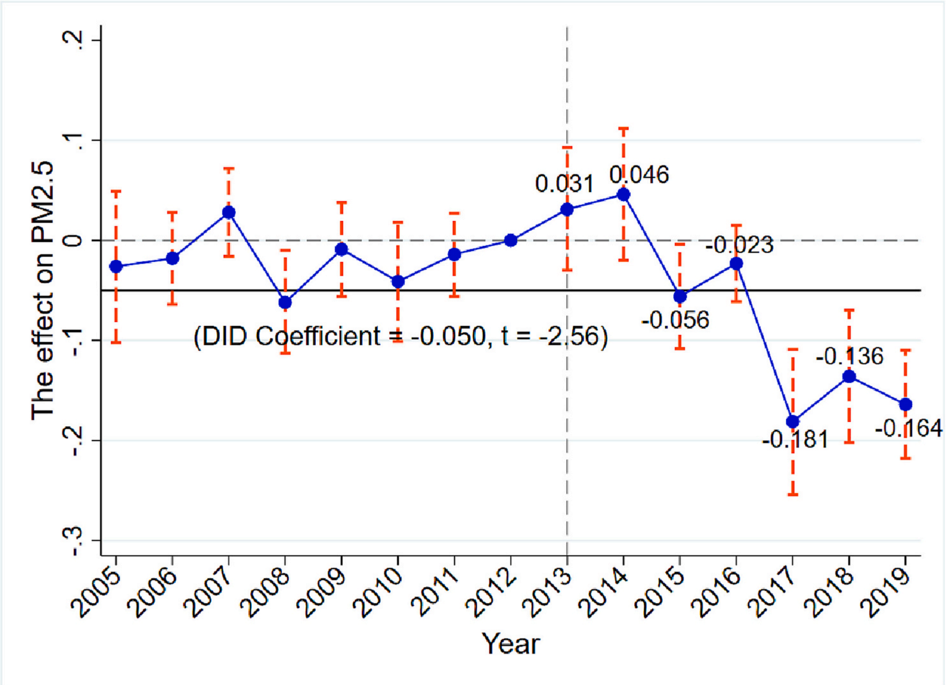
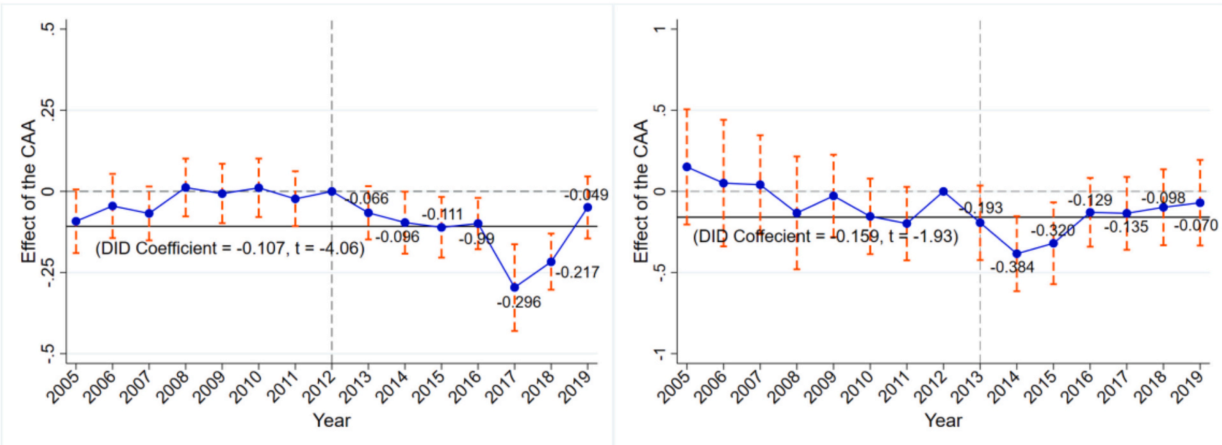


**Fig. 6.** Dynamics of $PM_{2.5}$.

**Notes:** This figure shows the difference of $PM_{2.5}$ between the treatment and the control group using the model expressed by Eq. (9). The baseline is 2012, and the orange line segment indicates the 90% confidence interval. The horizontal black line indicates the benchmark result estimated using the model expressed by Eq. (7), with its coefficients and t-values in parentheses.



(a) City-level data (b) Firm-level data

**Fig. 7.** Dynamics of labor demand.

**Notes:** This figure shows the difference in labor demand between the treatment and the control group using the model expressed in Eq. (10). The baseline is 2012, and the orange line segment indicates a 90% confidence interval. The horizontal black line indicates the benchmark result estimated using the model expressed in Eq. (8), with its coefficients and t-values in parentheses.

2015. This dynamic trend is consistent with the results of the nearest neighbor 1:4 matching, indicating that a high accuracy can already be achieved using the nearest neighbor 1:4.

To solve the second problem, we used the nearest neighbor 1:5 matching to increase the number of matched control units. The sample sizes of city-level data and firm-level data after using the nearest neighbor 1:5 matching were 801 and 2870, respectively, with a great increase in the size of the control group compared to the nearest neighbor 1:4 matching. The results of the dynamic analysis of the nearest neighbor 1:5 matching are shown in Fig. 9. For both city-level data and firm-level data, the dynamic changes in labor demand after the issue of the policy were similar to the results of the nearest neighbor 1:4 matching. However, Fig. 9a shows that this matching was weaker in satisfying the common trend assumption, perhaps because biased control units were added when the matching accuracy was relaxed. The above results show that the nearest neighbor 1:4 matching had good matching accuracy and representativeness.

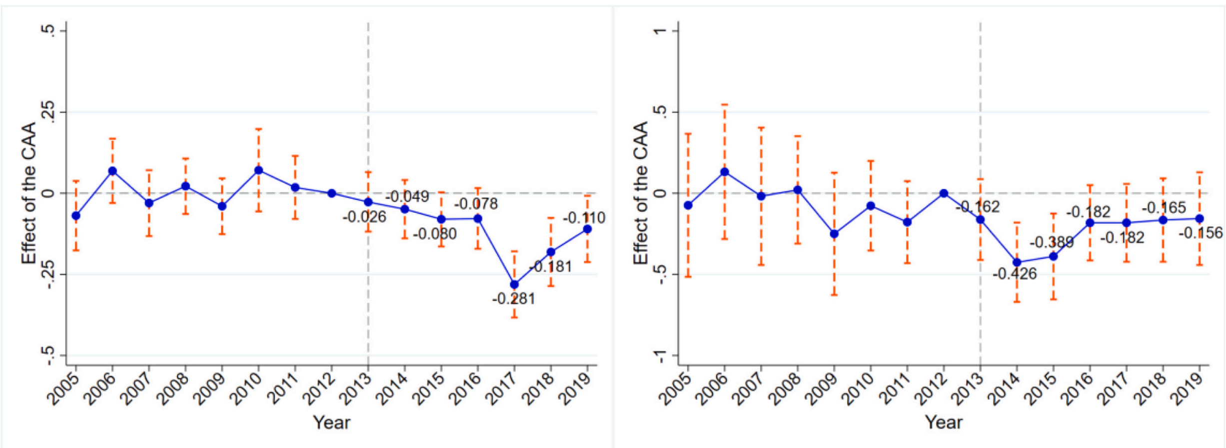
*5.4.2. Placebo test*

As many factors affect labor demand, the model built in this study could be affected by a problem of missing variables. In addition, air pollution in the Beijing-Tianjin-Hebei region may lead to population outflow (Chen, Oliva and Zhang, 2022), which would aggravate the reduction in labor demand. These problems would lead to a bias in the estimation results of this study. Accordingly, we drew on the method of Chen, Li and Lu (2018), and performed a placebo test to verify whether the results of this study were affected by these problems.

First, a placebo test was performed using city-level data. The total number of 13 treatment cities was kept unchanged, and we randomly selected 13 cities from all cities as fake treatment cities. One year was randomly selected from 2010 to 2016 as the start year of the fake policy. The model proposed in Eq. (8) was used for estimation and this process was repeated 2000 times. Fig. 10a shows the distribution of coefficients for $CAA_i \times Post_t$ and the location of the benchmark estimates. The coefficients of the 2000 randomized experiments were uniformly distributed on both sides of zero and approximated the normal distribution, while the coefficients of the benchmark estimates were located at the left edge of the entire distribution. These observations suggest that the decline in labor demand for city-level data was not affected by missing variables or other problems.

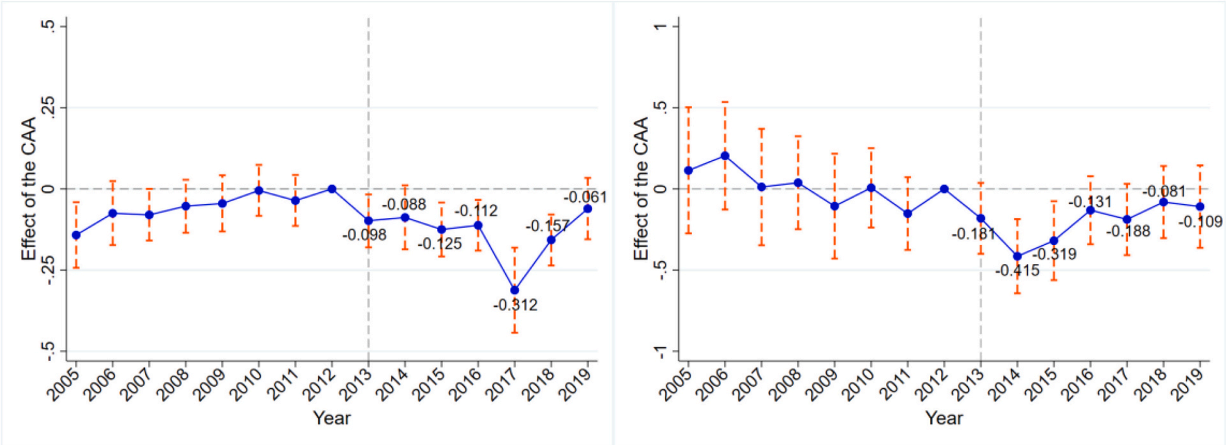
Second, a placebo test was performed using firm-level data. A total of 162 listed firms were included in the treatment group; accordingly, 162 firms were randomly selected from all listed firms as fake treatment firms, and the rest of the firms was included in the control group. One year was randomly selected from 2010 to 2016 as the start year of the fake policy. This process was repeated 2000 times using the model proposed in Eq. (8) for estimation. The results are shown in Fig. 10b, where it can be seen that the coefficients of the 2000 fake experiments approximated a normal distribution, and the benchmark estimates were located at the leftmost end of the entire distribution. The above findings suggest that the results of the firm-level data were also not affected by missing variables or other problems.

The above placebo tests were conducted for the aggregate impact and were not convincing enough to demonstrate the robustness of the dynamic analysis. Therefore, with reference to Abadie et al. (2010), we designed a dynamic placebo test. Different from the above mentioned placebo tests, we only randomly selected the fake experimental group in this test, keeping the policy start year as 2013. We used the model presented in Eq. (10) for estimation and repeated this process 200 times. In order to ensure that the common trend assumption was satisfied for each randomized experiment, the pre-policy mean square error (MSPE) was calculated as follows: $MSPE = \frac{1}{8}\sum_{2005}^{2012}(\beta_t)^2$. We retained the results smaller than the MSPE of actual dynamic analysis, and plotted the retained dynamic change curves in Fig. 11. As shown in Fig. 11, the actual post-policy dynamic change curve was at the bottom of all curves for both the city-level data and the firm-level data. This suggests that a larger negative effect was not possible under the randomized experiment, that is, the lower labor demand in Beijing-Tianjin-Hebei region was caused by the CAA.



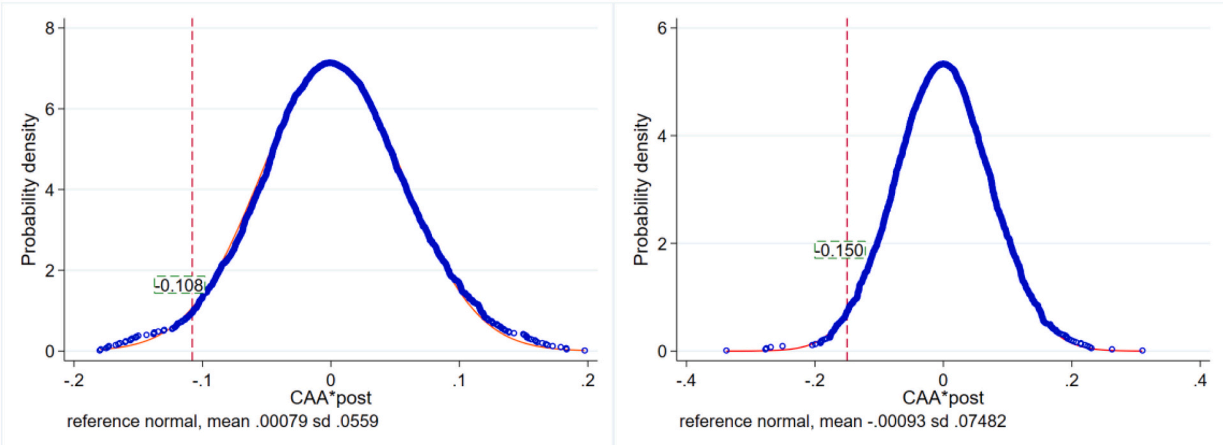

(a) City-level data (b) Firm-level data

**Fig. 8.** Nearest neighbor 1:3 matching.




(a) City-level data (b) Firm-level data

**Fig. 9.** Nearest neighbor 1:5 matching.




(a) City-level data (b) Firm-level data

**Fig. 10.** Results of the placebo test.
**Notes:** The blue circles indicate the coefficient distribution of the $CAA_i \times Post_t$ calculated from 2000 random experiments; the orange curve indicates the normal distribution, and the dotted line indicates the location of the benchmark estimate.

## 6. Inter-industry labor reallocations

### *6.1. The impacts on different industries*

Achieving the reallocation of surplus labor among industries is the optimal way to maintain total employment and stabilize the economic development in a city. Therefore, in this Section we estimated the impact of the CAA on labor demand in different industries, which will help to discover the current labor reallocation patterns. The level of industry employment can indicate the change in the employment stock in each industry, and the ratio of industry employment to total employment can reflect the change of each industry in relation to the whole city labor market. Therefore, in this study the changes in both indicators were estimated simultaneously.

The results indicate that the CAA has changed the distribution of employment in the labor market, boosting the flow of labor from polluting industries to clean industries including financial, science and technology, environmental management, and rental services industries. The specific analysis process is as follows.

#### *6.1.1. Primary industry*

Fig. 12 shows the results of estimation using the model proposed in Eq. (8), where the blue dots illustrate the impact of the CAA on the level of industry employment and the red dots indicate the effect of the CAA on the ratio of industry employment to total

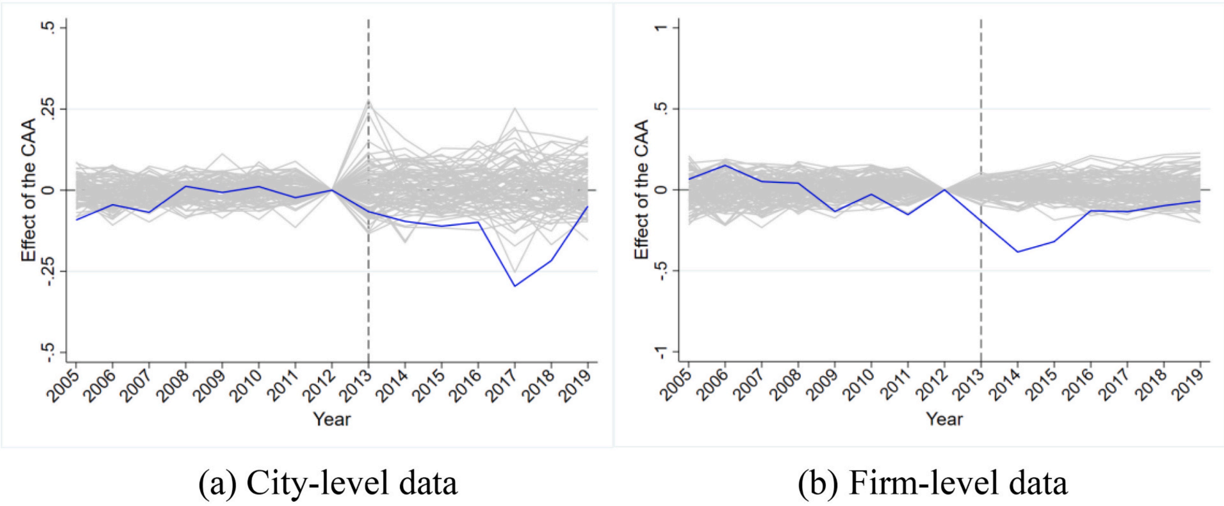



**Fig. 11.** Results of the dynamic placebo test.
**Notes:** The blue curve indicates the actual dynamic change curve, which is consistent with Fig. 7; and the gray line indicates the results of the dynamic analysis of the random experiment.

employment based on city-level data. A positive but insignificant effect was found on both indicators in the primary industry. China has a large number of migrant workers in low-skilled jobs (Tang, Hao and Feng, 2020). These low-skilled workers are the most vulnerable, and when they lose their jobs, some may return to agriculture.

### 6.1.2. Secondary industry

The two indicators of each industry in the secondary industry have decreased to some extent. Manufacturing, transportation experienced significant decreases in both indicators, Exhaust emissions from industrial production and traffic are the key governance issues related to the implementation of the CAA, which may be the main reason for the significant reduction in both indicators of the manufacturing and transportation industries. The elimination of small coal-fired boilers and the control of total coal consumption are also key measures included in the CAA, while the power, heating, and gas supply industries, which are related to these measures, were not significantly affected. This may be because the industry includes livelihood activities, and in order to ensure normal heating and power supply, there will not be a large-scale reduction of workforce. While the effect of the CAA on the other three industries is negative but statistically insignificant.

### 6.1.3. Tertiary industry

The wholesale and retail industries were significantly negatively impacted, as a downstream industry, by the upstream industry. When the production cost of manufacturing and other industries increases, the cost of the wholesale and retail industry will also

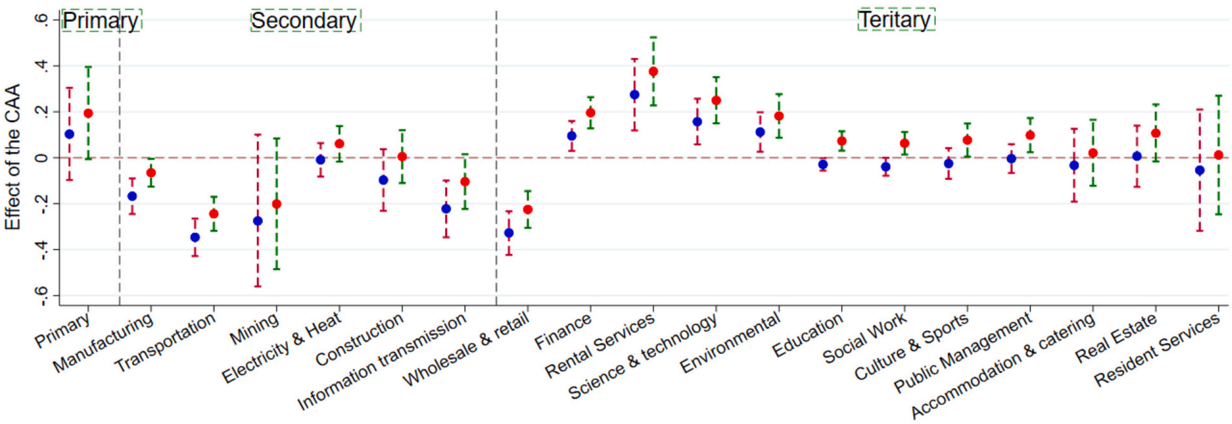
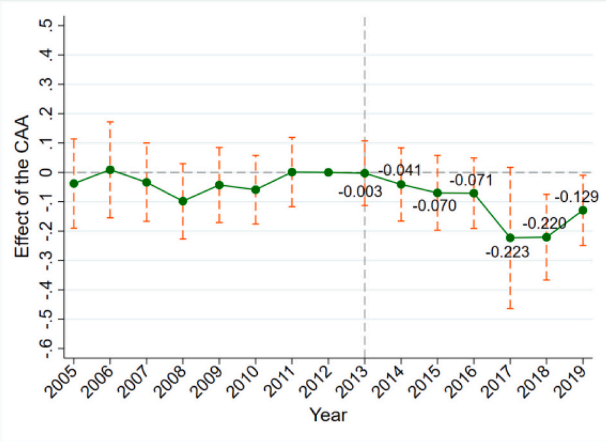
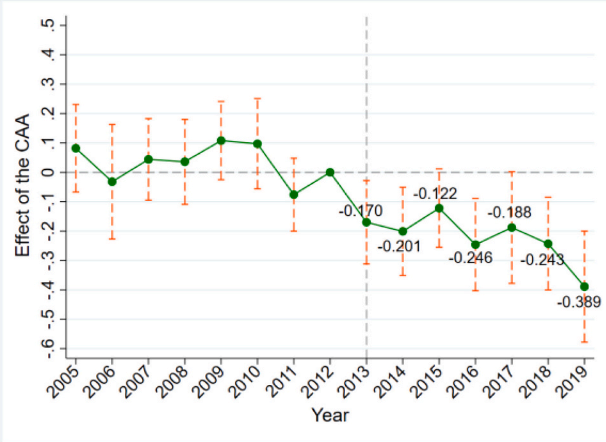


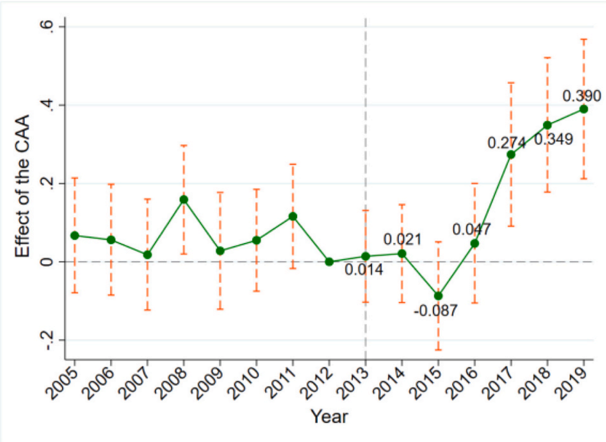

**Fig. 12.** Inter-industry labor reallocation.
**Notes:** the blue dots illustrate the impact of the CAA on the level of industry employment; and the red dots indicate the effect of the CAA on the ratio of industry employment to total employment, using city-level data. The line segments indicate the 90% confidence intervals. The results are sorted by sector and industry type. The city-level data are used here.



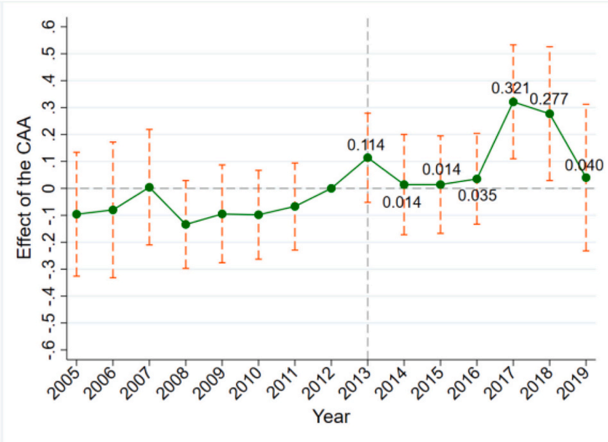

(a) Manufacturing



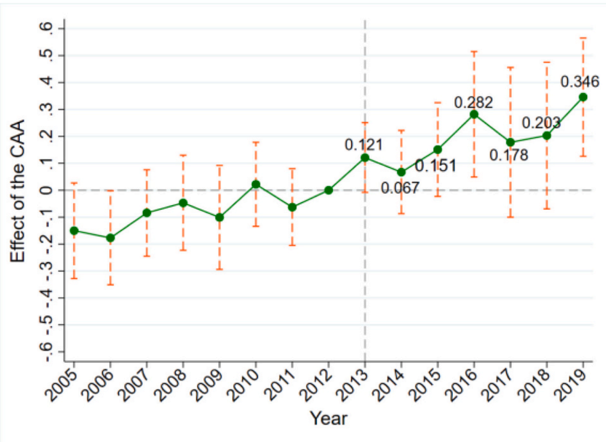

(b) Transportation



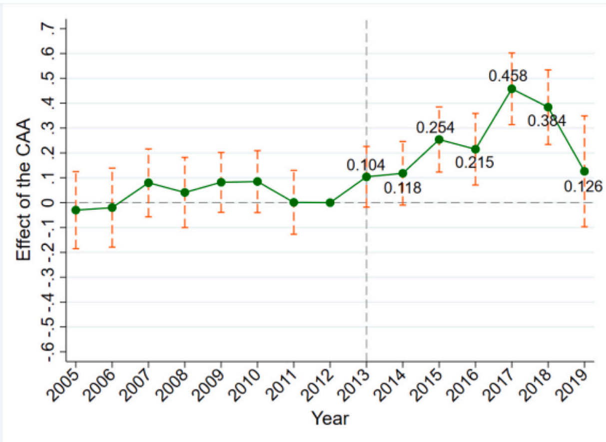

(c) Power, heating, and gas supply




(d) Environmental management

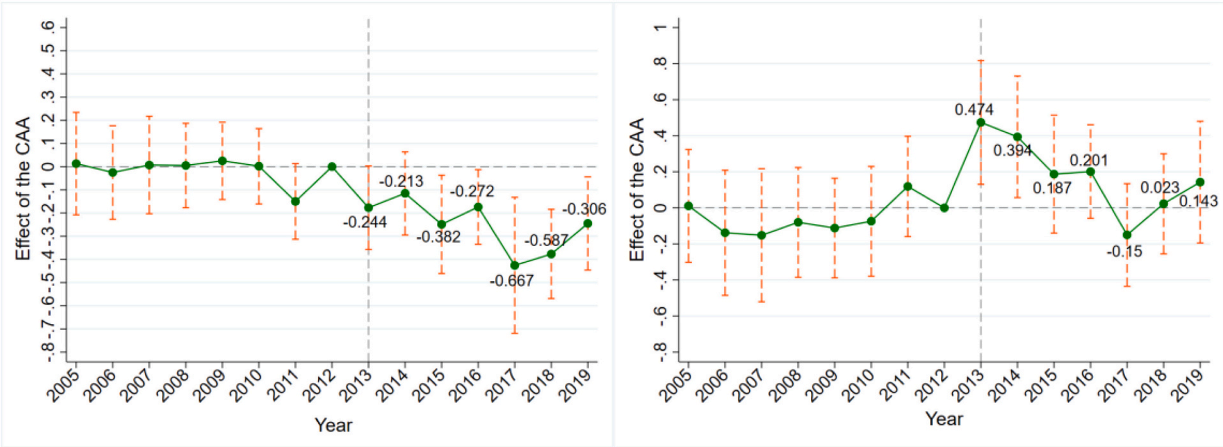



(e) Science and technology




(f) Financial

**Fig. 13.** Dynamics of key industrial sectors.
**Note:** This figure is based on city-level data.




(g)Wholesale & retail (h) Rental Services

**Fig. 13.** (*continued*).

increase, which will further reduce employment. Financial, science and technology, environmental management, and rental services recorded significant increases in total employment and employment share. The positive impacts of finance, science and technology, and environmental management were partially due to the effect of the CAA, which helped these sectors to scale up their production. In China, the rental service industry has a low barrier to entry and employees from other industries can quickly acquire skills in this industry; therefore, the inflow of employees from other industries may be the reason for this positive effect. The employment level in other industries in the tertiary sector was little affected, and the increase in the employment ratio may be driven by the decrease in the total level of employment.

### 6.2. *The dynamics of key industries*

Winter heating, industrial emissions, and automobile exhaust emissions are the key pollution sources addressed by the CAA. This study analyzed the dynamics of labor demand in the three related industrial sectors belonging to the secondary sector, namely manufacturing, transportation, and power, heating, and gas supply. In addition, we have analyzed the key industries belonging to the tertiary sector, such as: finance, technology and environmental management. The results are shown in Fig. 13.

#### 6.2.1. *Manufacturing industry*

Fig. 13a shows the estimation results for the manufacturing industry, where labor demand continued to decline from 2013 to 2017, plummeted in 2017, and recovered in 2018 and 2019. Before 2017, manufacturing industries such as steel, cement, and chemical industries were required to upgrade their clean production technologies and install end-of-pipe pollution equipment, while those that failed to meet pollution emission standards were asked to shut down for rectification. In addition, the upgraded enterprises needed more highly skilled workers, and a large number of low-skilled workers were eliminated, resulting in structural unemployment (Liu et al., 2021). After 2017, the manufacturing industry completed the rectification and resumed its production capacity, while more workers received training and acquired new skills. Therefore, labor demand gradually recovered in 2018 and 2019.

#### 6.2.2. *Transportation*

Fig. 13b presents the results for the transportation industry, where labor demand decreased over the period 2013–2019. As vehicle emissions are an important source of $PM_{2.5}$, the Beijing-Tianjin-Hebei region has adopted stringent measures to reduce them, including controlling the number of motor vehicles, improving fuel quality, and phasing out diesel vehicles. As a result, the transportation industry was also classified as affected by structural unemployment.

#### 6.2.3. *Power, heating, and gas supply*

The results for the power, heating, and gas supply industry, presented in Fig.13c, show that labor demand was not significantly affected during the period 2013–2016, and continued to increase significantly during the period 2017–2019. This industry includes livelihood activities; as such, the total energy consumption of the whole society was not excessively affected by the CAA, which ensured that the output of this industry was not reduced. In addition, the implementation of coal-to-gas and coal-to-electricity transition in other industries also increased the demand for gas and electricity. The increase in the total demand for energy may be the reason for the increase in labor demand at a later stage.

#### 6.2.4. *Environmental management*

The results for the environmental management industry are shown in Fig. 13d. The labor demand in this industry increased significantly in 2017, and gradually decreased in 2018 and 2019. The environmental management industry is responsible for activities such as environmental and sanitation management, and municipal facility management. The final assessment of the CAA took place in 2017, requiring a considerable amount of manpower for environmental governance and assessment. Therefore, the demand for labor in this industry increased significantly in 2017. After the final assessment, air quality improved significantly. Moreover, as the high amount of labor was no longer required for governance and regulation, labor demand in this industry gradually declined.

#### 6.2.5. *Science and technology*

The results for the science and technology industry, illustrated in Fig. 13e, show that the share of labor demand increased along the whole study period. When faced with strict environmental regulations, firms will invest in technological research to improve their production efficiency (Zhang, Zhou and Tian, 2022). In addition, the improvement of technological innovation capacity is also one of the requirements of the CAA. This may be the reason why the ratio of labor employment in the science and technology industry grew continuously during the study period.

#### 6.2.6. *Financial Industry*

The estimation results for the financial industry are presented in Fig. 13f. It was found that the ratio of labor demand in the financial industry increased continuously from 2013 to 2017, and gradually decreased in 2018 and 2019. The CAA encouraged private capital and social capital to enter the field of air pollution prevention and control, and guided banking and financial institutions to increase credit support for air pollution prevention and control projects. The development of green finance may be the reason for the significant increase in labor demand in the period 2013–2017. With the completion of the upgrade of polluting enterprises, the green credit required by these enterprises was reduced. As a result, the employment gap of the financial sector between the Beijing-Tianjin-Hebei region and the control group narrowed in 2018 and 2019.

#### 6.2.7. *Wholesale & retail*

The dynamic results for the wholesale & retail industry are shown in Fig. 13g. Labor demand in this industry showed a decline between 2013 and 2017, and began to recover in 2018 and 2019. As the downstream component of the manufacturing industry, the output value of the wholesale and retail industry is affected by the upstream industry. Therefore, the change in labor demand in this industry was similar to that of the manufacturing industry, and was also characterized by structural unemployment.

#### 6.2.8. *Rental services*

The results for the rental services sector are presented in Fig. 13h. We found that labor demand in the rental services sector increased significantly in 2013; then, from 2014 to 2017 it gradually decreased and was not statistically significant, and increased again in 2018 and 2019. There is a low friction transfer in China's rental services sector, and employees from other industries can quickly acquire skills in this industry; for these reasons, the number of workers increased rapidly in 2013. The economic conditions of the rental service industry and other industries are closely related. Therefore, its trend from 2013 to 2019 is consistent with the change trend of labor demand at the city level.

Through the dynamic analysis of labor demand in key sectors, we found that structural and frictional unemployment were the reasons for lower city-level labor demand from 2013 to 2017. Specifically, polluting industries such as manufacturing and transportation industries needed to reduce or shut down production to complete their rectification, thereby reducing labor demand and leading to structural unemployment. Frictional unemployment resulted from the failure of clean businesses to quickly absorb large numbers of unemployed workers and the inability of unemployed workers to quickly acquire new skills. In 2018 and 2019, the recovery in labor demand was due to the end of structural and frictional unemployment. After the CAA final assessment, the majority of polluting companies completed their rectification and started to gradually resume production, increasing the demand for labor. Several unemployed workers also returned to their original industries or moved to new industries through training and re-employment.

## 7. Intra-firm labor reallocations

### 7.1. *Firm responses to the CAA*

As discussed in Section 3, Firms will respond to the CAA in three components, namely the output effect, the substitution effect of labor for pollution, and the substitution effect of capital for labor. We estimated the three components use the firm-level data. Following Liu et al. (2021) and Liu, Liu, and Zhang (2022), we applied a joint model for estimation, which consists of three steps.

Step 1. Two dummy variables were constructed to determine the high and low groups, as follows:

$$I_i = \frac{\frac{1}{7}\sum_{t=2013}^{2019} M_{it} - \frac{1}{8}\sum_{t=2005}^{2012} M_{it}}{\frac{1}{8}\sum_{t=2005}^{2012} M_{it}} \tag{11}$$

In the following analysis, $M$ represents output or capital investment; and $I_i$ represents the growth rate of $M$ before and after the policy:

$$M_{i,high} = \begin{cases} 1, I_i \geq mean(I_i) \\ 0, I_i < mean(I_i) \end{cases} \tag{12}$$

$$M_{i,low} = 1 - M_{i,high} \tag{13}$$

where both $M_{i,\ high}$ and $M_{i,\ low}$ are dummy variables, with $M_{i,\ high}$ denoting the high groups and $M_{i,\ low}$ denoting the low groups.

Step 2. It was assessed whether the increase in $M_{it}$ was larger in the higher treatment groups than in the lower treatment groups during the CAA; in other words, the reasonableness of the grouping was evaluated, as follows:

$$ln(M_{it}) = \alpha_0 + \beta_1 (CAA_i \times Post_t \times M_{i,high}) + \beta_2 (CAA_i \times Post_t \times M_{i,low}) + \gamma X_{it} + \varphi_i + \phi_t + \varepsilon_{it} \tag{14}$$

Step 3. The post-policy changes in labor demand for the high and low treatment groups were estimated as follows:

$$Ln(Labor)_{it} = \alpha_0 + \beta_1 (CAA_i \times Post_t \times M_{i,high}) + \beta_2 (CAA_i \times Post_t \times M_{i,low}) \gamma X_{it} + \varphi_i + \phi_t + \varepsilon_{it}$$
$$+ \tag{15}$$

Eqs. (14) and (15) were combined to evaluate the influence of $M$ on labor demand. In the case of reasonable grouping, it can be considered that the only difference between the high groups and the low groups is that the former have a greater increase in $M$ during the CAA. At the same time, if the labor demand of the high groups is greater than that of the low groups, it was assumed that $M$ has a positive impact on the labor demand, and vice versa. Unlike Liu et al. (2021) and Liu et al. (2022), we added Step 2 to determine the reliability of the grouping, thereby largely increasing the robustness of the results.

The results showed that the CAA drove labor reallocation within firms. On the one hand, it led to a reduction in firm output and a corresponding reduction in labor input. On the other hand, in response to environmental regulations, firms will hire more highly skilled workers and increase capital investment, although capital investment will reduce labor demand. The specific analysis process is as follows.

### 7.1.1. Output effects

Using firm's operating income to measure firm's output ($Y_{it}$), the treatment group was classified into a high group and a low group. As shown in column (1) of Table 2, we found that the interaction term $CAA_i \times Post_t$ was significantly positive for the high group, and negative but not significant for the low group; this demonstrates that the high group had a larger growth rate of output than the low group. We further estimated the change in labor demand for both groups; the results are presented in column (2) of Table 2. The labor demand of the high group decreased by 6.4%, although not significantly, while that of the low group significantly decreased by 20.5%. These results suggest that a decrease in firm output will further reduce labor demand.

### 7.1.2. Substitution effect of capital for labor

We used the cash from the acquisition of fixed assets, intangible assets, and long-term assets to measure capital investment ($K_{it}$). The treatment group was classified into a high group if its capital growth rate was higher than the mean of the index, and in a low group otherwise. As shown in column (3) of Table 2, we found that the coefficient of the interaction term $CAA_i \times Post_t$ for the high group was

**Table 2**
Testing firm responses to CAA using firm-level data.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | LnY | *Ln(Labor)* | LnK | *Ln(Labor)* | *Ln(RDLabor)* |
| CAA*Post *Yhigh | 0.239* | −0.067 | | | |
| | (1.792) | (−0.557) | | | |
| CAA*Post *Ylow | −0.068 | −0.229** | | | |
| | (−1.069) | (−2.331) | | | |
| CAA*Post *Khigh | | | 1.247** | −0.252** | |
| | | | (2.502) | (−2.043) | |
| CAA*Post *Klow | | | −0.237 | −0.109 | |
| | | | (−1.166) | (−1.118) | |
| CAA*Post | | | | | 0.612** |
| | | | | | (3.670) |
| _cons`` | −3.508** | −10.874*** | −11.643*** | −10.959*** | −7.782 |
| | (−2.196) | (−5.918) | (−2.657) | (−6.011) | (−2.250) |
| Control variables | Yes | Yes | Yes | Yes | Yes |
| *N* | 2331 | 2333 | 2333 | 2333 | 2399 |
| Firm fixed | Yes | Yes | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.917 | 0.866 | 0.734 | 0.866 | 0.841 |

**Notes:** T values are indicated in parentheses; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

1.247 and statistically significant, and was negative in the low group. This indicates that the capital growth of the high group was faster than that of the low group. We further captured the difference in labor demand for both groups; the results are shown in column (4) of Table 2. We found that labor demand significantly decreased by 22.28% for the high group and by 10.33% for the low group, although not significantly. The above results indicate that the CAA promoted capital investment, which, however, further reduced the level of employment.

#### *7.1.3. Substitution effect of labor for pollution*

Column (5) of Table 2 presents the estimation result of the substitution effect of labor for the pollution factor. New technologies can reduce pollution emissions per unit output of firms (Zhang et al., 2022). When faced with strict environmental regulations, firms will hire more personnel for technology research and development (R&D). Therefore, we estimated the impact of the CAA on the number of R&D workers in listed firms, and used it to assess whether firms would hire more labor to replace pollution factors. As shown in column (5) of Table 2, the number of R&D workers significantly increased by 45.78% during the CAA. These results show that when environmental regulation is strengthened, firms will use more labor to replace pollution factors.

#### *7.1.4. Test using city-level data*

City-level data were used again for estimation to enhance the robustness of the results. We used gross domestic product (GDP) to measure city output. The treatment cities were classified into a high group and a low group. As shown in columns (1) and (2) of Table 3, the GDP of the high group was not significantly affected, while that of the low group was significantly reduced by 11.4%. Furthermore, we found that the low group experienced a greater reduction in labor demand than the high group. This finding is consistent with the results estimated using firm-level data.

We further examined the substitution effect of capital for labor using city-level data. Columns (3) and (4) of Table 3 present the estimation results. We found that the high group had higher capital investment and lower labor demand. This result suggests that the CAA promotes capital investment, further reducing labor demand.

From Section 5.2, it can be seen that the number of people working in the science and technology industry increased, which is consistent with the result that firms will hire more R&D workers, presented in this Section.

### *7.2. Heterogeneous firms' responses to the CAA*

The clean and polluting firms underwent different intensities of regulation during the CAA. As a result, they may have exhibited different responses in terms of output effects and substitution effects. From Section 6.1, it is clear that labor demand in manufacturing, construction, mining, transportation, information transmission, and wholesale and retail trade sectors was negatively affected by the CAA. Accordingly, we classified a firm as in the polluting group if it belongs to one of these six sectors, and in the clean group otherwise. We first captured the impact of the CAA on labor demand for the two groups; the estimation results are presented in column 1 of Table 4. These results show that only the polluting group experienced job destruction. Hence, it was interesting to further analyze the heterogeneous responses of these two groups.

#### *7.2.1. Output effects*

We divided the treatment group into a high group if the output growth rate of a firm was higher than the mean of the index, and into a low group otherwise. These two groups were further sorted into a clean and a polluting group. As shown in columns (2) and (3) of Table 4, neither the output nor the labor demand of both clean and polluting firms in the high group was significantly affected by the CAA. Notably, In the low group, the output of clean firms significantly decreased without a significant reduction in their labor demand, while the output of polluting firms did not significantly decreased with a significant reduction in their labor demand. These observations suggest that polluting firms had a significant negative output effect, which was not evident in the clean group.

#### *7.2.2. Substitution effect of capital for labor*

First, the treatment group was divided into a high group if the capital growth rate of a firm was higher than the mean of index, and in a low group otherwise. Then, these two groups were further sorted into a clean and a polluting group. The estimation results are reported in columns (4) and (5) of Table 4. We found that the high group had higher capital and experienced a greater reduction in labor demand than the low group. In addition, the labor demand of polluting firms decreased more than that of clean firms. These results suggest that higher levels of capital investment will reduce labor demand, and polluting firms will experience a greater capital-to-labor substitution effect.

#### *7.2.3. Substitution effect of labor for pollution*

We estimated the impact of the CAA on the number of R&D workers in clean and polluting firms, to assess whether these firms will have different responses in hiring high-skill workers when facing environmental regulations. Column (6) of Table 4 presents the estimation results. We found that polluting firms increased the hiring of R&D workers even as their labor demand decreased, suggesting that they will hire more highly skilled people to replace the pollution factors. Moreover, clean firms decreased the hiring of R&D workers. A possible explanation of this result is that clean industries are not subject to environmental regulations.

**Table 3**
Robustness check using city-level data.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | LnY | *Ln(Labor)* | LnK | *Ln(Labor)* |
| CAA*Post *Yhigh | 0.011<br>(0.407) | −0.092***<br>(−2.810) | | |
| CAA*Post *Ylow | −0.142***<br>(−7.057) | −0.121***<br>(−3.912) | | |
| CAA*Post *Khigh | | | 0.267***<br>(5.183) | −0.123***<br>(−3.913) |
| CAA*Post *Klow | | | −0.043<br>(−0.698) | −0.094***<br>(−3.067) |
| _cons | 12.020***<br>(13.551) | 10.189***<br>(11.890) | 1.530<br>(0.870) | 10.150***<br>(12.010) |
| Control variables | Yes | Yes | Yes | Yes |
| *N* | 666 | 687 | 685 | 687 |
| Firm fixed | Yes | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes | Yes |
| $R^2$ | 0.994 | 0.973 | 0.972 | 0.973 |

**Notes:** T values are indicated in parentheses; $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

**Table 4**
Testing heterogeneous firms' responses to CAA using firm-level data.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Ln(Labor)* | LnY | *Ln(Labor)* | LnK | *Ln(Labor)* | *Ln(RDLabor)* |
| CAA*Post *Clean | −0.003<br>(−0.021) | | | | | −0.862***<br>(−2.682) |
| CAA*Post *Dirty | −0.211**<br>(−2.359) | | | | | 1.101***<br>(6.696) |
| CAA*Post *Yhigh*Clean | | 0.339<br>(1.535) | 0.080<br>(0.460) | | | |
| CAA*Post *Yhigh*Dirty | | 0.152<br>(1.033) | −0.191<br>(−1.297) | | | |
| CAA*Post *Ylow*Clean | | −0.586***<br>(−3.094) | −0.352<br>(−1.231) | | | |
| CAA*Post *Ylow*Dirty | | −0.010<br>(−0.154) | −0.215**<br>(−2.108) | | | |
| CAA*Post *Khigh*Clean | | | | 2.318**<br>(2.372) | −0.047<br>(−0.254) | |
| CAA*Post *Khigh*Dirty | | | | 0.468<br>(1.209) | −0.399***<br>(−2.685) | |
| CAA*Post *Klow*Clean | | | | −0.652<br>(−1.144) | 0.008<br>(0.032) | |
| CAA*Post *Klow*Dirty | | | | −0.164<br>(−0.796) | −0.129<br>(−1.264) | |
| _cons | −10.804***<br>(−6.022) | −3.683**<br>(−2.297) | −10.987***<br>(−5.946) | −12.196***<br>(−2.809) | −11.011***<br>(−6.008) | −7.730**<br>(−2.306) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 2399 | 2331 | 2333 | 2333 | 2333 | 2399 |
| Firm fixed | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.866 | 0.917 | 0.866 | 0.737 | 0.867 | 0.845 |

**Notes:** T values are indicated in parentheses; $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## 8. Conclusions and policy recommendations

For China, which has more labor-intensive and energy-intensive enterprises compared with developed countries, it may suffer greater employment destruction when faced with stricter environmental regulation. Therefore, it is of great significance for government to understand how environmental regulation affects labor demand in China. In this paper, we shed light on the labor reallocation entailed by the Clean Air Action (CAA) in China. Specifically, by using city-level data, we analyze the change of labor demand and inter-industry labor reallocation at city level, and by using firm-level data, we analyze the change of labor demand and intra-firm labor reallocation at firm level. The combination of the two levels data ensures the robustness and representativeness of our results.

We found that the implementation differences of environmental regulation have generated different levels of job destruction and job creation across time, industries, and firm types, boosting labor reallocation. Firstly, The CAA has entailed more job destruction and less job creation in regulated cities and listed firms, and its net negative impact first increases and then decreases over time. However, the labor demand of cities and listed firms still fell by 4.8% and 6.8%, respectively, in 2019. Secondly, The CAA reduced labor demand in manufacturing, transportation, and wholesale and retail trade sectors, and increased it in financial, science and technology, and environmental management sectors. This led to inter-industry labor reallocation. Lastly, the CAA resulted in a reduction in firms' output and a corresponding reduction in labor inputs. In response to stricter environmental regulation, firms hired more highly skilled workers to improve their technical level, while the firms' investment in capital indirectly reduced labor demand. This led to intra-firm labor reallocation.

Based on these results, this study put forward the following two recommendations on how to stabilize employment. First, the government can conduct a comprehensive investigation of the enterprises within its jurisdiction, and accurately gather information such as enterprises' rectification willingness, rectification ability, and workers' technical level. This accurate enterprise information may be used to help polluting enterprises carry out rectification in batches. The purpose of batch rectification is to decompose the unemployed workforce into different periods of policy implementation to complete employment training. This can reduce the pressure on the government to mobilize various resources in the short time, while at the same time more people can receive training and obtain re-employment. Second, the government can train the unemployed workforce according to the city industrial upgrading plan. On the one hand, this can improve the employment skills of workers and the production efficiency of enterprises. On the other hand, government-led employment training can provide corresponding skilled labor for the future industrial development of the city, and can promote industrial upgrading through labor mobility.

## Data availability

Data will be made available on request.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