

Business & Society

Labor Protection, Artificial Intelligence, and Labor Allocation Efficiency

Journal:	<i>Business & Society</i>
Manuscript ID	BAS-25-0733
Manuscript Type:	Original Manuscript - Full Length
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1. Introduction

In the post-pandemic era, prolonged hiring processes and high employee retention costs have further escalated labor-related expenses for businesses. With China's skyrocketing labor costs and fading demographic dividends, the transition of production methods toward flexibility, intelligence, and refinement becomes imperative. Establishing decisive manufacturing systems with intelligence as the fundamental feature is essential, and the demand for artificial intelligence (AI) is expected to grow significantly.¹ Notably, AI has become the primary driver of digital economic development.² The distortion of labor resource allocation is inherent to labor protection, whereby labor costs exceed labor output (Petrin and Sivadasan, 2013). Can the advent of AI address this traditional challenge? Hicks (1932) argues that when a production factor becomes expensive, technology evolves to replace it. As labor costs rise, businesses turn to capital–labor substitution to transform and upgrade (Elvin, 1972; Allen, 2009; Acemoglu, 2010; Bena and Simintz, 2015; Zhang, 2015; Irmen, 2017; Acemoglu and Restrepo, 2018). Labor protection disrupts the equilibrium between marginal labor output and wages, leading to labor costs surpassing labor productivity. In the short term, labor productivity struggles to improve, prompting businesses to choose capital–labor substitution to enhance productivity. Capital–skill complementarity theory posits that capital substitutes (complements) low (high)-skilled workers (Griliches, 1969; Duffy et al., 2004; Liu and Zhao, 2020). Capital–labor substitution enhances labor productivity in two ways: reducing the relative quantity of labor and upgrading the labor structure with an increase in high-skilled labor. Capital, which substitutes for labor, is more likely to entail AI (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020), indicating that AI can narrow the labor productivity–pay gap, thus improving labor allocation efficiency.

Accordingly, we examine whether AI enhances labor allocation efficiency and whether heterogeneity exists among enterprises. Using the implementation of the *2011 Social Insurance*

¹ The notification issued by the three ministries—namely, the Chinese Ministry of Industry and Information Technology, National Development and Reform Commission, and Ministry of Finance—pertains to the issuance of the "Development Plan for the Robotics Industry (2016–2020)" in China. Website resource:

<http://www.scio.gov.cn/xwfbh/xwfbfh/wqfbh/33978/34888/xgzc34894/Document/1484894/1484894.htm>

² Website resource http://jckb.xinhuanet.com/2018-01/24/c_136920832.htm?from=groupmessage

Law as a quasi-natural experiment for labor protection, we construct a mathematical model and employ a triple-differences strategy (DDD) to investigate the relationship among labor protection, AI, and labor allocation efficiency. The results reveal that labor protection increases employee wages, thereby lowering enterprise labor allocation efficiency. Without appropriate efficiency, enterprises may experience gradual output contraction. However, introducing AI to alter the production function enhances labor allocation efficiency and fosters output growth.

The empirical analysis, which employs the 2008–2015 national tax survey data and robot data from the International Federation of Robotics (IFR), is conducted from a small and micro-sized enterprise (SMSE) perspective. The national tax survey data used herein pertain to factories rather than listed companies; SMSEs account for a significant portion of identifiable urban labor.³ Notably, SMSEs are more susceptible to the influence of labor protection policies, while non-SMSEs are more inclined to introduce AI. Overall, enterprises improve their labor allocation efficiency through AI adoption. However, this relationship is predominantly evident among non-SMSEs, with SMSEs showing no similar phenomenon. The impact of AI lies in its substitution of low-skilled labor, while increasing the capital–labor ratio, narrowing the marginal labor output–wage gap, and enhancing labor allocation efficiency. However, this impact is observed only in non-SMSEs. Under the influence of labor protection, AI-integrated non-SMSEs achieve output growth, whereas non-AI-integrated SMSEs experience output decline.

This study’s contributions are threefold: First, while the existing literature primarily explores the causes of labor allocation distortions (Bentolila and Bertola, 1990; Hopenhayn and Rogerson, 1993; Olley and Pakes, 1996; Hsieh and Klenow, 2009; Petrin and Sivadasan, 2013), discussions on specific solutions are lacking. We analyze the impact of labor protection from the perspective of resource allocation efficiency, outpacing conventional discussions regarding employment and wage effects. Grounded in factor substitution and capital–skill complementarity theories, AI is more likely to substitute low-skilled labor with high-skilled

³ The 2021 China SMSE Development Report highlights that SMSEs contribute to greater than 50% of the tax revenue, over 60% of the GDP, and over 95% in terms of quantity. Moreover, they account for greater than 70% of technological innovation and urban labor employment.

counterparts, thereby enhancing marginal labor output, narrowing the gap between productivity and pay, improving efficiency, and, consequently, expanding AI's theoretical and practical utility. The impact of rising labor factor prices on innovation and the type of innovation it promotes remain unknown. Neoclassical growth theory posits that new technologies are embedded in capital, and labor scarcity or high wages reduce the adoption of such technologies, thereby obstructing technological advancement (Ricardo, 1951). Endogenous growth theory shares a similar view, arguing that innovation exhibits scale effects, whereby an increase in labor factors promotes technological progress (Romer, 1986, 1990; Aghion and Howitt, 1992). However, another strand of the literature presents opposing viewpoints. Hicks (1932) and Allen (2011) contend that when a factor becomes relatively expensive, technology will evolve toward substituting that factor. This perspective not only asserts that factor scarcity compels technological advancement but also indicates the direction of such progress. Subsequent literature has identified the positive effects of labor market regulations, such as labor protection, minimum wages, and labor costs, on technological innovation (Acemoglu, 2003; Karabarbounis and Neiman, 2014; Alesina and Zeira, 2018). Labor shortages and rising labor costs are the primary drivers for adopting labor-saving technologies (Gallardo and Sauer, 2018). Labor-saving technologies tend to replace low-skilled workers with high-skilled ones (Acemoglu and Restrepo, 2020). The present study supports this substitution effect, particularly in transitional economies like China, where the demographic dividend is gradually disappearing and labor costs are rapidly rising. In this context, AI predominantly reflects a substitution effect, and this study provides evidence for that assertion.

Second, the existing literature primarily focuses on labor protection research within listed companies or large-scale enterprises rather than SMSEs that are particularly influenced by labor protection policies and, thus, warrant comprehensive investigation. We examine labor protection, AI, and labor allocation efficiency in SMSEs to compare the characteristics of different types of enterprises. Additionally, using DDD to investigate the impact of labor protection and enterprise responses helps mitigate the influence of unobservable factors that change over time in different industries (Berck and Villas-Boas, 2016; Yan and An, 2021). Labor protection is a typical labor market institution that implies rising labor factor prices,

which can subsequently lead to biased technological progress. This study encompasses all types of businesses and finds that labor-saving technologies including AI are effective only in non-SMSEs, with no corresponding effects observed in the SMSE sample. This indicates that biased technological progress occurs exclusively in non-SMSEs, thus providing empirical evidence for the heterogeneity analysis of labor protection and biased technological progress.

Third, this study has practical implications. It proposes a new digital economy function (i.e., AI) that effectively solves the traditional challenges of labor allocation distortions caused by labor protection. However, only non-SMSEs can leverage this new digital economy function, while SMSEs experience neither efficiency enhancement nor output growth through digital economic means. Thus, determining how SMSEs can respond to rising labor costs remains a pressing issue for local governments, and future policies should focus more on SMSEs. In transitional economies like China, labor costs have shifted from low to high, with labor-saving biased technologies playing a crucial role (Wei et al., 2017; Liu and Xiao, 2023). In the Chinese economy, which is predominantly labor-intensive rather than capital-intensive, AI primarily manifests as a labor-saving technology, exerting a substitution effect. This characteristic makes the Chinese economy more susceptible to unemployment among low-skilled workers while simultaneously increasing the demand for high-skilled labor, indicating that transitional economies face a labor market environment characterized by both unemployment and demand.

2. Literature Review and Theoretical Analysis

2.1 Literature Review

Labor protection is a crucial topic in labor economics, with extensive literature examining its impact from both theoretical and empirical perspectives (Banker et al., 2013; Autor et al., 2007; Acharya et al., 2013, 2014; Serfling, 2016). This literature review primarily discusses the roles of factor substitution theory and capital–skill complementarity theory in the context of resource allocation distortion caused by labor protection. Improvements in firm productivity arise not only from the factors of production but also from the efficiency of resource allocation (Olley and Pakes, 1996; Hsieh and Klenow, 2009). The literature generally suggests that labor protection leads to efficiency losses. Bentolila and Bertola (1990) argue that labor protection

increases labor adjustment costs, reduces hiring flexibility, and distorts labor resource allocation. Hopenhayn and Rogerson (1993) establish a general equilibrium model of labor resource allocation efficiency, finding that reduced hiring flexibility is a primary cause of inefficiency. Empirical evidence consistently shows a negative relationship between labor protection and labor resource allocation efficiency (Petrin and Sivadasan, 2013; Andrews and Cingano, 2014). This indicates that labor protection inherently affects allocation efficiency and prevents overall productivity growth due to misalignment between marginal product value and actual wages.

Factor substitution theory posits that when a production factor becomes expensive, technology evolves to replace it, exemplifying labor-saving technologies (Hicks, 1932). Rising labor costs due to labor protection make labor more expensive, prompting firms to increase capital investment to substitute for labor. Consequently, companies increase capital investment as labor costs rise, rendering material capital relatively cheaper (Caballero et al., 2013). Griliches (1969) introduces capital–skill complementarity theory, suggesting that skilled and educated labor is more complementary to material capital than unskilled labor. Acemoglu (2003) asserts that an increase in skill supply over time leads to technological change and heightened demand for skilled labor. Rising labor costs due to labor protection primarily manifest as low-skilled labor costs exceeding labor productivity (Li and Freeman, 2015), resulting in the substitution of low-skilled workers. The acquisition of advanced machinery often leaves existing low-skilled workers unable to operate new equipment, necessitating the hiring of higher-skilled workers and consequently increasing the average human capital of firms. Undoubtedly, AI represents such material capital. Bessen et al. (2018) find that half of AI startups report that their automation products help clients reduce labor costs by substituting for routine workers. Alekseeva et al. (2021) discover that firms with high cash reserves, profits, and R&D intensity invest more in AI and also demonstrate higher growth rates. Acemoglu et al. (2020) find significant productivity increases in companies using AI.

In summary, this study shifts the focus from analyzing the inherent inefficiencies caused by labor protection to investigating whether digital economy solutions, particularly AI, can address these traditional challenges. The literature has primarily focused on analyzing the

causes of inefficient labor allocation while exploring fewer concrete solutions. Factor substitution and capital–skill complementarity theories have garnered empirical support and can inform AI analyses. Additionally, cross-sectional differences in AI adoption at the factory level warrant further investigation. Accordingly, we focus on whether AI can mitigate the resource allocation distortions caused by labor protection and design a comprehensive research plan to explore the strategies different firms employ, from both theoretical and empirical perspectives.

2.2 Theoretical Analysis

We assume firms' profit maximization problem in a competitive market as follows, where r represents the subjective discount rate; L , K , and M represent labor, capital, and intermediate goods inputs, respectively, with K as the state variable; and $\text{Cov}(dM, dL) = 0$; R , W , and P^M represent capital, labor, and intermediate goods prices, respectively. The value function is given by

$$V_{it} = \text{Max}_{L_{it} M_{it}} E_t \left\{ \int_t^\infty e^{-r(T-t)} [Q(L_{it}, K_{it}, M_{it}) P_i - R K_{it} - W L_{it} - P^M M_{it}] dt \right\} \quad (1)$$

where the price of the final product P_i is normalized to 1. Q represents output and is defined as the $C-D$ production function (2), where A represents Hicks-neutral technological progress,⁴ satisfying properties including continuity, differentiability, positive definiteness, decreasing marginal product, and constant returns to scale. α , β , and $1-\alpha-\beta$ represent the output elasticities of capital K , intermediate goods M , and labor L , respectively. Equation (3) represents the per capita output production function, where q , k , and m represent output, capital, and intermediate goods inputs per capita, respectively.

$$Q(K_{it}, M_{it}, L_{it}) = A_t K_{it}^\alpha M_{it}^\beta L_{it}^{1-\alpha-\beta} \quad (2)$$

$$q = k_{it}^\alpha m_{it}^\beta \quad (3)$$

From Equation (1) and the Euler theorem, Equation (4) is derived, where $c(dL)$ represents the cost incurred by labor protection in terms of hiring or firing one unit of labor dL .

⁴ This model assumes exogenous technological progress and considers neither capital- nor labor-augmenting technologies.

W_{it}^* represents the wage after labor protection, and labor productivity MP_{Lit} is significantly lower than wage W_{it+1}^* , thus increasing labor costs, which is the wage distortion caused by labor protection (Petrin and Sivadasan, 2013).

$$MP_{Lit} = (1 - \alpha - \beta)q_{it} = W_{it} < W_{it} + c(dL) = W_{it+1}^* \quad (4)$$

$$(k_{it+1}^*, m_{it+1}^*) > (k_{it}, m_{it}) \quad (5)$$

As $\frac{\partial MP_L}{\partial k} > 0$, $\frac{\partial MP_L}{\partial m} > 0$. Equation (5) implies that the capital and intermediate goods are inputs corresponding to wage W_{it+1}^* after labor protection exceeds the original inputs. Based on labor protection cost, if firms do not adapt, they will gradually shrink, as shown in Equation (6), eventually exiting the market in the long run (Acemoglu, 2007).

$$q_{it+1}^* = k_{it+1}(k_{it+1}^*)^{\alpha-1}(m_{it+1}^*)^\beta < q_{it} \quad (6)$$

$$\lim_{t \rightarrow \infty} q_{it+1}^* = 0$$

How would firm output change if firms adopt AI to modify their production function, reduce labor input, and increase intelligent machine input? The reconstructed production function is expressed in Equation (7), where E represents labor. We further substitute labor E with low-skilled labor L and high-skilled labor H . The specific combination of L and H does not affect the model derivation; for example, we can use a Cobb–Douglas form $L^w H^{1-w}$ or CES form $(L^{\frac{1}{w}} + H^{\frac{1}{w}})^w$, allowing us to directly substitute labor with an equivalent income share of L and H . Accordingly, we derive Equation (8), where we replace low-skilled labor with $(1+AI)$, where $AI \in R_+$. This substitution specifically pertains to replaceable low-skilled labor, excluding non-replaceable low-skilled labor, which does not affect the results.

$$Q(A_t, K_t, M_t, L_t, H_t) = A_t K_{it}^\alpha M_{it}^\beta [E]^{1-\alpha-\beta} = A_t K_{it}^\alpha M_{it}^\beta [L_{it} H_{it}]^{1-\alpha-\beta} \quad (7)$$

We further equate labor productivity with labor protection costs.

$$Q(K_{it+1}, M_{it+1}, E_{it+1}, H_{it+1}) = A_{t+1} K_{it+1}^\alpha M_{it+1}^\beta [(1 + AI_{it+1}) H_{it+1}]^{1-\alpha-\beta} \quad (8)$$

Based on the new production function, firms can achieve at least on an iso-output line, as shown in Equation (9), through labor adjustment, where labor productivity equals the labor protection cost.

$$MP_{Hit+1} = W_{it+1}^* \quad (9)$$

Under this production condition, firm output becomes as shown in Equation (10), indicating that firms achieve stable growth.

$$q_{it+1}^* = k_{it+1}^{*\alpha} (m_{it+1}^*)^\beta (1 + AI_{it+1})^{1-\alpha-\beta} > q_{it} \tag{10}$$

Summarily, from Equations (5), (6), and (10), we infer that AI increases the capital–labor ratio and output. Moreover, per Equations (4) and (9), AI enhances labor allocation efficiency.

3. Research Design

3.1 Data Source and Sample Selection

We primarily utilize the National Tax Statistics Database (NTSD) and AI robot data for empirical research. The NTSD is compiled by the Chinese Ministry of Finance and State Taxation Administration through a stratified random sampling method. The database contains detailed financial and social insurance contribution information of enterprises; encompasses hundreds of thousands of sample enterprises across all sectors of the national economy; and covers various types of enterprises, including listed companies, large-scale industrial enterprises covered by the China Industrial Enterprise Database, and SMSEs. Therefore, it is among the most comprehensive datasets for studying Chinese enterprises (Chen et al., 2019). Existing studies predominantly use robot data released by the IFR to represent AI (Chen et al., 2022; Wang and Dong, 2020; Yu et al., 2021). The IFR provides annual data on robot installations by industry for each country, starting from 2006 for China. These data have been widely used to study robots’ impact on the labor market (Cheng et al., 2019; Giuntella and Wang, 2019; Acemoglu and Restrepo, 2020; Dauth et al., 2021).

The selection of tax survey data as the main database rather than listed company data is driven by several reasons. First, the listed companies’ financial reports do not directly disclose labor protection data. Researchers duly use employee wages or manually identify "employee compensation payable" accounts to construct social insurance indicators, which may introduce measurement errors into the explanatory variables. The NTSD includes detailed information on social insurance and employment security funds, facilitating accurate estimations of the main explanatory variables and providing a scientific basis for the empirical results. Second, listed company data provide comprehensive financial information, given that factories are distributed

across multiple regions. The average wages and social insurance contribution rates vary across regions, eliminating factory-level heterogeneity in the listed company-level data. Finally, SMSEs are a significant component of our sample, albeit excluded from listed company data.

Following the criteria for defining SMSEs based on the standards set by the Ministry of Industry and Information Technology in 2011, we employ indicators such as the number of employees, operating income, and total capital to distinguish SMSEs (See Appendix A). Referring to Wang et al. (2020) and Fan and Liu (2020), the initial dataset is processed as follows: (1) matching the data as panel data based on the enterprise taxpayer identification number; (2) removing samples with data from only one year; (3) excluding erroneous samples with social insurance less than or equal to zero, as well as samples with missing data; (4) utilizing the three-digit industry codes from the Chinese 2002 industry classification (GB/T4754-2002) and the latest classification standards from the United Nations Statistics Division (ISIC Rev.4) to match industries successively and obtain the robot installation data for each industry in China; and (5) removing samples with major variable missingness and other anomalies. Provincial-level macroeconomic data are sourced from the National Bureau of Statistics. Ultimately, 1,230,128 factory-year observations are obtained. To mitigate the influence of outliers, we employ winsorization at the upper and lower 1% levels.

3.2 Model Design and Variable Definitions

We employ the DDD model to examine the relationship among labor protection, AI, and labor allocation efficiency. The model includes individual control variables for $Treat_i$, $Post_t$, $AI_{j,t}$, and interaction terms. $Post_t$ is fully collinear with time fixed effects, while $Treat_i$, $AI_{j,t}$ and $Treat_i \times AI_{j,t}$ are absorbed by firm fixed effects. The model is expressed as follows:

$$LAE_{i,j,p,t} = \alpha_0 + \alpha_1 Post_t \times Treat_i \times AI_{j,t} + \alpha_2 Controls_{i,j,p,t} + \lambda_i + \mu_t + \tau_{jt} + \psi_{pt} + \varepsilon_{i,t} \quad (11)$$

where i , j , p , and t represent enterprise, industry, province, and year, respectively.

3.2.1 Outcome variables: LAE measurement

LAE represents the labor allocation efficiency of enterprises. Following Petrin and

Sivadasan (2013), we measure labor allocation efficiency by calculating the difference between a firm's marginal labor output and labor cost, as shown in Equation (12):

$$LAE_{it} = \ln |MP_{Hit} - W_{it}^*| \quad (12)$$

where W_{it}^* represents the total average wages and benefits paid by the enterprise to individual employees. Per the aforementioned theoretical analysis, in the absence of labor protection, MP_{Hit} is equal to W_{it}^* , resulting in LAE being equal to 0. However, after labor protection, W_{it}^* increases, thus increasing LAE and efficiency losses. Therefore, a larger LAE indicates a lower labor allocation efficiency. However, if businesses adopt AI, MP_{Hit} increases, thereby reducing LAE .

We obtain MP_{Hit} from the following equation:

$$MP_{Hit} = (1 - \alpha - \beta)K_{it}^{\alpha}M_{it}^{\beta}(1 + E_i)^{1-\alpha-\beta}H_{it}^{-\alpha-\beta} = r \cdot q_{it}^* \quad (13)$$

where r can be calculated as follows:

$$\ln Q_{it} = c_i + \alpha \ln K_{it} + \beta \ln M_{it} + r \ln H_{it} + \eta_{it} \quad (14)$$

where Q_{it} represents firm's output; H_{it} , K_{it} , and M_{it} represent the labor, capital, and intermediate inputs used by firms in the production process, respectively; H_{it} is measured in logarithmic form based on the number of employees, K_{it} is measured in logarithmic form of net fixed assets, and M_{it} is measured as the logarithm of the sum of operating costs, selling expenses, administrative expenses, financial expenses, minus depreciation and amortization, and cash payments to employees.⁵

3.2.2 Explanatory variables: AI adoption industries and treatment definition

In Equation (11), *Post* represents labor protection. Herein, the implementation of the *Social Insurance Law* in 2011 is used as a proxy variable for labor protection.⁶ Specifically,

⁵ Building on the preceding theoretical analysis, this study reformulates Equation (8) based on the definition and estimation method of the Solow residual, leading to Equation (a). Taking the logarithm of both sides results in Equation (b). Finally, this is transformed into an econometric model represented by Equation (14).

$$Q(K_{it}, M_{it}, E_{it}, H_{it}) = e^{\eta_{it}} K_{it}^{\alpha} M_{it}^{\beta} [(1 + E_{it}) H_{it}]^{1-\alpha-\beta} \quad (a)$$

$$\ln Q_{it} = \alpha \ln K_{it} + \beta \ln M_{it} + (1 - \alpha - \beta) \ln(1 + E_i) + (1 - \alpha - \beta) \ln H_{it} + \eta_{it} \quad (b)$$

⁶ Labor market institutions encompass important forms of labor protection, including unemployment, social security, and

from 2011 to 2015, *Post* equals 1, whereas from 2008 to 2010, *Post* equals 0.

Treat serves as a treatment variable, indicating the enterprises significantly impacted by labor protection policies. Following Liu et al. (2021), the pre-policy social insurance contribution rate is used to construct this variable. Enterprises are grouped based on whether their average social insurance contribution rate during the three years before the implementation of the *Social Insurance Law* (2008–2010) is below the median. If below the median, the value is set to 1, otherwise, it is set to 0. The social insurance contribution rate is defined as the annual social insurance contribution divided by revenue. Enterprises with lower social insurance contribution rates before the implementation of the *Social Insurance Law* are more likely to be affected by labor protection (Li and Wang, 2017; Wei and Xia, 2020; Liu et al., 2021).

Higher factor substitution elasticity increases the likelihood of enterprises adopting AI (Piketty, 2014). As factor substitution elasticity exhibits similarity within the same industry and considering existing company-level interaction terms, industry-level robot counts are used to calculate *AI*. Enterprises are grouped based on the median of the average IFR robot installation values for the three years before the implementation of the *Social Insurance Law* (2008–2010). If it exceeds the median, the value is set to 1, otherwise, it is set to 0.

Controls represent a series of control variables. Referring to Armstrong et al. (2015), Liu et al. (2018), and Du et al. (2021), the following variables are included: firm size (*Size*), leverage (*Lev*), return on assets (*ROA*), asset growth rate (*Capitalgrow*), working capital ratio (*Lqrat*), and fixed asset intensity (*PPE*). Additionally, considering possible influences from macroeconomic and social factors on enterprises, we control for per capita regional gross domestic product (*GDP*). Furthermore, we control for individual fixed effects (λ_i), time fixed effects (μ_t), industry-specific time trends (τ_{jt}), and province-specific time trends (ψ_{pt}). All standard errors are clustered at the firm level, and the details of the variables are presented in Appendix B.

dismissal regulations (Betcherman, 2012). Moreover, the existing literature directly employs social security legal frameworks as proxy variables for labor protection (Xu and Li, 2020).

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3.3 Descriptive Statistics

Table 1 presents the main variables’ descriptive statistics: *LAE* ranges from -9.44 to 14.51. The mean of *Treat* is 0.52, indicating that 52% of the total sample has a lower prior social insurance contribution rate. The mean of *Post* is 0.58; the sample proportion for post-policy implementation is 58%. The mean of *AI* is 0.45, suggesting that 45% of the total sample exhibits a higher installation rate of industrial robots.

Regarding the control variables, the average *Size* is 10.81, with a median of 10.74. The size varies considerably, with values ranging from 6.24 to 16.67. The average and median values of *Lev* are 0.62 and 0.65, respectively. The mean of *ROA* is 0.02, with minimum and maximum values of -0.59 and 0.61, respectively. The average of *Capitalgrow* is 0.18, ranging between -4.70 and 8.41, indicating significant variations in asset growth rates across firms. The averages of *Lqrat* and *PPE* are 0.12 and 0.20, respectively. The mean and median of *GDP* are 10.69 and 10.71, respectively.

[Insert Table 1 here]

3.4 Sample Structure Analysis

Here, t-tests are conducted between the treatment and control groups as well as the SMSE and non-SMSE groups.⁷ These tests are conducted to assess whether significant differences exist among the groups. Columns (1) and (5) of Table 2 report the SMSE means in the treatment and control groups. Columns (2) and (6) report the non-SMSE means. Columns (4) and (8) report the overall means for the treatment and control groups, respectively. Columns (3), (7), and (9) report the differences in means between SMSEs and non-SMSEs within the treatment group, the same comparison within the control group, and the differences in means between the treatment and control groups, respectively. Table 2 indicates that the dependent and control variables exhibit statistically significant differences among the groups, suggesting

⁷ We conduct a univariate test prior to the event, estimating the average differences based on pre-treatment (before 2011) and the adoption of artificial intelligence, with conclusions consistent with the overall sample.

the grouped regression's meaningfulness.

[Insert Table 2 here]

Appendix C presents the kernel density plots for the entire sample, SMSEs, and non-SMSEs. These plots illustrate the impact of labor protection on labor allocation efficiency among various enterprise groups. For SMSEs, the decrease in labor allocation efficiency is not substantial, as indicated by the almost overlapping solid and dashed lines, suggesting that labor protection and AI have not precipitated significant differences in labor allocation efficiency. However, for non-SMSEs, the distance between the solid and dashed lines is more pronounced, indicating a more significant decrease in labor allocation efficiency after introducing labor protection and AI. The distance between the solid and dashed lines for the entire sample falls between the SMSE and non-SMSE samples. The sample's preliminary tests align with the empirical analyses presented later in the text.

Herein, we define firms with robot installation levels above the median as *Machine1* and those below the median as *Machine2* to display the trends in labor allocation efficiency (*LAE*) across groups, as shown in Panel A of Figure 1. Prior to the implementation of the *social insurance law* in 2011, the trends in *LAE* for firms using AI extensively and those using it less were similar. However, after the law's implementation, the two curves converged. In SMSEs, the *LAE* trends for firms with high and low AI usage were not parallel before the law was enacted, particularly in the year prior. Conversely, for non-SMSEs, the *LAE* trends for firms with high and low AI usage were largely parallel before the law's implementation, with no significant changes in 2010. However, significant changes occurred after the law was enacted.

[Insert Figure 1 here]

Furthermore, we categorize firms with robot installation levels and social security contribution rates, both above the median, as *Machine1*, those with robot installation levels below the median and social security rates above the median as *Machine2*, those with robot installation levels above the median and social security rates below the median as *Machine3*, and those with both robot installation and social security rates below the median as *Machine4*.

We analyze the *LAE* trends for these categories, with the results shown in Panel B of Figure 1. Notably, for non- SMSEs, the trends were consistent across groups prior to policy implementation, especially in the years before 2011. After the social security law was implemented in 2011, *Machine2* and *Machine3* began to intersect. For the full sample, all groups maintain similar trends before 2011 but diverge after the law's implementation. In SMSEs, the groups exhibit a converging trend before 2011, aligning with our analysis in the main text and indicating that the identified causal relationships do not exist in SMSEs.

To enhance the precision of our descriptions of the primary explanatory variables, *AI* and *Treat*, we construct income distribution graphs, annual social insurance payment distribution graphs, social insurance contribution rate distribution graphs, and density distribution graphs based on the sample structure prior to the implementation of the social insurance law between 2008 and 2011. We categorize the income of larger firms as the *mean of lrb_yysr1* and the income of smaller firms as the *mean of lrb_yysr2*. Similarly, the annual social insurance payments for larger firms are designated as the *mean of dfs_ynshbx1*, while those for smaller firms are the *mean of dfs_ynshbx2*. The social insurance contribution rates are categorized as the *mean of sscr1* for larger firms and the *mean of sscr2* for smaller firms. As shown in Appendix D, small firms generally have lower income, annual social insurance payments, and contribution rates compared to larger firms. Notably, in 2008, small firms' annual social insurance payments are slightly higher than those of larger firms, but in subsequent years, their payments, income, and contribution rates remain lower. For non-small enterprises, smaller firms also exhibit lower income, annual social insurance payments, and contribution rates than larger firms. These data align with our intuition that smaller firms tend to have lower income and social insurance contributions.

Following the approaches of Liu et al. (2021) and Angrist and Pischke (2009), we define firms with lower social insurance contribution rates prior to the law's implementation as the treatment group. Before the law was enacted, governmental oversight was lax, leading to non-compliance in social insurance payments. Consequently, firms with low contribution rates were more likely to underreport or evade payments. After the implementation of the social insurance law, these firms would need to significantly adjust their payment strategies to comply with the

new legal requirements, resulting in a greater impact of the law on them. This is the primary rationale for designating firms with lower contribution rates as the treatment group.

4. Empirical Analysis

4.1. Main Analysis

Table 3 presents the results for Equation (10). Columns (1)–(3) report the regression results for the entire sample, SMSEs, and non-SMSEs. In Column (1), the coefficient of $Treat \times Post \times AI$ is significantly negative at the 1% level, indicating that AI significantly enhances labor allocation efficiency for the entire sample. In Column (2), the coefficient of $Treat \times Post \times AI$ is positive but non-significant, suggesting that the labor allocation efficiency for SMSEs does not improve significantly. In Column (3), the coefficient of $Treat \times Post \times AI$ is significantly negative at the 1% level, indicating that AI mitigates the efficiency loss caused by labor protection for non-SMSEs. Ultimately, we find that AI mitigates the efficiency loss caused by labor protection; however, this relationship is observed only among non-SMSEs.

Regarding the control variables, the coefficient of *Size* is significantly positive for the entire sample, SMSEs, and non-SMSEs, indicating a negative correlation between firm size and labor allocation efficiency. The coefficients of *Lev* are significantly negative for the entire sample and non-SMSEs, suggesting a significantly positive correlation between leverage ratio and labor allocation efficiency. For non-SMSEs, the coefficient of *ROA* is significantly positive, indicating a negative correlation between *ROA* and labor allocation efficiency; however, for SMSEs, the coefficient is significantly negative, implying a positive correlation between *ROA* and labor allocation efficiency. The coefficients of *Capitalgrow* are significantly negative for the entire sample and non-SMSEs, indicating a positive correlation between asset growth rate and labor allocation efficiency. The coefficients of *Lqrat* are significantly negative for the entire sample and non-SMSEs, suggesting a positive correlation between the operating capital ratio and labor allocation efficiency. In all columns, the results show a negative correlation between *PPE* and labor allocation efficiency, and the coefficient of *GDP* is significantly positive, implying a relationship between labor allocation efficiency and regional economic development level.

[Insert Table 3 here]

4.2. Robustness Test

4.2.1 Parallel trends test

To estimate the policy effect using the DDD method, satisfying the parallel trends assumption—that no significant differences should exist in labor allocation efficiency between the treatment and control groups before policy implementation—is necessary. Following Liu et al. (2021), we consider the year immediately before the labor protection policy was implemented (i.e., 2010) as the base year. The following regression model is constructed to conduct the parallel trends test:

$$LAE = \beta_0 + \sum_{k=1}^7(\beta_kTreat \times AI \times T_k + \alpha_kTreat \times T_k + \sigma_kTreat \times T_k + \delta_kT_k) + \Phi Treat \times AI + \phi Treat + \theta AI + \eta Controls + \lambda + \mu + \tau + \psi + \varepsilon \quad (15)$$

where T_1 (T_2) is a dummy variable taking the value of 1 if the sample is from the third (second) year before policy implementation, that is, 2008 (2009), and 0 otherwise. T_3 is a dummy variable taking the value of 1 if the sample is from the year of policy implementation (i.e., 2011) and 0 otherwise. T_4 (T_5 , T_6 , and T_7) is a dummy variable that takes the value of 1 if the sample comes from the first (second, third, and fourth) year after the policy implementation of 2012 (2013, 2014, and 2015) and 0 otherwise. Figure 2 shows the parallel trends. In both the full sample and non-SMSEs, a significant decline is exhibited in LAE after the policy implementation, while no significant differences are observed before the policy. This satisfies the parallel trends assumption.

[Insert Figure 2 here]

Table 4 reports the parallel trends results. The coefficients of $T_1 \times Treat \times AI$ and $T_2 \times Treat \times AI$ for the entire sample and non-SMSEs are not significantly different from zero, indicating that no significant differences exist in labor allocation efficiency between the treatment and control groups before policy implementation. The coefficients of $T_4 \times Treat \times AI$, $T_5 \times Treat \times AI$, $T_6 \times Treat \times AI$, and $T_7 \times Treat \times AI$ for SMSEs are non-significant, suggesting that

no significant differences exist in labor allocation efficiency for SMSEs after policy implementation. However, for 2012–2015, the coefficients of $T_6 \times Treat \times AI$ for the entire sample and non-SMSEs are significantly negative at the 5% level. Additionally, the coefficients of $T_3 \times Treat \times AI$ for the entire sample and non-SMSEs are significantly negative, indicating the policy's significant impact on labor allocation efficiency for the entire sample and non-SMSEs after policy implementation.

[Insert Table 4 here]

4.2.2 Strict placebo test

To address the concern of spurious regression results, we conduct a strict placebo test by artificially shifting the labor protection policy one year earlier. If the policy effect remains significant in this scenario, the baseline regression may suffer from endogeneity bias. To mitigate this risk, the definition of the first interaction factor, $Post$, is altered. Specifically, 2010 and subsequent years are defined as $Post_{false}=1$, while the other years are defined as $Post_{false}=0$. Table 5 presents the placebo test results. The coefficients of $Treat \times Post \times AI$ are non-significant in all three columns, indicating that the fabricated policy lacks a significant impact.

[Insert Table 5 here]

4.2.3 Other robustness tests

We conduct various robustness tests to ensure the results' reliability. First, a general placebo test is performed to examine whether the observed effects are specific to the policy implementation. The core idea behind the placebo test is to simulate a randomized situation. If the coefficient remains significant even under randomization, the estimation in the baseline regression may be biased. While policies rarely impact labor allocation efficiency across all three dimensions simultaneously, which is the focus of this study's three-way interactions, considering this possibility remains necessary. In the placebo test, we explicitly examine $Treat \times Post \times AI$. To perform the placebo test, the core explanatory variable, $Treat \times Post \times AI$, is randomly assigned values, and this process is repeated 500 times. The coefficients and standard

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errors of the interaction terms are recorded for each iteration. Figure 3 illustrates the placebo test results for the entire sample, SMSEs, and non-SMSEs. Per the results, the coefficients of $Treat \times Post \times AI$ follow a normal distribution centered around zero. The vertical dashed lines in the graph represent the estimated coefficient from the baseline regression. These lines are significantly distant from zero, indicating that randomly setting the core explanatory variable does not reveal any relationship among labor protection, AI, and labor allocation efficiency. Hence, the analysis' results are robust.

[Insert Figure 3 here]

Second, we redefine SMSE classification, deviating from the initial classification of enterprises according to the standards of the 2011 National Ministry of Industry and Information Technology. However, following Wang et al.'s (2020) approach, we reclassify the sample based on the criteria for identifying micro-enterprises outlined in the New Enterprise Income Tax Law implemented in 2008. Panel A of Table 6 presents the results. Evidently, for the entire sample and non-SMSEs, the coefficient of $Treat \times Post \times AI$ is significantly negative. However, the coefficient for SMSEs is non-significant, consistent with the original finding, indicating that the causal relationship among labor protection, AI, and labor allocation efficiency identified herein remains valid.

Third, we adjust the sample year. Owing to the implementation of the *Social Insurance Law* on July 1, 2011, which might lead to an unclear differentiation between treatment and control groups in 2011, we exclude the 2011 sample. Panel B of Table 6 presents the regression results. Consistent with the baseline regression, $Treat \times Post \times AI$ is significantly negative for the entire sample and non-SMSEs but remains insignificant for SMSEs.

Fourth, we add combined fixed effects to control for additional sources of heterogeneity and introduce trend effects along with two-way fixed effects. Specifically, stricter interaction fixed effects, namely, industry-year (Φ_{s-t}) and province-year (Π_{p-t}) interaction fixed effects, are added to Equation (10) for robustness testing. The results (Panel C of Table 6) show that the

coefficient of $Treat \times Post \times AI$ is significantly negative for the entire sample and non-SMSEs but remains insignificant for SMSEs, consistent with the original finding.

Finally, we redefine the pre-policy social insurance contribution rate to examine whether the definition of $Treat$ affects the regression results. Following Liu et al.'s (2021) approach, we directly employ the median of companies' average social insurance contributions in the 2008–2010 period as the treatment group threshold. Enterprises with contribution rates below the median are defined as 1 ($Treat1 = 1$), while others are defined as 0 ($Treat1 = 0$). Panel D of Table 6 presents the regression results, which indicate that the coefficient of $Treat \times Post \times AI$ is significantly negative for the entire sample and non-SMSEs.

[Insert Table 6 here]

5. Further Analysis

5.1 Corporate Burden: Labor Protection Shocks

First, the labor protection policy increases labor costs, thus exacerbating the burden on enterprises. Therefore, examining labor protection's impact on labor costs is necessary. Panel A of Table 7 presents the regression results for all enterprises, SMSEs, and non-SMSEs for labor costs ($Ingw$)—the natural logarithm of cash paid to and received by employees divided by the natural logarithm of sales revenue.⁸ The coefficients of $Treat \times Post$ are all significantly positive, indicating that the labor protection policy has generally increased the burden on enterprises, compelling them to respond.⁹

[Insert Table 7 here]

Second, the greater the impact of labor protection, the heavier the burden on enterprises. From a labor payment perspective, the labor protection policy itself imposes a heavier burden

⁸ Including social insurance fees does not alter the fundamental regression results. Consistent with the Social Insurance Law literature, this labor protection policy has increased labor costs (Xu and Li, 2020; Wang and Huang, 2022).

⁹ Here, a difference-in-differences (DiD) approach is employed primarily to examine whether labor protection has increased the burden on businesses. The DDD model considers the impact of AI as the third interaction factor, representing how businesses are addressing labor cost burdens. Table 8 presents the DDD model's regression results.

on some enterprises, creating a more urgent need to introduce AI to alleviate the labor protection burden. Based on the labor protection policy, before 2019, China's enterprise social insurance contribution base calculation method was grounded on the average wage of non-private urban employees, setting a range of 60–300% in most areas. Thus, the lowest social insurance contribution base is 60% of the average regional wage. Social insurance contributions have a minimum payment base; enterprises farther from this base pay higher social insurance fees. Following Yan and An (2021), enterprises closer to the payment base were more likely to pay lower contributions before the implementation of the *Social Insurance Law*. With the increased enforcement of the *Social Insurance Law*, the impact on enterprises closer to the payment standard became more significant. We define an enterprise's *R*-value as follows:

$$R = \text{Enterprise Average Wage} / \text{Regional Average Wage} \tag{16}$$

The average wage data for each province are collected manually. Based on the median *R*-values in the year before the implementation of the *Social Insurance Law* in 2010, enterprises with *R*-values above (below) the median are defined as having a light (heavy) burden (*burden*=0 and 1, respectively). Enterprises with heavier burdens are more likely to use AI to alleviate the factor distortion caused by labor protection policies. Panel B of Table 7 shows the results. Columns (2), (4), and (6) show that the coefficients of *Treat*×*Post*×*AI* are non-significant, suggesting that the labor efficiency of various types of enterprises has not changed significantly in the group wherein the impact of labor protection is light. Column (5) shows that the coefficient of *Treat*×*Post*×*AI* is significantly negative, indicating that non-SMSEs significantly alleviate efficiency losses caused by labor protection through AI adoption. Columns (1) and (3) show that the coefficients of *Treat*×*Post*×*AI* are non-significant and significantly positive, indicating that the labor efficiency of the entire enterprise and SMSEs remains unchanged. Analyzing the cross-sectional differences in labor protection levels further confirms the causal relationship among labor protection, AI, and labor allocation efficiency.

Finally, introducing AI requires sound financial conditions. Faced with labor protection policies' burden, enterprises primarily use AI to replace labor. Enterprises with funds for introducing AI can better cope with this burden, while those under severe financing constraints find the burden exacerbated by labor protection policies. After labor payment, they may lack

funds to invest in AI. Therefore, enterprises with weak financing constraints are more likely to purchase AI to enhance their labor efficiency. To validate the theoretical inference, we draw on the methods used by Almeida et al. (2004) and Hadlock and Pierce (2010) to characterize enterprise financing constraints using the *SA* index: enterprises with median values above (below) the median are classified as the high (low) financing constraint group (*constraint*=1 and 0, respectively). Panel C of Table 7 presents the results. Columns (2), (4), and (6) show that the coefficients of *Treat*×*Post*×*AI* are non-significant, indicating that in the high financing constraint group, the labor efficiency of various types of enterprises has not changed significantly. Columns (1) and (5) show that the coefficients of *Treat*×*Post*×*AI* are significantly negative, indicating that the entire enterprise and non-SMSEs significantly alleviate efficiency losses caused by labor protection through AI adoption. Column (3) shows that the coefficient of *Treat*×*Post*×*AI* is significantly positive, indicating that SMSEs' labor efficiency remains unchanged. Further evidence for AI's role in enhancing labor efficiency is provided by analyzing financing constraints' impact on AI introduction.

5.2 Corporate Response: AI Introduction

Enterprises primarily utilize AI to replace low-skilled workers, thereby increasing labor's marginal productivity and narrowing the gap between marginal productivity (MP_H) and equilibrium wage (W^*), which enhances labor allocation efficiency. First, we examine whether AI introduction reduces the burden on enterprises. Panel A of Table 8 presents the results. Noting that the coefficients of *Treat*×*Post*×*AI* are significantly negative for all enterprises and non-SMSEs. However, the coefficient of SMSEs is non-significant, suggesting that AI does not significantly lower labor costs for SMSEs.

The theoretical analysis (Equation 5) indicates that AI integration increases the capital–labor ratio ($k_{it+1}^* > k_{it}$). Panel B of Table 8 presents the results. The capital–labor ratio (K/L) is defined as the ratio of total fixed assets to the number of employees at the end of the period. The coefficients of *Treat*×*Post*×*AI* are significantly positive for all enterprises and non-SMSEs. However, the coefficient for SMSEs is non-significant, implying that SMSEs have not adopted AI to enhance labor allocation efficiency, resulting in no significant change in their capital–

labor ratio.

Based on capital–skill complementarity and factor substitution theories, introducing AI is more likely to replace low-skilled workers. Consequently, AI’s positive impact on labor allocation efficiency should be more pronounced in groups with higher proportions of low-skilled workers. Enterprises with lower average wages employ more low-skilled workers. Therefore, the relationship among labor protection, AI, and labor allocation efficiency is expected to be more significant in enterprises with lower average wages. Panel C of Table 8 presents the results. We divide enterprises into three equal parts based on their average wages in 2010. Enterprises with average wages below (above) the two-thirds percentile are defined as having higher (lower) proportions of low-skilled workers (*Lowskill*=1 and 0, respectively). Columns (3) and (4) report the SMSEs’ results; labor allocation efficiency exhibits no significant negative—predominantly because the SMSEs have not integrated with AI, and thus, their labor allocation efficiency remains unchanged. Columns (1), (2), (5), and (6) present the results for all enterprises and non-SMSEs, revealing that only enterprises with a higher proportion of low-skilled workers significantly improve in labor allocation efficiency. This is primarily attributable to non-SMSEs adopting AI to replace low-skilled workers, thereby increasing marginal output (MP_H) and enhancing labor allocation efficiency.

[Insert Table 8 here]

5.3 Corporate Output

Combining the theoretical analysis from Equations (6) and (10) with AI adoption, enterprises can enhance their labor allocation efficiency and stimulate output growth. We appropriately transform Equations (6) and (10) as follows:

$$g_q = \frac{q_{it+1}-q_{it}}{q_{it}} = \begin{cases} < 0 & \text{No AI Adoption} \\ > 0 & \text{AI Adoption} \end{cases} \tag{17}$$

In the short term, the growth rate of enterprise output (g_q) depends on whether an enterprise adopts AI to alter its production function. For enterprises that have not introduced AI, their output gradually declines, ultimately converging to zero. However, with AI integration, enterprise output can achieve stable growth; g_q is defined as the increase in per capita main business revenue divided by the previous year's main revenue. Table 9 presents the results. In

Columns (1) and (3), the coefficient of $Treat \times Post \times AI$ is significantly positive, indicating an increase in per capita output growth for non-SMSEs. This implies that non-SMSEs use AI integration to replace low-skilled workers, enhance labor allocation efficiency, and promote output growth. Column (2) displays an insignificant negative coefficient for $Treat \times Post \times AI$, consistent with Equation (17), thus suggesting that non-AI-integrated SMSEs continue using their original production function, hence causing a decline in output.

[Insert Table 9 here]

6. Conclusion

We examine the relationship among labor protection, AI, and labor allocation efficiency using the implementation of the *Social Insurance Law* in 2011 as a quasi-natural experiment. Through mathematical modeling and the DDD model, we investigate the impact of labor protection and AI on labor allocation efficiency. Per the results, labor protection increases (decreases) employee wages (enterprise labor allocation efficiency). Without appropriate efficiency, enterprises may experience a gradual output decline. However, AI adoption can enhance labor allocation efficiency and output growth. Overall, enterprises improve labor allocation efficiency through AI adoption, albeit only in non-SMSEs. Notably, AI's mechanism lies in its ability to replace low-skilled workers, raise the capital–labor ratio, narrow the marginal labor productivity–wage gap, and enhance labor allocation efficiency. This mechanism is predominantly evident in non-SMSEs. Moreover, the theoretical analysis of per capita output receives empirical support. Regarding labor protection shocks, AI-introducing non-SMSEs achieve output growth, while non-AI-embracing SMSEs experience output decline.

This study has several policy implications. First, it highlights the importance of applying new tools to address old issues. Labor allocation distortion via labor protection represents an old problem, while the digital economy signifies a new paradigm. As a vital infrastructure, key technology, leading industry, and empowering engine in the digital economy era, AI serves as a core driving force for industrial transformation, upgrading, and digital economy advancement in developing countries. Enterprises require incentives to introduce AI to enhance their efficiency and stimulate growth.

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Second, it emphasizes the importance of focusing on SMSEs. These findings suggest that SMSEs must harness AI capabilities to address traditional inefficiencies. Their inability to do so may be owing to a notable inertia in AI adoption, resulting in unchanged resource allocation efficiency and factor structures, and potentially leading to a decline in output. These insights highlight the necessity of policies aimed at promoting SMSE participation in the digital economy, which could serve as a key breakthrough for economic growth. However, such policies inevitably involve costs; not only direct financial expenditures, such as capital investment and project-related expenses, but also indirect costs, such as societal adaptation, economic restructuring, administrative burdens, and opportunity costs. Given that China has already introduced numerous incentive policies for SMSEs, the marginal cost of additional policies is relatively low. The government could refine these incentives by, for example, stipulating that a portion or all of the tax savings be allocated to AI adoption rather than other uses. In this case, SMSEs would continue to benefit from tax reductions, while the marginal cost of such policies would be nearly zero. This approach could help enhance resource allocation efficiency in SMSEs. Therefore, guiding existing incentive policies with consideration of their costs is a viable policy option.

Finally, this study offers valuable insights for other transitioning economies. As economies advance, workers increasingly share in economic rents, leading to rising labor costs for firms. Consequently, wage levels may exceed labor productivity, causing distortions in labor resource allocation. This is a challenge that nearly all transitioning economies face. The findings of this study suggest that, to enhance labor resource allocation efficiency, firms can introduce AI to automate certain production processes, thereby driving economic transformation. Moreover, some regions, although not directly impacted by social security systems, encounter resource misallocation issues due to rising labor costs. For instance, in Latin America, where social security enforcement is relatively lax, labor markets exhibit a core-periphery segmentation, and issues arise from other labor protection policies. In such cases, AI can similarly improve labor resource allocation efficiency. Thus, AI technology has the potential to not only mitigate inefficiencies caused by rising labor costs but also optimize resource allocation across a wide range of economies.

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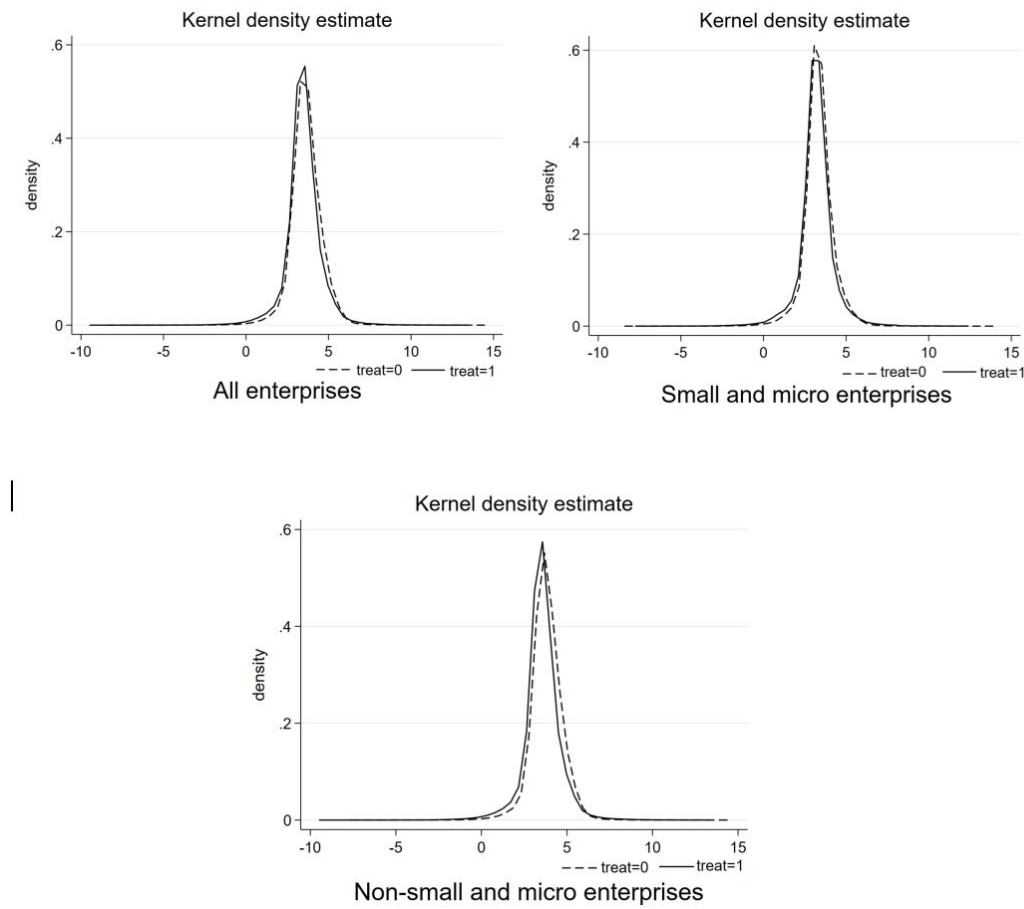
Appendix A. Classification of Enterprises

Industry	Indicator	Measurement Unit	Large	Medium	Small	Micro
Agriculture, Forestry, Animal Husbandry, Fishing	Revenue (Y)	10,000 RMB	$Y \geq 20000$	$500 \leq Y < 20000$	$50 \leq Y < 500$	$Y < 50$
Manufacturing	Employees (X)	Persons	$X \geq 1000$	$300 \leq X < 1000$	$20 \leq X < 300$	$X < 20$
	Revenue (Y)	10,000 RMB	$Y \geq 40000$	$2000 \leq Y < 40000$	$300 \leq Y < 2000$	$Y < 300$
Construction	Revenue (Y)	10,000 RMB	$Y \geq 80000$	$6000 \leq Y < 80000$	$300 \leq Y < 6000$	$Y < 300$
	Total Assets (Z)	10,000 RMB	$Z \geq 80000$	$5000 \leq Z < 80000$	$300 \leq Z < 5000$	$Z < 300$
Wholesale Trade	Employees (X)	Persons	$X \geq 200$	$20 \leq X < 200$	$5 \leq X < 20$	$X < 5$
	Revenue (Y)	10,000 RMB	$Y \geq 40000$	$5000 \leq Y < 40000$	$1000 \leq Y < 5000$	$Y < 1000$
Retail Trade	Employees (X)	Persons	$X \geq 300$	$50 \leq X < 300$	$10 \leq X < 50$	$X < 10$
	Revenue (Y)	10,000 RMB	$Y \geq 20000$	$500 \leq Y < 20000$	$100 \leq Y < 500$	$Y < 100$
Transportation	Employees (X)	Persons	$X \geq 1000$	$300 \leq X < 1000$	$20 \leq X < 300$	$X < 20$
	Revenue (Y)	10,000 RMB	$Y \geq 30000$	$3000 \leq Y < 30000$	$200 \leq Y < 3000$	$Y < 200$
Warehousing	Employees (X)	Persons	$X \geq 200$	$100 \leq X < 200$	$20 \leq X < 100$	$X < 20$
	Revenue (Y)	10,000 RMB	$Y \geq 30000$	$1000 \leq Y < 30000$	$100 \leq Y < 1000$	$Y < 100$
Postal Services	Employees (X)	Persons	$X \geq 1000$	$300 \leq X < 1000$	$20 \leq X < 300$	$X < 20$
	Revenue (Y)	10,000 RMB	$Y \geq 30000$	$2000 \leq Y < 30000$	$100 \leq Y < 2000$	$Y < 100$
Accommodation	Employees (X)	Persons	$X \geq 300$	$100 \leq X < 300$	$10 \leq X < 100$	$X < 10$
	Revenue (Y)	10,000 RMB	$Y \geq 10000$	$2000 \leq Y < 10000$	$100 \leq Y < 2000$	$Y < 100$
Restaurants	Employees (X)	Persons	$X \geq 300$	$100 \leq X < 300$	$10 \leq X < 100$	$X < 10$
	Revenue (Y)	10,000 RMB	$Y \geq 10000$	$2000 \leq Y < 10000$	$100 \leq Y < 2000$	$Y < 100$
Information and Communication	Employees (X)	Persons	$X \geq 2000$	$100 \leq X < 2000$	$10 \leq X < 100$	$X < 10$
	Revenue (Y)	10,000 RMB	$Y \geq 100000$	$1000 \leq Y < 100000$	$100 \leq Y < 1000$	$Y < 100$
Software and Information Technology Services	Employees (X)	Persons	$X \geq 300$	$100 \leq X < 300$	$10 \leq X < 100$	$X < 10$
	Revenue (Y)	10,000 RMB	$Y \geq 10000$	$1000 \leq Y < 10000$	$50 \leq Y < 1000$	$Y < 50$
Real Estate Development and Operation	Revenue (Y)	10,000 RMB	$Y \geq 200000$	$1000 \leq Y < 200000$	$100 \leq Y < 1000$	$Y < 100$
	Total Assets (Z)	10,000 RMB	$Z \geq 10000$	$5000 \leq Z < 10000$	$2000 \leq Z < 5000$	$Z < 2000$
Property Management	Employees (X)	Persons	$X \geq 1000$	$300 \leq X < 1000$	$100 \leq X < 300$	$X < 100$
	Revenue (Y)	10,000 RMB	$Y \geq 5000$	$1000 \leq Y < 5000$	$500 \leq Y < 1000$	$Y < 500$
Leasing and Business Services	Employees (X)	Persons	$X \geq 300$	$100 \leq X < 300$	$10 \leq X < 100$	$X < 10$
	Total Assets (Z)	10,000 RMB	$Z \geq 120000$	$8000 \leq Z < 120000$	$100 \leq Z < 8000$	$Z < 100$
Other Unspecified Industries	Employees (X)	Persons	$X \geq 300$	$100 \leq X < 300$	$10 \leq X < 100$	$X < 10$

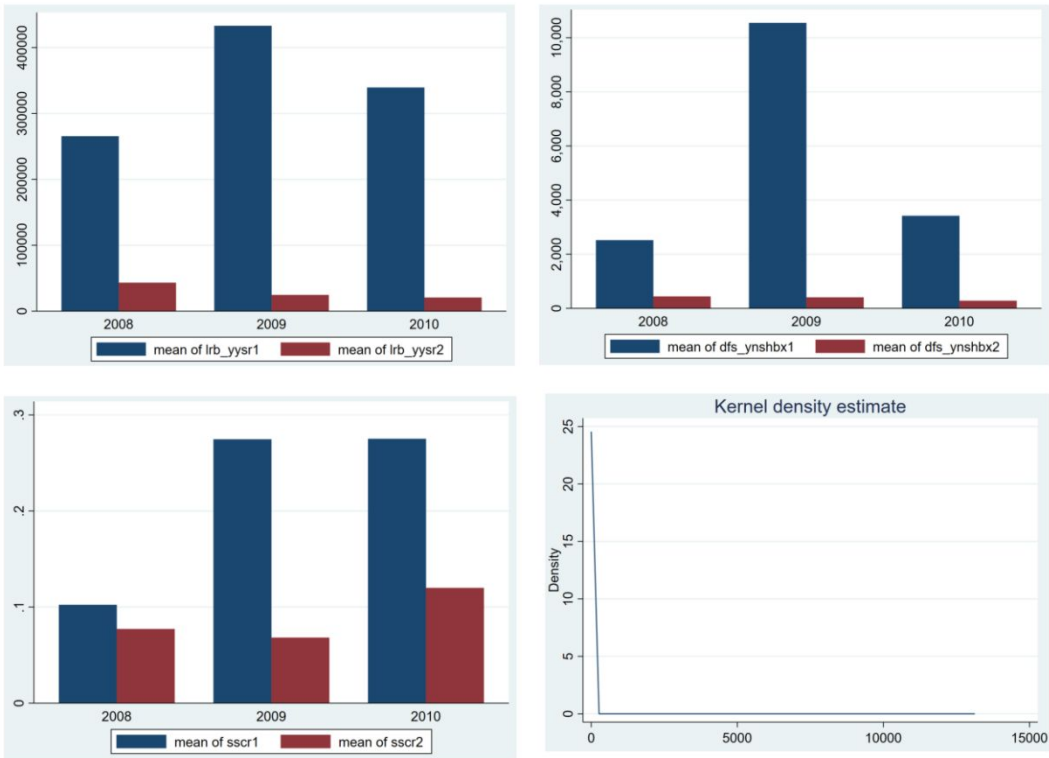
Appendix B. Variable Definitions

Variable Name	Variable Symbol	Variable Definition
Labor Allocation Efficiency	<i>LAE</i>	Defined as per Equation (15)
Treatment Variable	<i>Treat</i>	Assigned a value of 1 if a company's average social insurance payment rate for the three years before the implementation of the "Social Insurance Law" (2008-2010) is below the median; otherwise, assigned a value of 0. Social insurance payment rate is defined as the annual social insurance payment divided by revenue.
Policy Variable	<i>Post</i>	Assigned a value of 1 for the year 2011 and onwards; otherwise, assigned a value of 0.
Treatment Variable	<i>AI</i>	Categorized based on the median of robot installation volume for the years 2008-2010. Assigned a value of 1 if a company's robot installation volume exceeds the median of robot installations during those years; otherwise, assigned a value of 0.
Firm Size	<i>Size</i>	Natural logarithm of total assets
Debt Ratio	<i>Lev</i>	Total liabilities divided by total assets
Return on Assets	<i>ROA</i>	Net profit divided by total assets
Capital Growth Rate	<i>Capitalgrow</i>	Year-end owner's equity divided by year-beginning owner's equity and then minus 1
Working Capital Ratio	<i>Lqrat</i>	Current assets minus Current liabilities divided by total assets
Fixed Asset Intensity	<i>PPE</i>	Net value of fixed assets divided by total assets
Per Capita Gross Domestic Product	<i>GDP</i>	Natural logarithm of per capita gross domestic product

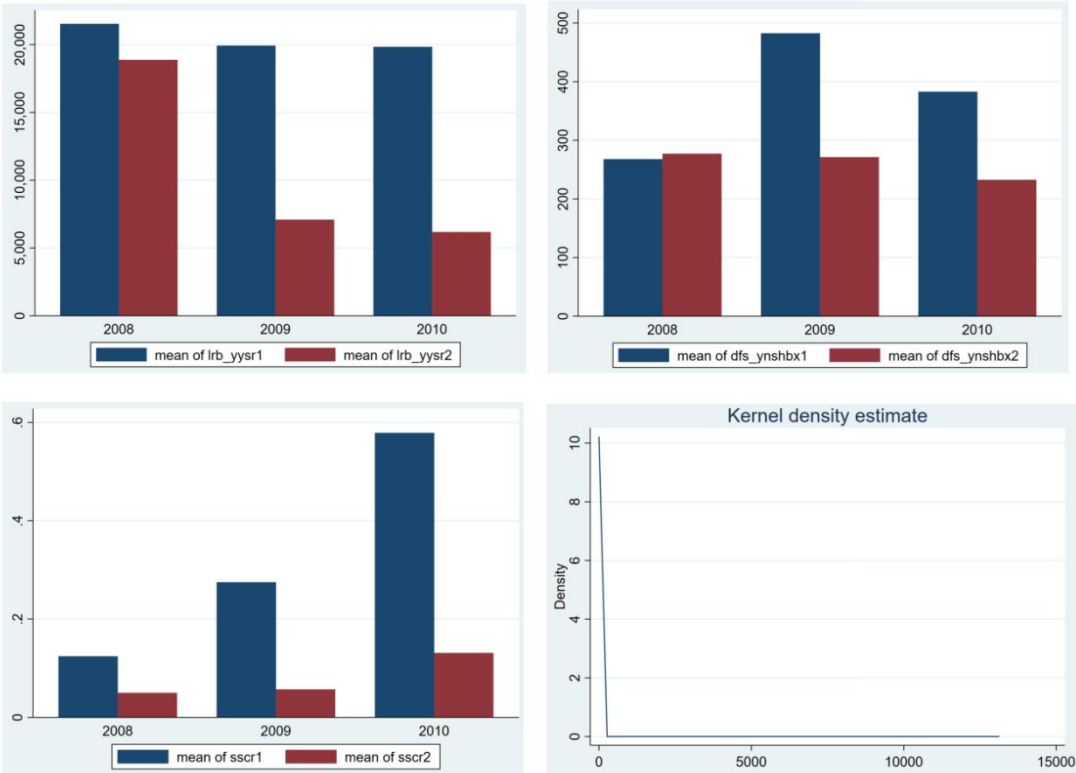
Appendix C. Kernel Density Plot



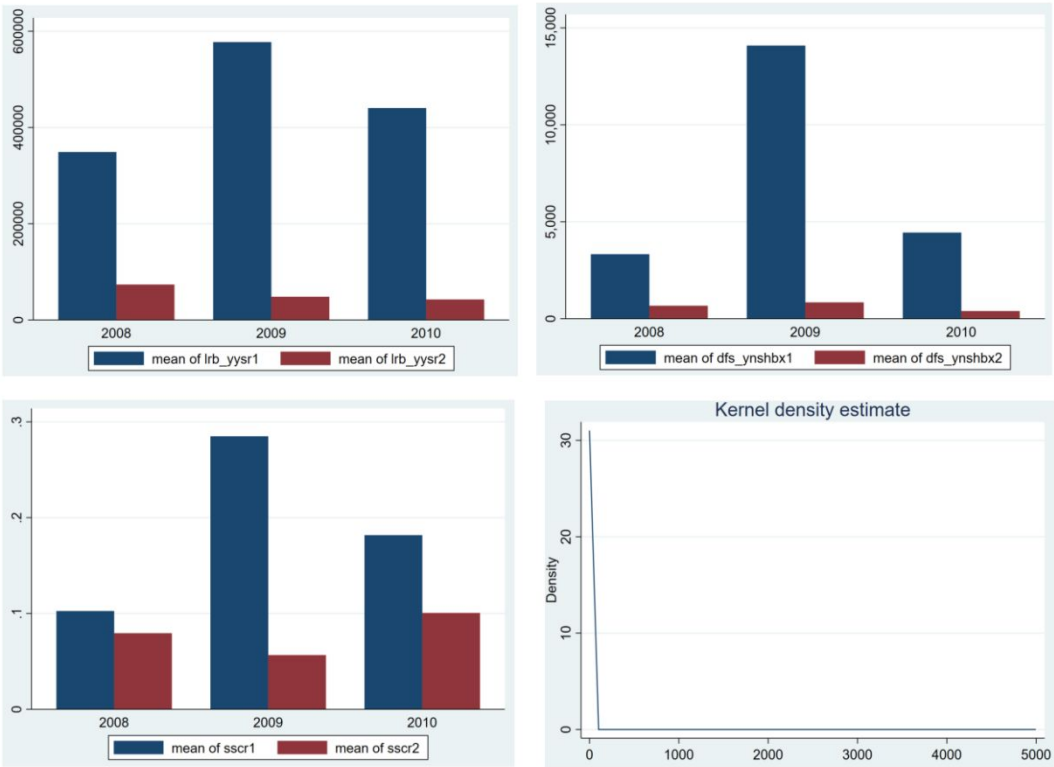
Appendix D. Distribution map



Panel A. All enterprises

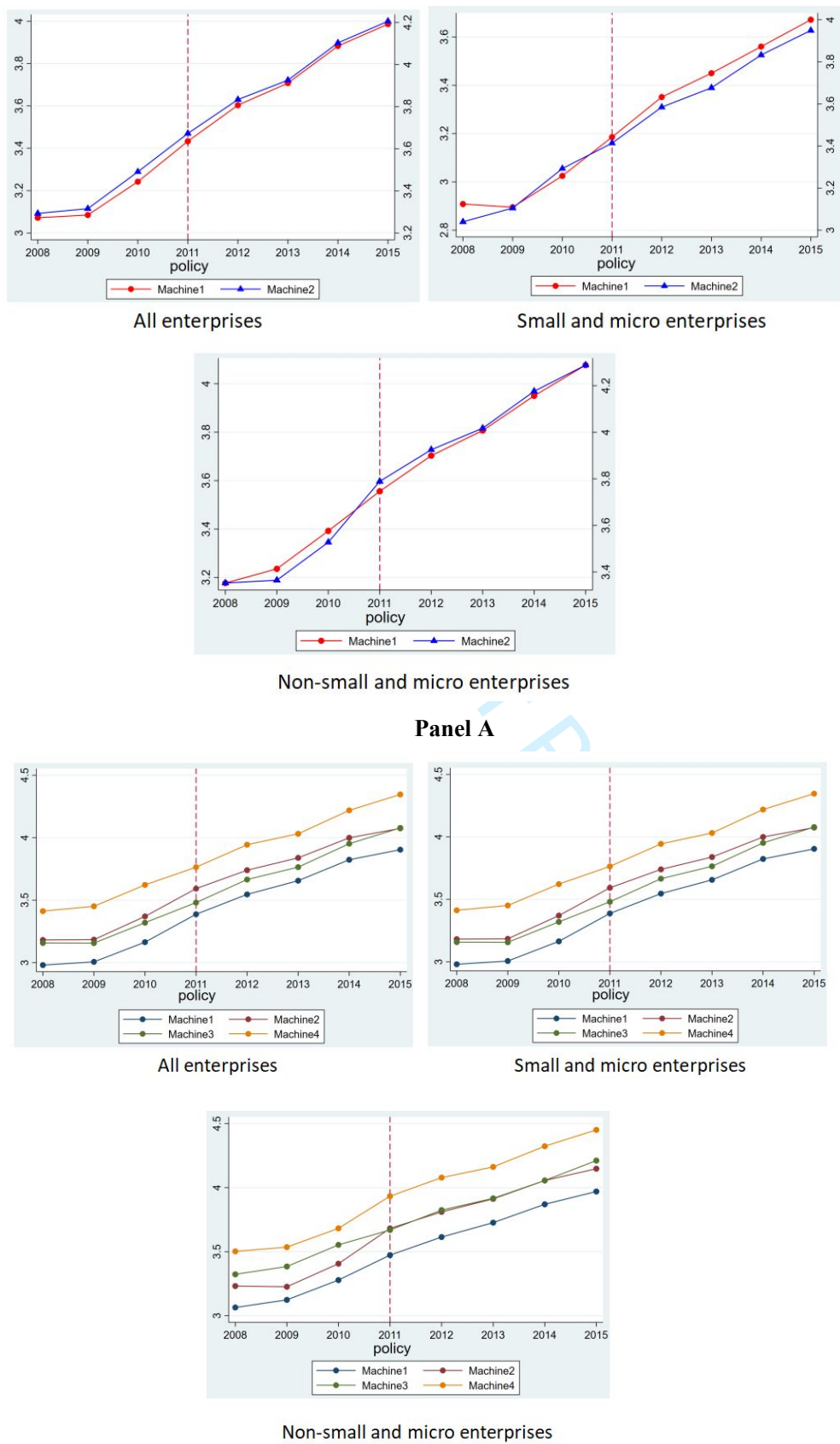


Panel B. SMSEs

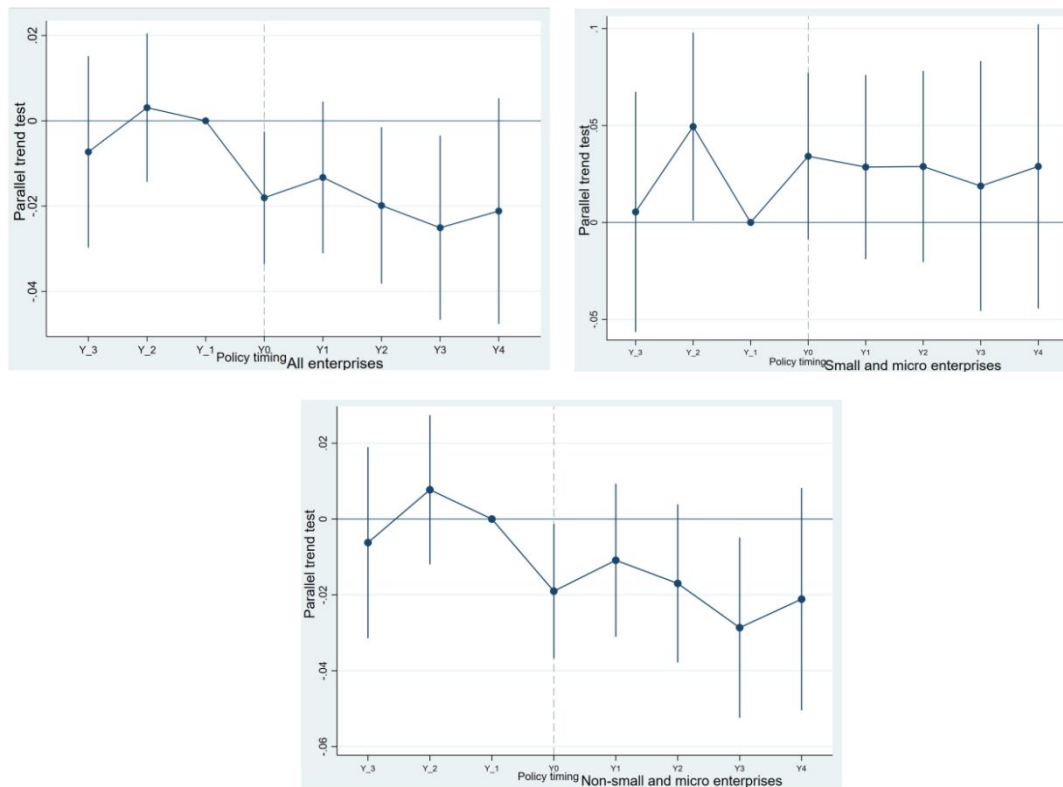
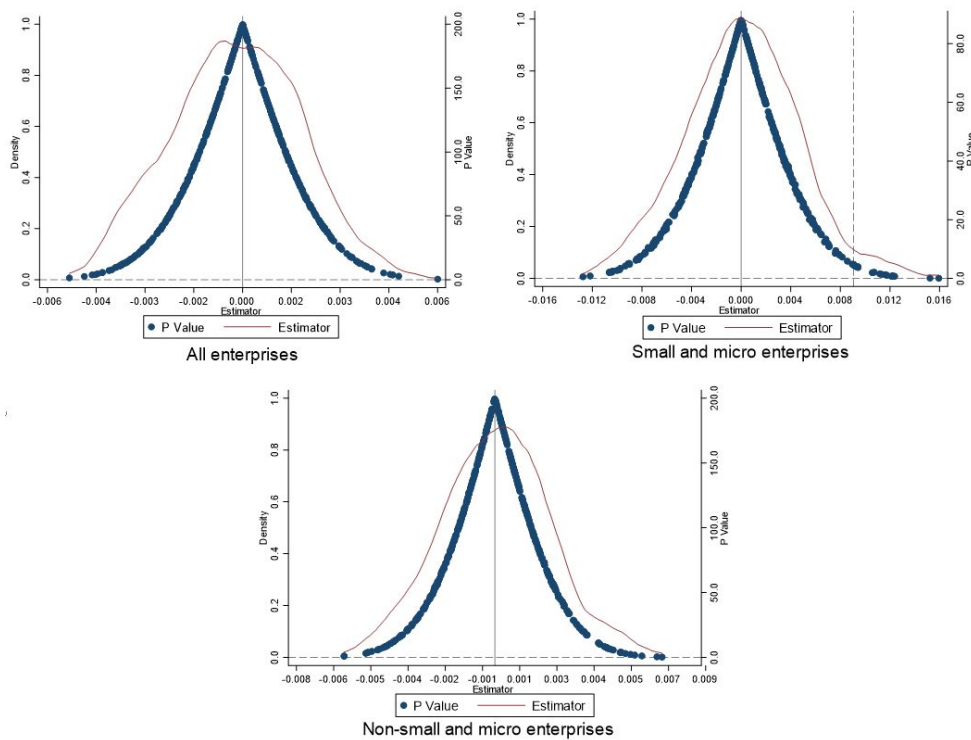


Panel C. Non-SMSEs

Figure 1. Trend charts



Panel B

Figure 2. Parallel trends**Figure 3. Placebo test**

Notes: The underlying coefficients for full firms and non-SMSEs are far from zero and are not plotted in the figure

Table 1. Descriptive Statistics

Variable	Observations	Mean	Std	p25	Median	p75	Min	Max
<i>LAE</i>	1,230,128	3.5630	0.9990	3.0630	3.5330	4.0610	-9.4440	14.5050
<i>Treat</i>	1,230,128	0.5160	0.5000	0.0000	1.0000	1.0000	0.0000	1.0000
<i>Post</i>	1,230,128	0.5770	0.4940	0.0000	1.0000	1.0000	0.0000	1.0000
<i>AI</i>	1,230,128	0.4520	0.4980	0.0000	0.0000	1.0000	0.0000	1.0000
<i>Size</i>	1,230,128	10.8070	1.9880	9.4280	10.7350	12.0900	6.2400	16.6730
<i>Lev</i>	1,230,128	0.6200	0.2720	0.3980	0.6530	0.8550	0.1640	1.0000
<i>ROA</i>	1,230,128	0.0200	0.1230	-0.0080	0.0100	0.0490	-0.5860	0.6050
<i>Capitalgrow</i>	1,230,128	0.1840	1.2750	-0.0470	0.0370	0.2030	-4.6970	8.4130
<i>Lqrat</i>	1,230,128	0.1150	0.4020	-0.0750	0.1170	0.3560	-1.5900	0.9740
<i>PPE</i>	1,230,128	0.2010	0.2080	0.0340	0.1320	0.3030	0.0000	0.9180
<i>GDP</i>	1,230,128	10.6890	0.4950	10.3580	10.7090	11.0650	9.4820	11.5500

Table 2. T-test results for the means of different sample groups

	Treatment group (N=634,629)				Control group (N=595,499)				Total difference
	SMSE (N=134655)	Non-SMSE (N=499974)		Total mean	SMSE (N=212326)	Non-SMSE (N=383173)		Total mean (N=134655)	
<i>Variables</i>	(1) Mean	(2) Mean	(3) Difference	(4)	(5) Mean	(6) Mean	(7) Difference	(8)	(9)
<i>LAE</i>	3.2020	3.5600	0.3580***	3.4840	3.3480	3.8140	0.4660***	3.6480	0.1630***
<i>Size</i>	9.2810	11.4400	2.1590***	10.9820	9.1510	11.4340	2.2830***	10.6200	-0.3620***
<i>Lev</i>	0.6130	0.6560	0.0430***	0.6470	0.5790	0.5980	0.0200***	0.5910	-0.0560***
<i>ROA</i>	0.0030	0.0320	0.0290***	0.0260	-0.0100	0.0260	0.0360***	0.0130	-0.0130***
<i>Capitalgrow</i>	0.1600	0.2200	0.0600***	0.2070	0.1280	0.1760	0.0490***	0.1590	-0.0480***
<i>Lqrat</i>	0.1430	0.1240	-0.0190***	0.1280	0.1090	0.0960	-0.0130***	0.1000	-0.0280***
<i>PPE</i>	0.1960	0.1660	-0.0300***	0.1720	0.2370	0.2280	-0.0080***	0.2310	0.0590***
<i>GDP</i>	10.6310	10.7040	0.0740***	10.6890	10.6060	10.7350	0.1300***	10.6890	0.0010

Table 3. Main result

	LAE		
	Full sample	SMSE	Non-SMSE
	(1)	(2)	(3)
<i>Treat×Post×AI</i>	-0.0172*** (0.0058)	0.0199 (0.0157)	-0.0219*** (0.0067)
<i>Treat×Post</i>	0.0724*** (0.0047)	0.0223 (0.0136)	0.0778*** (0.0055)
<i>Post×AI</i>	0.0265*** (0.0036)	-0.0061 (0.0073)	0.0333*** (0.0044)
<i>Size</i>	0.0957*** (0.0031)	0.1112*** (0.0067)	0.0776*** (0.0036)
<i>Lev</i>	-0.0418*** (0.0083)	-0.0032 (0.0163)	-0.0452*** (0.0100)
<i>ROA</i>	0.0162 (0.0102)	-0.0838*** (0.0183)	0.0468*** (0.0128)
<i>Capitalgrow</i>	-0.0023*** (0.0007)	-0.0016 (0.0013)	-0.0025*** (0.0008)
<i>Lqrat</i>	-0.0192*** (0.0056)	0.0026 (0.0108)	-0.0207*** (0.0069)
<i>PPE</i>	0.1094*** (0.0102)	0.1655*** (0.0193)	0.0818*** (0.0125)
<i>GDP</i>	0.1716*** (0.0145)	0.0865*** (0.0304)	0.1916*** (0.0172)
<i>Constant</i>	2.5290*** (0.7937)	4.4067*** (1.7087)	2.2220*** (0.7211)
ψ_{pt}	Yes	Yes	Yes
τ_{jt}	Yes	Yes	Yes
μ_t	Yes	Yes	Yes
λ_i	Yes	Yes	Yes
<i>N</i>	1230128	346981	883147
<i>R</i> ²	0.1184	0.0968	0.1247

Note: The values in parentheses represent firm-level clustered standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "Constant" represents the intercept term. λ_i and μ_t correspond to individual and time fixed effects, while τ_{jt} and ψ_{pt} represent industry and province trend effects. If Treat and Post are defined in three panels, the regression results are consistent with the baseline regression results.

Table 4 Parallel trend test

	<i>LAE</i>		
	Full sample	SMSE	Non-SMSE
	(1)	(2)	(3)
$T_1 \times Treat \times AI$	-0.0058 (0.0115)	0.0130 (0.0312)	-0.0063 (0.0129)
$T_2 \times Treat \times AI$	0.0038 (0.0088)	0.0494** (0.0238)	0.0084 (0.0100)
$T_3 \times Treat \times AI$	-0.0185** (0.0078)	0.0405* (0.0209)	-0.0218** (0.0089)
$T_4 \times Treat \times AI$	-0.0099 (0.0090)	0.0429* (0.0233)	-0.0112 (0.0102)
$T_5 \times Treat \times AI$	-0.0185** (0.0092)	0.0325 (0.0242)	-0.0177* (0.0105)
$T_6 \times Treat \times AI$	-0.0229** (0.0109)	0.0252 (0.0323)	-0.0276** (0.0120)
$T_7 \times Treat \times AI$	-0.0164 (0.0133)	0.0605 (0.0368)	-0.0235 (0.0148)
<i>Controls</i>	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes
τ_{it}	Yes	Yes	Yes
μ_t	Yes	Yes	Yes
λ_i	Yes	Yes	Yes
<i>N</i>	1230128	346981	883147
<i>R</i> ²	0.1185	0.0969	0.1250

Note: The values in parentheses represent firm-level clustered standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Constant represents the intercept term, and Controls represent the control variables, including *Size*, *Lev*, *ROA*, *Capitalgrow*, *Lqrat*, *PPE*, and *GDP*. λ_i and μ_t represent individual and time fixed effects, while τ_{it} and ψ_p represent industry and province trend effects. The regressions are performed according to equation (16), and the regressions also control for each cross-multiplier term of the firms, with the table showing only the important elements.

Table 5. Strict placebo test

	LAE		
	Full sample	SMSE	Non-SMSE
	(1)	(2)	(3)
$Treat \times Post_{false} \times AI$	0.0047 (0.0047)	-0.0081 (0.0100)	0.0005 (0.0055)
$Treat \times Post_{false}$	0.0631*** (0.0034)	0.0377*** (0.0078)	0.0677*** (0.0040)
$Post_{false} \times AI$	0.0315*** (0.0039)	0.0035 (0.0080)	0.0421*** (0.0047)
Controls	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes
τ_{it}	Yes	Yes	Yes
μ_t	Yes	Yes	Yes
λ_i	Yes	Yes	Yes
N	1230128	346981	883147
R ²	0.1184	0.0968	0.1248

Notes: The values in parentheses represent firm-level clustered standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Constant represents the intercept term, and Controls represent the control variables, including *Size*, *Lev*, *ROA*, *Capitalgrow*, *Lqrat*, *PPE*, and *GDP*. λ_i and μ_t represent individual and time fixed effects, while τ_{it} and ψ_p represent industry and province trend effects.

Table 6. Other robustness test

Panel A: Regrouping of firm types

	LAE		
	Full sample	SMSE	Non-SMSE
	(1)	(2)	(3)
$Treat \times Post \times AI$	-0.0182*** (0.0059)	-0.0037 (0.0169)	-0.0228*** (0.0064)
$Treat \times Post$	0.0729*** (0.0048)	0.0669*** (0.0141)	0.0733*** (0.0052)
$Post \times AI$	0.0253*** (0.0037)	0.0047 (0.0095)	0.0316*** (0.0040)
Controls	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes
τ_{it}	Yes	Yes	Yes
μ_t	Yes	Yes	Yes
λ_i	Yes	Yes	Yes
N	1230104	267732	962372
R ²	0.1160	0.0732	0.1257

Panel B: Delete 2011 sample

	LAE		
	Full sample	SMSE	Non-SMSE
	(1)	(2)	(3)
$Treat \times Post \times AI$	-0.0146** (0.0067)	0.0154 (0.0193)	-0.0160** (0.0078)
$Treat \times Post$	0.0653*** (0.0056)	0.0278* (0.0166)	0.0669*** (0.0065)
$Post \times AI$	0.0281*** (0.0042)	-0.0048 (0.0090)	0.0340*** (0.0051)
Controls	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes
τ_{it}	Yes	Yes	Yes
μ_t	Yes	Yes	Yes

λ_i	Yes	Yes	Yes
N	1009761	275257	734504
R^2	0.1431	0.1218	0.1470
Panel C: Add industry-year joint fixed effects and province-year joint fixed effects			
	<i>LAE</i>		
	Full sample	SMSE	Non-SMSE
	(1)	(2)	(3)
$Treat \times Post \times AI$	-0.0210*** (0.0060)	0.0142 (0.0157)	-0.0214*** (0.0071)
$Treat \times Post$	0.0826*** (0.0051)	0.0299** (0.0138)	0.0868*** (0.0060)
$Post \times AI$	0.0160*** (0.0057)	-0.0009 (0.0106)	0.0105 (0.0071)
Controls	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes
τ_{it}	Yes	Yes	Yes
μ_t	Yes	Yes	Yes
λ_i	Yes	Yes	Yes
Φ_{s-t}	Yes	Yes	Yes
Π_{p-t}	Yes	Yes	Yes
N	1230128	346981	883147
R^2	0.1253	0.1073	0.1318
Panel D: Changing treatment group definition			
	<i>LAE</i>		
	Full sample	SMSE	Non-SMSE
	(1)	(2)	(3)
$Treat1 \times Post \times AI$	-0.0542*** (0.0061)	-0.0188 (0.0136)	-0.0464*** (0.0085)
$Treat1 \times Post$	0.0936*** (0.0049)	0.0920*** (0.0112)	0.1041*** (0.0067)
$Post \times AI$	0.0435*** (0.0034)	0.0056 (0.0106)	0.0439*** (0.0037)
Controls	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes
τ_{it}	Yes	Yes	Yes
μ_t	Yes	Yes	Yes
λ_i	Yes	Yes	Yes
N	1247164	354076	893088
R^2	0.1184	0.0973	0.1248

Notes: The values in parentheses represent firm-level clustered standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Constant represents the intercept term, and Controls represent the control variables, including *Size*, *Lev*, *ROA*, *Capitalgrow*, *Lqrat*, *PPE*, and *GDP*. λ_i and μ_t represent individual and time fixed effects, while τ_{it} and ψ_p represent industry and province trend effects.

Table 7. Corporate burden

Panel A: Labor costs						
	<i>Ingw</i>					
	Full sample		SMSE		Non-SMSE	
	(1)		(2)		(3)	
<i>Treat</i> × <i>Post</i>	0.0226*** (0.0007)		0.0136*** (0.0017)		0.0233*** (0.0008)	
<i>Controls</i>	Yes		Yes		Yes	
ψ_{pt}	Yes		Yes		Yes	
τ_{jt}	Yes		Yes		Yes	
μ_t	Yes		Yes		Yes	
λ_i	Yes		Yes		Yes	
<i>N</i>	839954		221327		618627	
<i>R</i> ²	0.0198		0.0207		0.0200	
Panel B: Social insurance contribution costs						
	<i>LAE</i>					
	Full sample		SMSE		Non-SMSE	
	burden=1	burden=0	burden=1	burden=0	burden=1	burden=0
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Treat</i> × <i>Post</i> × <i>AI</i>	-0.0072 (0.0098)	-0.0089 (0.0090)	0.0494* (0.0278)	-0.0096 (0.0291)	-0.0316*** (0.0119)	0.0028 (0.0102)
<i>Treat</i> × <i>Post</i>	0.0556*** (0.0086)	0.0478*** (0.0070)	-0.0041 (0.0258)	0.0283 (0.0254)	0.0677*** (0.0107)	0.0399*** (0.0082)
<i>Post</i> × <i>AI</i>	-0.0168*** (0.0063)	0.0160*** (0.0054)	-0.0556*** (0.0129)	0.0031 (0.0121)	-0.0018 (0.0083)	0.0112* (0.0063)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes	Yes	Yes	Yes
τ_{jt}	Yes	Yes	Yes	Yes	Yes	Yes
μ_t	Yes	Yes	Yes	Yes	Yes	Yes
λ_i	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	402539	450981	86250	85222	279130	320599
<i>R</i> ²	0.1445	0.0967	0.1353	0.0872	0.1579	0.0985
Panel C: Financial constrains						
	<i>LAE</i>					
	Full sample		SMSE		Non-SMSE	
	<i>constraint</i> =0	<i>constraint</i> =1	<i>constraint</i> =0	<i>constraint</i> =1	<i>constraint</i> =0	<i>constraint</i> =1
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Treat</i> × <i>Post</i> × <i>AI</i>	-0.0223** (0.0114)	-0.0088 (0.0081)	0.0710** (0.0311)	-0.0093 (0.0247)	-0.0537*** (0.0136)	0.0072 (0.0093)
<i>Treat</i> × <i>Post</i>	0.0730*** (0.0095)	0.0564*** (0.0068)	-0.0151 (0.0284)	0.0319 (0.0216)	0.1016*** (0.0115)	0.0481*** (0.0079)
<i>Post</i> × <i>AI</i>	0.0087 (0.0069)	0.0294*** (0.0051)	-0.0298** (0.0140)	0.0095 (0.0110)	0.0363*** (0.0093)	0.0232*** (0.0060)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes	Yes	Yes	Yes
τ_{jt}	Yes	Yes	Yes	Yes	Yes	Yes
μ_t	Yes	Yes	Yes	Yes	Yes	Yes
λ_i	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	348097	481914	80655	86186	230631	351908
<i>R</i> ²	0.0955	0.1301	0.0935	0.1202	0.1051	0.1321

Notes: The values in parentheses represent firm-level clustered standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Constant represents the intercept term, and Controls represent the control variables, including *Size*, *Lev*, *ROA*, *Capitalgrow*, *Lqrat*, *PPE*, and *GDP*. λ_i and μ_t represent individual and time fixed effects, while τ_{jt} and ψ_p represent industry and province trend effects.

Table 8. Corporate response

Panel A: Labor cost						
	<i>Ingw</i>					
	Full sample		SMSE		Non-SMSE	
	(1)		(2)		(3)	
<i>Treat</i> × <i>Post</i> × <i>AI</i>	-0.0168*** (0.0013)		-0.0051 (0.0034)		-0.0247*** (0.0014)	
<i>Treat</i> × <i>Post</i>	0.0307*** (0.0011)		0.0170*** (0.0027)		0.0349*** (0.0013)	
<i>Post</i> × <i>AI</i>	0.0081*** (0.0011)		0.0010 (0.0021)		0.0210*** (0.0013)	
<i>Controls</i>	Yes		Yes		Yes	
ψ_{pt}	Yes		Yes		Yes	
τ_{it}	Yes		Yes		Yes	
μ_t	Yes		Yes		Yes	
λ_i	Yes		Yes		Yes	
<i>N</i>	839954		221327		618627	
<i>R</i> ²	0.0201		0.0207		0.0213	
Panel B: Capital-labor ratio						
	<i>K/L</i>					
	Full sample		SMSE		Non-SMSE	
	(1)		(2)		(3)	
<i>Treat</i> × <i>Post</i> × <i>AI</i>	0.2397** (0.1208)		0.3097 (0.2978)		0.3075* (0.1585)	
<i>Treat</i> × <i>Post</i>	-0.2768** (0.1253)		-0.3496 (0.3037)		-0.3486** (0.1714)	
<i>Post</i> × <i>AI</i>	-0.1770* (0.1026)		-0.3787 (0.2933)		-0.1450 (0.1300)	
<i>Controls</i>	Yes		Yes		Yes	
ψ_{pt}	Yes		Yes		Yes	
τ_{it}	Yes		Yes		Yes	
μ_t	Yes		Yes		Yes	
λ_i	Yes		Yes		Yes	
<i>N</i>	1265423		358992		906431	
<i>R</i> ²	0.0011		0.0007		0.0013	
Panel C: Low wage employee						
	<i>LAE</i>					
	Full sample		SMSE		Non-SMSE	
	<i>Lwage</i> =1 (1)	<i>Lwage</i> =0 (2)	<i>Lwage</i> =1 (3)	<i>Lwage</i> =0 (4)	<i>Lwage</i> =1 (5)	<i>Lwage</i> =0 (6)
<i>Treat</i> × <i>Post</i> × <i>AI</i>	-0.0230*** (0.0075)	-0.0197 (0.0170)	0.0132 (0.0231)	0.0674* (0.0345)	-0.0280*** (0.0083)	-0.0297 (0.0269)
<i>Treat</i> × <i>Post</i>	0.0665*** (0.0065)	0.0868** (0.0096)	0.0223 (0.0211)	0.0201 (0.0280)	0.0798*** (0.0072)	0.0818*** (0.0129)
<i>Post</i> × <i>AI</i>	-0.0036 (0.0043)	-0.0307*** (0.0108)	-0.0398*** (0.0096)	-0.0301* (0.0170)	0.0068 (0.0051)	-0.0643*** (0.0195)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes	Yes	Yes	Yes
τ_{it}	Yes	Yes	Yes	Yes	Yes	Yes
μ_t	Yes	Yes	Yes	Yes	Yes	Yes
λ_i	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	619631	233889	118869	52603	452738	146991
<i>R</i> ²	0.1588	0.0512	0.1407	0.0647	0.1659	0.0461

Notes: The values in parentheses represent firm-level clustered standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Constant represents the intercept term, and Controls represent the control variables, including *Size*, *Lev*, *ROA*, *Capitalgrow*, *Lqrat*, *PPE*, and *GDP*. λ_i and μ_t represent individual and time fixed effects, while τ_{it} and ψ_p represent industry and province trend effects.

Table 9. Corporate output

	g_a		
	Full sample	SMSE	Non-SMSE
	(1)	(2)	(3)
$Treat \times Post \times AI$	0.0405*** (0.0151)	-0.0023 (0.0136)	0.0433** (0.0186)
$Treat \times Post$	-0.0394*** (0.0142)	-0.0070 (0.0109)	-0.0378** (0.0176)
$Post \times AI$	-0.0240*** (0.0080)	0.0075 (0.0126)	-0.0280*** (0.0095)
Controls	Yes	Yes	Yes
ψ_{pt}	Yes	Yes	Yes
τ_{jt}	Yes	Yes	Yes
μ_t	Yes	Yes	Yes
λ_i	Yes	Yes	Yes
N	723498	186257	537241
R^2	0.0005	0.0019	0.0003

Notes: The values in parentheses represent firm-level clustered standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Constant represents the intercept term, and Controls represent the control variables, including *Size*, *Lev*, *ROA*, *Capitalgrow*, *Lqrat*, *PPE*, and *GDP*. λ_i and μ_t represent individual and time fixed effects, while τ_{jt} and ψ_p represent industry and province trend effects.