From Employer Responsibility to Environmental Irresponsibility: Unintended Effects of Social Insurance Law on Pollution Emissions

Yanan Li[1]

Yu Qin[2]

Wenjun Wang[3]

Abstract

This study examines the unintended impact of the introduction of the 2011 Social Insurance Law on firms' pollution emissions. Using a difference-in-differences research design, we find that enhanced social insurance contributions provoke higher industrial pollution emissions. The effect is more pronounced in non-SOE firms, firms in heavy-polluting industries, and those subject to lax environmental regulations. The mechanism analysis reveals that the implementation of the Social Insurance Law increases firms' labor cost and financial distress, and motivates them to reduce efforts on end-of-pipe treatment activities and measures taken during production process, thus leading to higher pollution emission intensity. Overall, our study highlights the potential conflict between employee protection and corporate environmental goals, providing important implications for policy making.

JEL: J32, Q50, Q53

Key Words: Social Insurance Law; ESG; Pollution Emissions; Pollution Reduction Activity

---

[1] Business School, Beijing Normal University. E-mail: yananli@bnu.edu.cn
[2] Department of Real Estate, Business School, National University of Singapore. E-mail: bizqyu@nus.edu.sg
[3] Investment Banking Division, Agricultural Bank of China. E-mail: wenjunwang00@gmail.com

1 Introduction

Paying social insurance contributions is widely recognized as an important aspect of the Social component within Environmental, Social and Governance (ESG) frameworks (Han et al., 2014). In recent years, several developing countries, such as Ethiopia, China, Brazil, and Thailand, have implemented significant enhancements to their social insurance systems, mandating employers to contribute insurance premiums on behalf of their employees (Liu et al., 2021a; Bedi et al., 2022). While these policies have expanded social insurance coverage, they have concurrently introduced additional labor costs, generating potential financial constraints for businesses (Rauh, 2006; Almaghrabi, 2023; Shivdasani and Stefanescu, 2010). Such financial circumstances may precipitate managerial short-termism, wherein corporate executives prioritize short-term financial outcomes over long-term growth strategies in response to cost pressures (Shleifer, 2004; Liu et al., 2021b; Xu and Kim, 2022). One manifestation of such unintended short-termism behavior pertains to environmental emissions. This study aims to examine whether increased social insurance contributions lead to a negative externality, captured by higher pollution emissions among affected entities.

Social insurance contributions and environmental initiatives both contribute to the broader concept of ESG. Investigating the interplay between social security contributions and corporate pollution activities offers critical insights into the relationship between employment-related ESG factors and environmental ESG. Environmental compliance costs associated with abatement efforts constitute a significant portion of a firm's operating expenses. If heightened social insurance contributions inadvertently lead to a surge in pollution emissions, this suggests a potential trade-off between these two ESG components. Understanding such conflicting interests can inform more effective policy decisions that promote sustainable development (Compagnie et al., 2023). Additionally, as stakeholders increasingly demand accountability for ESG performance, recognizing these trade-offs enables firms to better align their practices with long-term sustainability objectives. This analysis is thus crucial not only for corporate governance but also for policymakers seeking to create regulations that encourage holistic approaches to ESG.

However, it remains theoretically ambiguous whether firms would resort to environmentally irresponsible measures to offset the increased social insurance costs. On the one hand, enhanced social insurance contributions could increase labor cost, potentially leading to financial constraint (Shivdasani and Stefanescu, 2010; Rickne, 2013; Liu et al., 2021a). This financial pressure may motivate firms to shift toward risky but cash-saving corporate strategies, such as reducing investments in pollution abatement measures. For example, Xu and Kim (2022) documents that firms tend to cut back on pollution abatement efforts under financial distress, given that these expenditures can represent more than 20% of the total capital investment. On the other hand, pollution emission is not always a straightforward outcome because such strategies may damage firms' environmental, social, and governance (ESG) reputation and result in financial penalties (Shapira and Zingales, 2017). Therefore, the theoretical ambiguity surrounding whether firms modify their pollution emission behavior in response to heightened social insurance contributions warrants empirical investigation.

This article leverages the implementation of China's Social Insurance Law in 2011 as an exogenous shock to empirically test the impacts of increased social insurance contributions on corporate pollution emissions. The law imposes an obligation on firms operating in China to provide social security benefits to their employees and reinforces government monitoring to ensure compliance. As social security contributions account for nearly 30% of total payroll in China (Rickne, 2013), the implementation of this law results in a significant rise in firms' labor costs.

We combine the Annual Survey of Industrial Firms (ASIF) database and the Environmental Survey and Reporting (ESR) database from 2008 to 2013. Empirical findings demonstrate a significant increase in the chemical oxygen demand (COD) emissions intensity among labor intensive firms following the enactment of the social insurance law. Specifically, our findings indicate that a one standard deviation increase in pre-existing labor intensity within the average firm in the sample leads to a 2.95 percent increase in COD emission intensity. It implies that firms may prioritize meeting social insurance regulations over implementing pollution abatement measures, leading to a detrimental impact on the environment. Our dynamic analysis supports the parallel trend assumption associated with

DID estimation. We conduct various robustness checks of the main findings, including a propensity score matching analysis, permutation tests, and the use of alternative measures for outcome and independent variables. The outcomes remain materially unchanged.

The heterogeneity analysis reveals that the emission effects of enhancing social insurance coverage are more pronounced for non-state-owned enterprises, firms subject to less-stringent environmental regulations, and firms in heavy-polluting industries. We also conduct a mechanism analysis that shows the social insurance law substantially increases corporate labor cost and financial distress. In response to this financial pressure, firms choose to allocate fewer resources towards pollution abatement measures, both in terms of end-of-pipe treatment and production process strategy, which ultimately results in an increase in pollution emissions intensity.

The main contribution of this study lies in providing the first causal evidence between social insurance regulations and corporate environmental behavior. This study is particularly relevant to developing economies that face the dual challenge of expanding social insurance coverage to protect workers while moving towards environmental-friendly society. Our findings can inform policymakers about the potential trade-offs between the social and environmental components of ESG when implementing social insurance reforms. Given the significance of the topic, the paucity of existing studies is remarkable. While a few studies have documented the effects of insurance arrangements on various outcomes such as workers' compensation (Bedi et al., 2022), immigrant responses (Bratsberg et al., 2020), corporate investment (Bartram, 2017), capital structure (Shivdasani and Stefanescu, 2010; Bartram, 2016; Liu et al., 2021a), cash holdings (Almaghrabi, 2023), our study stands out as the initial inquiry into whether increased social insurance contributions result in greater pollution emissions. Our findings underscore that strengthening social insurance collection can have unintended consequences that negatively impact the environmental health of the surrounding community. Furthermore, our supplementary analysis indicates that monitoring mechanisms, reflected by enforcement of environmental regulations, may partially mitigate corporate pollution response.

We contribute novel empirical evidence suggesting that labor market policies may spill over to corporate environmental performance. Previous research has predominantly examined how environmental regulations affect labor market outcomes (Walker, 2011; Gray et al., 2014; Curtis, 2018; Liu et al., 2021c), with limited exploration into the reverse relationship (one exception is the work by Zhang et al. 2023). Recently, there has been growing interest in understanding the impacts of non-environmental policy shocks on pollution emissions, such as international trade, investment induced tax cuts, reforms in higher education expansion, and deregulation in banking (Rodrigue et al., 2022a; Rodrigue et al., 2022b; Qi et al., 2023; Chen et al., 2021; Chen et al., 2023).[4] Building on this emerging literature, we emphasize that social insurance policies, as a significant labor market intervention, could inadvertently influence firm emissions. This underscores the broader implications for understanding how labor market policies, such as wrongful discharge laws in the US and labor contract laws in China, might inadvertently impact environmental outcomes.

Additionally, we draw upon recent literature that emphasizes the adverse effects of corporate financial burden and credit constraints on corporate environmental behavior (Andersen 2016; 2017; Xu and Kim, 2022). Prior research has established that heightened financial pressures can lead to increased emissions. For example, Liu et al (2021b) demonstrate that Chinese firms tend to increase pollution emissions under earnings pressure and financial constraints. Likewise, Bartram et al. (2022) illustrate that financially constrained firms respond to climate policy regulations by shifting emissions from regulated states to non-regulated ones, thereby increasing total emissions. Interestingly, the impact of financial burden on emission seems to be symmetric – while increased financial burdens could increase emission, the relaxation of such constraints could potentially reduce emissions (Chen et al. 2023; Xu and Kim, 2022). Collectively, these studies support an earlier conjecture by Shleifer (2004) that market pressures may induce less ethical corporate

[4]There is a large literature documenting the role of environmental regulations in mitigating corporate emissions. Such policies include both command-and-control measures (e.g., emission standards) and market-based approaches (e.g., cap-and-trade programs) (e.g., Wang and Wheeler, 2000; Kathuria, 2006; Fowlie, 2010; Chen et al., 2018; Shapiro and Walker, 2018; Hu et al., 2022; Mao et al., 2023).

behavior in the short term. In line with this discourse, we contribute to the conversation by highlighting how increased labor costs from social insurance reforms could lead to short-term “unethical” behavior in pollution emissions.

The remainder of this paper is structured as follows: Section 2 provides an overview of the institutional background. Section 3 outlines the research design and sample selection process, as well as the data sources and variables used in our research. Section 4 presents and discusses our empirical findings with various robustness checks. Section 5 conducts a mechanism analysis. Finally, Section 6 concludes our study, offering policy implications based on the findings.

2 Institutional background: 2011 Social Insurance Law

Social insurance schemes are fundamental components of government social safety nets, designed to safeguard workers from financial insecurity caused by accidents, illnesses, unemployment, or other risks. In the early 2000s, the Chinese government established a comprehensive framework for its social security system, which includes pension insurance, medical insurance, maternity insurance, employment injury insurance, and unemployment insurance. Under this framework, the employer contribution rates for each type of insurance are set at 16%, 8%, 2%, 0.5%, and 0.5%, respectively, with variations across jurisdictions.[5] Employer monthly contributions are calculated by applying these rates to an employee’s payment base, which is determined by dividing the employee’s total annual income (before tax) from the previous calendar year by twelve.[6] Consequently, the overall employer social insurance contribution rate in China ranges from 26% to 29% across various provinces. This substantial rate positions China’s social insurance program as one of the most expensive in the world (Rickne, 2013).

Despite the high nominal contribution rates, the effectiveness of this system was undermined by lax enforcement, resulting in widespread non-payment and underpayment by many firms. To address these issues and enhance social protection for employees, the Chinese government promulgated the Social Insurance Law in October 2010, which came

[5] The corresponding contribution rates for employees are 8%, 2%, 0%, 0%, and 0.5% of their total pre-tax income, with variations depending on the region.

[6] https://www.china-briefing.com/doing-business-guide/china/human-resources-and-payroll/social-insurance

into effect in July 2011. The law introduced stricter enforcement measures to facilitate social insurance contribution collection. Under the new law, employers who fail to meet their obligations of making timely and complete social insurance payments for their staff are subject to fines that range from one to three times the amount of the underpaid contributions. Additionally, if the employer neglects to make the required payments for a specified period, the relevant government agency is authorized to directly withdraw the owed amounts from the employer's bank account.

By enhancing surveillance and enforcement mechanisms, the 2011 Social Insurance Law significantly improved firms' compliance with the social insurance obligation, as noted by Liu et al. (2021a). To facilite an understanding of the law's impact, we plot the pattern of social insurance contribution rates in Figure 1, based on the National Tax Survey Database.[7] Due to the lack of direct information on employees' social insurance contribution bases at the firm level, we approximate this base using annual payroll expenses, net of social insurance contributions.[8] Firm-level contribution rates are therefore calculated as the ratio of social insurance contributions to the approximated contribution base. As illustrated by the solid line in Figure 1, the average social insurance contribution rate increased from 8% in 2010 to 20% in 2012 following the implementation of the law.

Additionally, we calculate contribution rates by directly using total payroll expenses as a proxy for the contribution base, similar to the approach taken by Liu et al. (2021a). With a larger denominator, this approach yields a lower contribution rate, as depicted by the dashed line in Figure 1. However, the trend in average social insurance contribution rates remains materially consistent with that derived from the first approach (represented by the solid line). Overall, the 2011 Social Insurance Law has led to a substantial increase in social insurance

---

[7] The data we use for the main analysis only have information on social security contribution for the year 2007. We therefore use the National Tax Survey data for the graphical illustration. This database, compiled jointly by the State Administration of Taxation and the Ministry of Finance of China, includes approximately 700,000 firms annually, spanning all sectors and regions across the nation.

[8] Payroll expense typically comprises total salaries and wages paid to employees, bonuses, employer social insurance contributions, and other welfare payment within a given year. The net amount, after deducting social insurance contributions, may still include employee welfare expenses and other labor-related expenditures, potentially exceeding the pre-tax total income used to define the contribution base. Thus, this approximation is likely to overestimate the true contribution base. Additionally, the contribution base is usually capped at 300% of the city-level average salary from the preceding year, which is not reflected in this approximation, further contributing to the overestimation of the contribution base.

contribution rates, thereby raising labor costs for employers. This context provides a unique opportunity to evaluate the impact of labor policies on corporate polluting activities.

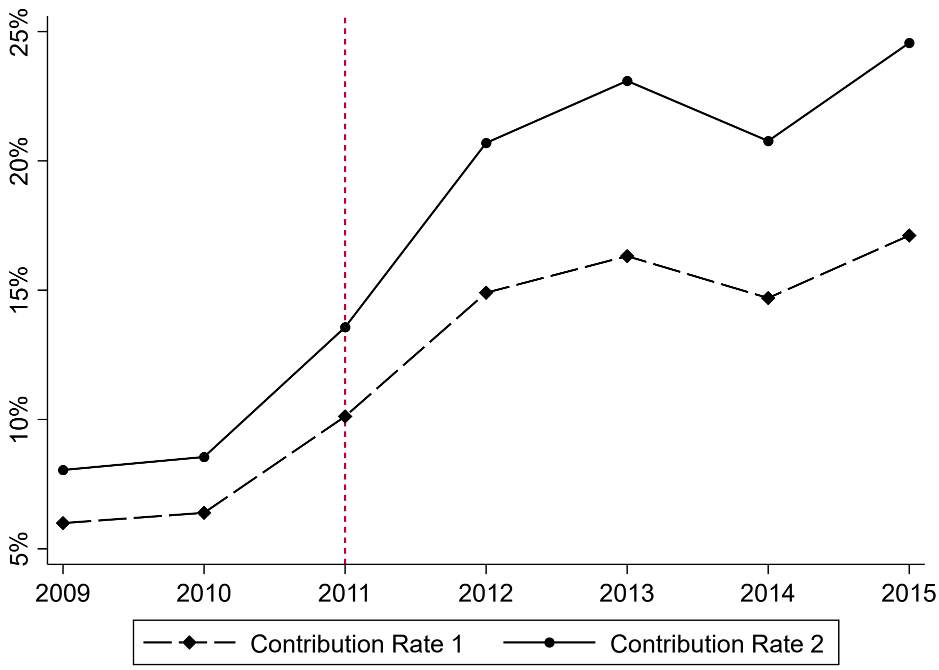


Figure 1 The Patterns of Social Insurance Contribution Rates

Note: The authors calculate social insurance contribution rates based on the National Tax Survey Database. Contribution rate 1 is calculated as the ratio of a firm's social insurance contributions to its gross payroll expense. Contribution rate 2 is calculated as a firm's social insurance contributions divided by the gross payroll expense net of social insurance contributions. Each dot represents the averaged social insurance contribution rates across firms for each year.

3 Data, variable and identification strategy

3.1 Data

We have effectively combined two distinct datasets that entail comprehensive insights into the performance of firms at the production, financial, and environmental levels. The first dataset we refer to is the Annual Survey of Industrial Firms (ASIF), compiled by China's National Bureau of Statistics, which encompasses all state-owned industrial enterprises and private industrial corporations with sales exceeding 5 million CNY. The ASIF database provides exhaustive coverage of the production and financial information of companies, such as output, sales, and profits. The second dataset utilized is the Environmental Survey and Reporting (ESR) database managed by the Ministry of Environmental Protection, which comprises data on the pollution emissions discharged by industrial enterprises, including COD (Chemical Oxygen Demand), ammonia nitrogen, sulfur dioxide, solid waste, and wastewater. Our analysis focuses on manufacturing firms since they are the primary source of industrial emissions. We merge these two datasets by employing firms' names and unique codes to construct a comprehensive panel dataset. This approach facilitates a thorough analysis of both the production and environmental profiles of the manufacturing firms.

The data we use in the analysis spans from 2008 to 2013. This time frame encompasses the five years leading up to the implementation of the Social Insurance Law in 2011, as well as the subsequent three years. We further refine the dataset by retaining firms within the manufacturing industry, exclude firms with an output value of less than 5 million CNY and exclude those that have observations only in pre-policy or post-policy periods. Our final sample comprises a total of 29,501 manufacturing firms, with 133,962 firm-year observations.

3.2 Variable construction

3.2.1 Dependent variable: pollution emission intensity

We use the emission intensity of Chemical Oxygen Demand (COD) as the dependent variable, calculated by dividing COD emissions by the total industrial output (as in He et al., 2020; Chen et al., 2021). To further diminish the influence of outliers, we have applied the natural logarithm transformation to the COD emission intensity variable. We choose to mainly focus on COD emission for two primary reasons. First, COD stands as a crucial indicator for water pollution, representing the quantity of oxidant required to degrade organic matter under specific conditions. Higher COD levels signify more pronounced organic pollution in freshwater ecosystems. Moreover, the 11th, 12th, and 13th Five-Year Plans of China have categorized COD emissions as critical pollutants and mandated a reduction of COD emissions of 10% during the 11th Five-Year Plan (2006-2010). Second, the data on COD emission has less missing observations thus exhibiting greater quality in comparison to other pollutants such as industrial wastewater, sulfur dioxide, and ammonia nitrogen, hence making it a more informative indicator for evaluating industrial pollution emissions.

3.2.2 Independent variables and control variables

We utilize labor intensity as a measure of firms' exposure to the Social Insurance Law. Specifically, we calculate the ratio of the number of employees to the total assets at the end of 2010 (Cui et al., 2018; Li et al., 2019), the year before the promulgation of the law. A higher ratio indicates greater degrees of labor intensity, and consequently increased exposure to the Social Insurance Law. In the robustness check section, we also consider firms' social insurance contribution rates prior to the law as an alternative measure of corporate exposure.[9]

The control variables include factors commonly employed in studies on firm-level pollution emissions (e.g., Chen et al., 2021; Qi et al., 2023). We use the natural logarithm of total assets to proxy for firm size (*Size*). Financial leverage (*Leverage*) is defined as total liabilities divided by total assets. The proportion of tangible assets (*Tangibles*) is calculated as the ratio of fixed assets to total assets. We also control the share of export (*Export*), which is measured as the value of export output divided by total sales.

Table 1 Summary Statistics

	Mean	SD	P25	Median	P75
Emission Intensity	4.942	14.315	0.107	0.551	2.975
Emission Intensity (log)	-0.595	2.311	-2.231	-0.596	1.09
Labor Intensity	0.062	2.127	0.014	0.027	0.052
Labor Intensity (log)	-3.639	1.055	-4.288	-3.61	-2.954
Firm Size	9.339	1.574	8.219	9.206	10.333
Financial Leverage	0.562	0.28	0.375	0.567	0.745
Tangibles	0.374	0.214	0.212	0.348	0.511
Share of Export	0.166	0.311	0	0	0.151
ROA	0.105	0.244	0.009	0.048	0.13

Notes: This table presents the descriptive statistics of the key variables. *Emission Intensity* is calculated as the amount of COD emitted divided by total output value (kg per 10,000 CNY). *Emission Intensity(log)* is defined as the natural logarithm of *Emission Intensity*. *Labor Intensity*(*log*) is proxied by the ratio of the number of employees to the total assets at the end of 2010 (in logarithm). *Firm Size* is defined as the natural logarithm of total assets (in ten thousand yuan). *Financial Leverage* is defined as total liabilities divided by total assets. *Tangibles* is defined as fixed assets divided by total assets. *Share of Export* is defined as the value of export output divided by total sales.

[9] We do not use contribution rates as the primary measure of policy exposure because this information is only available for or before 2007, and a substantial portion of firms lack data for our sample period.

3.3 Summary statistics

Table 1 provides a summary of key descriptive statistics for the variables used in the study. The COD emission intensity exhibited an average value of 4.94 (kg per 10,000 CNY output) with a standard deviation of 14.32. The natural logarithm of firm size has a mean value of 9.34 and standard deviation of 1.57. On average, debt accounted for more than half of manufacturing firms' assets. Fixed assets constituted 37.4% of total assets, on average. Additionally, we observed that the variable *Export* was right skewed and the average export value accounted for 16.6% of the manufacturer's total output. On average, the sample firms are profitable with average return on assets (ROA) at 10.5%.

3.4 Identification strategy

Our study examines the impact of corporate exposure to the social insurance law on environmental pollution emissions. The enactment of the 2011 social insurance law precipitated a discernible increase in corporate labor expenditures, notably impacting firms with a pronounced dependence on labor-intensive production processes. We acknowledge a simple comparison between firms with high versus low labor intensity bears endogeneity issues, due to firms' self-selection into different labor intensity status. To mitigate this concern, we employ a difference-in-differences methodology, which effectively accounts for the selection bias inherent in differences in firm-level characteristics.

By employing firm-level data, we compare pollution emission activities before and after the implementation of the policy across firms with different levels of labor intensity. Our underlying identifying assumption posits that, absent the policy implementation, the pollution emission intensity levels among firms characterized by varying degrees of labor intensity would exhibit parallel trends over time. Since individual firms had no control over the timing of the policy, they were unlikely to manipulate their labor intensity levels well in advance to avoid the compliance expenses post-implementation. We later adopt a dynamic model to evaluate the identifying assumption of a parallel trend in pollution emission among firms with different intensities of labor input use.

The specification of our baseline regression is as follows:

$$\boldsymbol{Y_{it} = \alpha_0 + \alpha_1 LaborIntensity_i \times Post_t + \beta X_{it} + \kappa_i + \delta_{st} + \varphi_{pt} + \varepsilon_{it}} \quad (1)$$

where $\boldsymbol{Y_{it}}$ is the natural logarithm of pollution emission intensity for firm *i* in year *t*; the dummy variable $\boldsymbol{Post_t}$ indicates whether the Social Insurance Law was implemented, and it takes a value of 0 from 2008 to 2011 and a value of 1 from 2012 to 2013. $\boldsymbol{LaborIntensity_i}$ is labor intensity for firm *i* at the end of 2010 (in logarithm); $\boldsymbol{X_{it}}$ indicates firm-level control variables, including firm size, financial leverage, tangibles and share of export. $\boldsymbol{\kappa_i}$ is a full set of firm-fixed effect, $\boldsymbol{\delta_{st}}$ is industry-year fixed effect that captures industry specific trends over time, $\boldsymbol{\varphi_{pt}}$ is province-year fixed effect that captures coincident province-level economic and policy changes, $\boldsymbol{\varepsilon_{it}}$ is error term, and standard error is clustered at the firm level.

The coefficient of our interest is $\boldsymbol{\alpha_1}$. A positive estimate of $\boldsymbol{\alpha_1}$ indicates that firms with higher preexisting levels of labor intensity exhibited a larger increase (or a smaller decrease) in pollution emission intensity after the law, compared to firms with relatively low labor intensity. Thus, a positive coefficient supports the hypothesis H1a that the social insurance law leads to an increase in the level of emission intensity by firms. Likewise, a negative estimated coefficient of the interaction term would support the hypothesis H1b.

Our study focuses on the continuous treatment variable of firms' labor intensity, so that our model examines a dose-response relationship between treatment intensity and the outcome variable. According to Callaway et al. (2024), in such a continuous treatment difference-in-differences model, an additional key assumption is that the average treatment effect function remains constant across different treatment intensities. This ''strong'' parallel trends assumption requires that if firms with low labor intensity had the same increase in labor intensity as those with high initial labor intensity, the effect on emissions would be identical. While this assumption is difficult to verify empirically, if the dose is normally distributed, then a two-way fixed effect specification like ours is likely to approximate the average casual response (Callaway et al., 2024; Parker and Vogl, 2023). Indeed, Appendix Figure A1 illustrates that the distribution of labor intensity closely resembles a normal distribution. Additionally, while recent studies caution that conventional difference-in-differences estimates can be biased due to staggered treatment timing (e.g., de Chaisemartin and D'Haultfoeuille, 2020; Goodman-Bacon et al. 2021), our study avoids these issues by examining a uniformly applied social insurance law with consistent labor intensity over time.

4 Empirical results

4.1 Main results

Table 2 reports the impact of the Social Insurance Law on pollution emission intensity for firms using the baseline model settings. Column (1) includes firm and year fixed effects. Column (2) adds industry-year fixed effects. Column (3) further controls for province-year fixed effects. We focus on the coefficient of the interaction term $LaborIntensity \times Post$, which captures the change in COD emission intensity for firms with relatively higher exposure to the 2011 social insurance law compared with those with less exposure. The outcomes derived from columns (1) through (3) elucidate that the coefficient manifests a positive and statistically significant association at conventional levels of significance. This implies a noteworthy escalation in pollution emission intensity for firms with a labor-intensive operational profile subsequent to the implementation of the policy. In summation, the empirical evidence robustly substantiates our hypothesized proposition (H1a) that the enactment of the Social Insurance Law resulted in a notable escalation in pollution emission intensity.

To gain a more intuitive understanding of the magnitude of emission intensity increase that resulted from social insurance policy reform, we use the estimated coefficients to interpret this effect. In column (3), the coefficient of $LaborIntensity \times Post$ is 0.028, indicating that a 10 percent increase in a manufacturing firm's pre-existing labor intensity raises the COD emission intensity by 0.28 percent following the implementation of the policy. To contextualize this effect, consider a firm with a mean value of the labor intensity distribution, referred as the average-labor-intensive firm. If its labor intensity (log) were to increase by one standard deviation (s.d. = 1.055) before the policy, the firm's COD emission intensity would rise by 2.95 (=1.055*0.028*100) percent. Given an average annual COD emission intensity of 4.94 kg per 10 thousand CNY, this observed effect translates to an additional 0.15 kg (=4.94*2.95%) of COD emissions for every 10 thousand industrial value-added generated. Further, as the average annual output in our sample is 567 million CNY, this effect correspondes to an additional 8.51 tons (567*1000/10*0.15/1000) of COD emissions annually for the average firm after the social insurance law.

The impact of social insurance contributions on corporate pollution emissions closely resembles that of other non-environmental policy shocks. For example, Chen et al. (2023) studied the effect of financing costs on corporate environmental performance, and found that firms in cities with a one standard deviation higher exposure to the 2009 bank deregulation policy shock experienced a 6.70% greater decline in average COD emission intensity. Similarly, Qi et al. (2023) investigated the impact of investment-related tax cuts on corporate emissions, revealing a 16.6% reduction in firms' SO2 emission intensity due to the adoption of emissions reduction strategies in the production processes. These findings underscore the substantial economic implications of social insurance contributions on pollution emissions, paralleling the effects observed in policy shocks.

Table 2 Baseline Results

	Ln(Emission Intensity)		
VARIABLES	(1)	(2)	(3)
Labor Intensity × Post	0.019**	0.027***	0.028***
	(0.008)	(0.008)	(0.009)
Firm Size	-0.059***	-0.060***	-0.056***
	(0.012)	(0.012)	(0.012)
Financial Leverage	-0.031	-0.033	-0.040
	(0.028)	(0.028)	(0.028)
Tangibles	0.062*	0.052	0.058*
	(0.034)	(0.034)	(0.034)
Share of Export	-0.079**	-0.085**	-0.077**
	(0.035)	(0.035)	(0.035)
Return on assets	-0.024	-0.023	-0.008
	(0.019)	(0.019)	(0.019)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-year FE	No	Yes	Yes
Province-year FE	No	No	Yes
Observations	132,446	132,446	132,445
Adjusted R-squared	0.772	0.773	0.776

Notes: This table reports the result for our baseline regression. The dependent variable is the emission intensity of COD (take the natural logarithm). *Post* is an indicator that equals zero in 2008-2011 and one in 2012-2013. *Labor Intensity* is the firm's labor intensity at the end of 2010 (in logarithm). Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.2 Evaluating the Parallel Trend Assumption

The core assumption of the DID model is the parallel trend assumption. In our analysis, the assumption of parallel trend implies that firms with different levels of labor intensity would have a similar trend in COD emission intensity, in the absence of the enactment of the Social Insurance Law. To test the parallel trends assumption, we explore the dynamic effects of the implementation of Social Insurance Law.

We estimate the following econometric regression equation, as suggested in Jacobson et al. (1993) and Graham et al. (2023).

$$Y_{it} = \alpha_0 + \sum_{t=2008}^{2013} \theta_t LaborIntensity_i \times Year_t + \beta X_{it} + \kappa_i + \delta_{st} + \varphi_{pt} + \varepsilon_{it} \quad (2)$$

We set 2011 as the reference year. $Year_t$ is an indicator variable that represents year t, θ_t is the variable of our interest and the other variables are the same as that in our baseline regression. The parameter θ_t refers to whether there are significant differences in COD emission intensities between year t and the reference year across firms with different levels of labor intensity. If the estimated effect is not statistically significant prior to the promulgation of the Social Insurance Law, it provides support for the parallel trend assumption.

Figure 2 depicts the estimated values of θ_t and the 95% confidence intervals. The estimated effects are statistically and economically indistinguishable from zero before the policy, suggesting that the trends of COD emission intensity are similar across firms with high versus low labor intensities. Additionally, after the enactment of the law (in year 2012 and 2013), the estimated effects are significantly positive. Put together, this dynamic analysis demonstrates that the social insurance law increased pollution emission intensities, indicating that labor-intensive firms exhibited higher pollution emission intensities. It can be observed that the the parallel trend assumption in DID model holds for our paper.

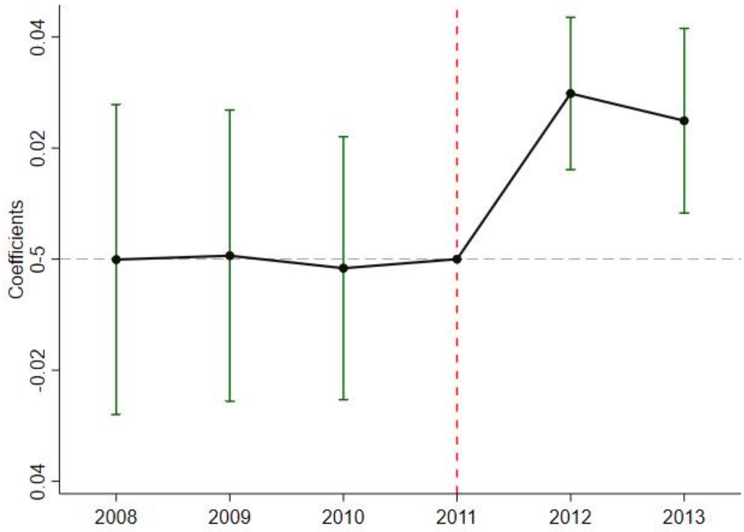


Figure 2 Dynamic Effect of the Implementation of the Social Insurance Law

Note: This figure plots the estimated coefficients (θ_t) and confidence intervals at the 95% level based on Equation 2. It reflects the dynamic effects of the implementation of Social Insurance Law on COD emission intensity.

4.3 Robustness checks

4.3.1 PSM-DID

Although the DID model employed in our paper satisfies the parallel trend assumption, systematic differences among firms with different labor intensities could potentially result in biased estimation results. To address this possibility, we employ a PSM-DID (Propensity -Score-Matching based Difference-in-Difference) method to test the robustness of our baseline regression findings. Specifically, we select firms with labor intensities greater than the median at the end of year 2010 (i.e., prior to the promulgation of the Social Insurance Law) as the treated firms (*High Labor Intensity*=1), while those with a labor intensity lower than the median are chosen as the control firms (*High Labor Intensity*=0). We use the nearest neighbor matching algorithms to perform the match with the same control variables utilized in the baseline regression. To assess the robustness of our findings, we employ varying matching ratios, specifically 1:10, 1:12, and 1:15, in constructing the matched samples.

We then performe a balance test to evaluate the effectiveness of the matching process. Figure A2 illustrates the distribution of propensity scores before and after matching for the 1:10 nearest-neighbor matching. A visual comparison of these distributions shows that PSM significantly reduces the bias between the treatment and control groups. We also compare the covariate differences before and after matching, revealing that the deviations in all variables are significantly reduced to less than 6%, indicating that the balance hypothesis is satisfied.

Finally, we conduct a DID estimation using the resulting matched samples. The results in Table 3 show that the coefficients of *High Labor Intensity×Post* are positive and statistically significant at the 5% level. Additionally, we assess the dynamic effects based on equation 2, and report the results in the appendix figure A4. The results confirm a common trend before the law and indicate substantial impacts after the enactment of the law. The analysis using the matched sample suggests that the baseline regression results are not driven by systematic differences across firms.

Table 3 Results from PSM-DID model

	Ln(Emission Intensity)		
VARIABLES	(1)	(2)	(3)
High Labor Intensity × Post	0.043**	0.044**	0.048**
	(0.020)	(0.019)	(0.019)
Covariates	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes
Observations	111,023	113,943	117,002
Adjusted R-squared	0.768	0.769	0.771

Notes: This table reports the result for difference-in-difference regression for PSM matched sample. Columns (1)-(3) employ nearest neighbor matching algorithms with ratios of 1:10, 1:12, and 1:15, respectively. The dependent variable is the natural logarithm of COD emission intensity. *Post* is an indicator that equals zero in 2008-2011 and one in 2012-2013. *High Labor Intensity* is a dummy variable which equals one if firm's labor intensity at the of 2010 is greater than the median of its distribution, and zero otherwise. All columns control for the same set of firm level covariates as in Table 2. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3.2 Alternative measures for labor intensity

To evaluate the influence of the Social Insurance Law on firms, the baseline regression employed the firm's labor intensity at the end of 2010 as the independent variable. To test the sensitivity of the labor intensity measure and its effect on our conclusions, two alternative measures are employed. First, a dummy variable is created based on the firm's labor intensity. The dummy variable is equal to one if the labor intensity is greater than the median value at the end of 2010, and zero otherwise. Second, the firm's average labor intensities from 2008 to 2010 are used as an alternative measure. The results of the DID estimation are presented in Table 4. The coefficients of the interaction term remain positive and statistically significant at the 1% level. We further estimtate the dynamic effects by applying Equation 2, using both measures of labor intensity. The results, as reported in Figure A4 of the appendix, reinforce the presence of a common pre-policy trend and highlight significant impacts post the law. This analysis indicates that the results of the study are robust to variations in the definition of labor intensity measures.

Table 4 Robustness：Alternative Measure for Labor Intensity

VARIABLES	*Ln(Emission Intensity)*	
	(1)	(2)
High Labor Intensity × Post	0.058***	
	(0.019)	
Labor Intensity before 2010 × Post		0.029***
		(0.009)
Covariates	Yes	Yes
Firm Fixed	Yes	Yes
Industry-Year Fixed	Yes	Yes
Province-Year Fixed	Yes	Yes
Observations	126,835	125,696
R-squared	0.825	0.819

Note: The dependent variable is the natural logarithm of COD emission intensity. *High Labor Intensity* is a dummy variable which equals one if firm's labor intensity at the of 2010 is greater than the median of its distribution, and zero otherwise. *Labor Intensity Before 2010* is the firm's average labor intensities during 2008-2010. *Post* is an indicator that equals zero in 2008-2011 and one in 2012-2013. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3.3 Alternative measures for exposure to reform

In the main analysis, we use preexisting labor intensity to define corporate exposure to the reform. Now we assess firms' exposure to the law based on their initial social insurance contribution rates in the year 2007, the only year for which we have social insurance contribution data (following Liu et al. 2021a). Firms with lower initial social insurance contribution rates experienced a greater increase in social security expenditure following the enactment of the law, thereby indicating higher exposure to the policy reform. As discussed in Section 2, social security contribution rates are typically computed by dividing social security contributions by the contribution base. However, due to the lack of precise information on firms' contribution base, we approximate it using firms' gross payroll expenses, which are directly observable from the data.

We employ three measures of contribution rates. The first measure, *Contribution Rate 1,* following Liu et al. (2021a), is calculated as the ratio of the firm's social insurance contributions to its total payroll expense in 2007. Given that payroll expense is an aggregate term—including total salaries and wages, social insurance contributions, bonuses, and other welfare payments—this measure may underestimate the true contribution rate. To better approximate the contribution rates, we develop two alternative measures by using the net of non-salary components as contribution bases. Specifically, *Contribution Rate 2* is determined by dividing the firm's social insurance contributions by its net payroll expense in 2007, where net payroll is defined as gross payroll expense minus social insurance contributions. Further, *Contribution Rate 3* is computed as the ratio of the firm's social insurance contributions to its expenditure on net payroll in 2007, with net payroll defined as gross payroll minus social insurance contributions and welfare expenditures.

The results presented in Table 5 indicate a significantly negative coefficient on the interaction term, suggesting that greater exposure to the reform (i.e., lower initial contribution rates) is associated with increased emission intensities, in line with our baseline regression findings. Therefore, our findings are not driven by the particular definition of policy exposure.

Table 5 Robustness：Alternative Measure for Exposure to Reform

VARIABLES	*Ln(Emission Intensity)*		
	(1)	(2)	(3)
Contribution Rate 1 × Post	-0.267***		

	(0.093)		
Contribution Rate 2 × Post		-0.160***	
		(0.054)	
Contribution Rate 3 × Post			-0.117***
			(0.041)
Covariates	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes
Industry-Year Fixed	Yes	Yes	Yes
Province-Year Fixed	Yes	Yes	Yes
Observations	76,069	75,616	75,315
R-squared	0.810	0.811	0.810

Note: The dependent variable is the natural logarithm of COD emission intensity. *Contribution Rate 1* is calculated as the ratio of the firm's social insurance contributions to its total expenditure on gross payroll. *Contribution Rate 2* is determined by dividing the firm's social insurance contributions by its net payroll, where net payroll is defined as gross payroll minus social insurance contributions. *Contribution Rate 3* is computed as the ratio of the firm's social insurance contributions to its expenditure on net payroll, with net payroll defined as gross payroll minus social insurance contributions and welfare expenditures. *Post* is an indicator that equals zero in 2008-2011 and one in 2012-2013. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3.4 Alternative measures for pollution emission

The previous results have been based on the pollutant of chemical oxygen demand (COD). To ensure the robustness of our results, we utilize three additional indicators. The first alternative metric is concerned with atmospheric pollution emissions, utilizing sulfur dioxide emission intensity, which is calculated as the amount of sulfur dioxide emitted divided by the total output value of the firm. The second alternative indicator deals with water pollution emissions, using ammonia nitrogen emission intensity as the metric, which is determined by dividing the amount of ammonia nitrogen emitted by the total output value. The third indicator relates to water pollution emissions, but measured by industrial wastewater emission intensity, which is calculated by dividing the amount of industrial wastewater discharged by the total output value. These supplementary measures allow for a comprehensive evaluation of our findings.

Table 6 presents the estimated results. In column (1), the dependent variable is the emission intensity of sulfur dioxide. The results indicate that a ten-percentage-point increase in labor intensity leads to an average rise of 0.3 percentage points in COD emission intensity.

Columns (2) and (3) utilize the emission intensity of ammonia nitrogen and industrial wastewater as the dependent variable, respectively. The coefficient on the interaction term for the industrial wastewater discharge is significantly positive. In general, the regression outcomes support our main finding and suggest a considerable increase in the emission intensity of the main atmospheric and water pollutants following the implementation of the Social Insurance Law.

Table 6 Robustness Checks: Alternative Measures for Emission Intensity

VARIABLES	*Ln(SO2)*	*Ln(NHN)*	*Ln(WasteWater)*
	(1)	(2)	(3)
Labor Intensity × Post	0.026**	-0.000	0.018**
	(0.011)	(0.011)	(0.007)
Covariates	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes
Observations	89,867	100,733	132,052
R-squared	0.863	0.798	0.833

Notes: In column (1), the dependent variable is the emission intensity of sulfur dioxide, which is measured as the amount of sulfur dioxide emitted divided by total output value (take the natural logarithm). In column (2), the dependent variable is the emission intensity of ammonia nitrogen, which is measured as amount of ammonia nitrogen emitted divided by total output value (take the natural logarithm). In column (3), the dependent variable is the emission intensity of industrial wastewater, which is calculated as the amount of industrial wastewater emitted divided by total output value (take the natural logarithm). *Post* is an indicator that equals zero in 2008-2011 and one in 2012-2013. *Labor* is the firm's labor intensity at the end of 2010. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3.5 Permutation test

In order to tackle the potential issue of omitted variables that might influence our findings, we perform a falsification test as suggested by Chetty et al. (2009) and Mastrobuoni and Pinotti (2015). To be specific, we randomly assign treatment variables to various firms, and then perform non-repeated random sampling of the firm labor intensity at the end of 2010, so as to fabricate a fake treatment variable. Subsequently, we re-estimate the difference-in-difference regression. Since our data generation process is random, it is expected that the interaction term *Labor Intensity*×*Post* will not have any impact on firm pollution emissions intensity. Following Mastrobuoni and Pinotti (2015), we repeat this process for 500 times, generating 500 regression coefficient estimates and their corresponding values.

Figure 3 illustrates the estimation results, with the blue hollow circle signifying the point estimate on the *x*-axis and its corresponding *p*-value on the *y*-axis. The vertical line indicates the estimate coefficient of *Labor Intensity* × *Post* in column (3) of Table 2 and the horizontal line denotes a 10% *p*-value level. If the conclusions of this paper were driven by coincidence caused by firm-level unobservable variables, the estimation values generated by the random numbers ought to be close to those generated using real data (represented by the vertical line). In fact, as Figure 3 shows, the estimation values generated by the random numbers approximately follow a normal distribution centered around zero, with most *p*-values above 10%. This indicates that the findings of the study are not driven by firm-level unobservables.

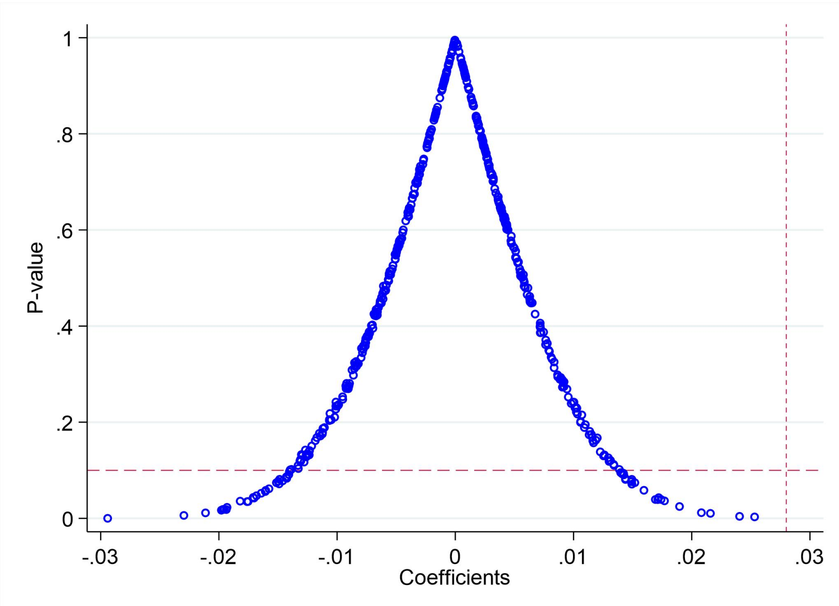


Figure 3 A Permutation Test

4.4 Heterogeneous analysis

In this section, we expand the scope of our investigation by analyzing whether the effects of the social insurance law on firm pollution activities vary across different firm characteristics.

We employ several heterogeneous analyses as follows: (1) ownership structure, (2) high-polluting industries, and (3) the stringency of environmental regulation.

4.4.1 Ownership structure

Chinese market is known for its prevalence of connections and concentration of government ownership (Tang, 2020; Wang, 2024). The state-owned enterprises (SOEs) are controlled by the government and have better compliance with labor legislation than non-SOEs (Cui et al., 2018; Liu et al., 2021a). Prior to the implementation of the Social Insurance Law, the average social insurance contribution rates were higher in SOEs than non-SOEs, largely due to their greater adherence to legal contribution rates (Liu et al., 2021a). Consequently, we anticipate that SOEs experienced relatively less policy shock amidst the implementation of the Social Insurance Law, while non-SOEs were more likely to face larger effects. To test this prediction, we split the firms into two subsamples based on their ownership structure, i.e., SOEs and non-SOEs. The regression outcomes are reported in Panel A of Table 7. A divergence of the policy effects was observed between SOEs and non-SOEs. The coefficient on the interaction term *Labor Intensity×Post* was insignificant but negative for SOEs, whereas for non-SOEs, the coefficient was positive and statistically significant at the 1% level. The discrepancy in these coefficients attains statistical significance at conventional thresholds (p-value = 0.014). This suggests that the the impact of the policy on COD emission intensity is considerably larger in non-SOEs relative to SOEs, corroborating our initial hypothesis.

4.4.2 High-polluting industries

High-polluting industries typically employ energy-intensive and fossil fuel-based methods, resulting in higher pollutant emissions (Becker and Henderson, 2000; Grether and Melo, 2003; Jiang et al, 2014). In general, these industries face higher marginal costs for pollution abatement, providing firms with a potential avenue for more cost savings by abstaining from abatement efforts (Hsu et al., 2023). Consequently, when confronted with adverse economic conditions, firms in high-polluting industries have a more pronounced incentive to reduce investments in emission abatement compared to their less polluting counterparts. Guided by this economic rationale, we posit that firms operating in high-polluting industries will exhibit a more substantial increase in pollution emission intensity in response to strengthened social insurance regulations, in contrast to their counterparts in low-polluting industries.

We divide the firms into two subsamples based on high- and low-polluting industries. An industry is classified as high-polluting (low-polluting) if the average COD emission intensity among the firms in this industry is greater (lower) than the median of the distribution in 2010. The results of this heterogeneous analysis are displayed in Panel B of Table 7. The coefficient on the interaction term *Labor Intensity*×*Post* in column (3) is over three times the magnitude of that in column (4). The difference in the coefficients is statistically significant (p-value = 0.024). This implies that the increase in social insurance contribution arising from the law has a more substantial impact on high-polluting industries as opposed to low-polluting industries.

4.4.3 Stringency of environmental regulation

Numerous studies imply that environmental regulation is a crucial factor that significantly influences a firm's pollution emissions (Shapiro and Walker, 2018; Chen et al., 2021; Xu and Kim, 2022). In regions with stringent environmental regulations, companies generally exhibit lower levels of pollution emissions. Therefore, we hypothesize that firms operating in regions with less rigorous environmental regulation encountered a more substantial increase in pollution emission intensity in light of the social insurance law.

Similar to Shangguan and Feng (2024), we use the local sulfur dioxide removal rate in 2010 as a proxy for the stringency of environmental regulation. We classify cities with sulfur dioxide removal rates above (below) the median as having strict (lax) environmental regulation.

The regression results for subsamples are presented in Panel C of Table 7, highlighting significant policy effect heterogeneity among regions with varying environmental regulation stringency. In column (5), the coefficient on the interaction term *Labor Intensity*×*Post* is insignificant for firms located in areas with strict environmental regulation. In contrast, in column (6), the coefficient on *Labor Intensity*×*Post* is larger and significant for the "lax environmental regulation" partition. The difference is also statistically significant (p-value =

0.001). This suggests that the impact of the social insurance law on emission is more pronounced for firms located in regions with less stringent regulatory environments. This observation aligns with the findings by Xu and Kim (2022), which highlight the importance of regulatory enforcement and external monitoring in influencing the relationship between financial constraints and toxic emissions.

Table 7 Heterogeneous Impacts

	Panel A: Ownership		Panel B: Polluting Industries		Panel C: Environmental Regulation	
	SOEs	Non-SOEs	High	Low	Strict	Lax
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Labor Intensity × Post	-0.007	0.031***	0.046***	0.014	0.005	0.043***
	(0.023)	(0.010)	(0.014)	(0.011)	(0.013)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
p-value [$\beta^{(1)} < \beta^{(2)}$]	0.014					
p-value [$\beta^{(3)} > \beta^{(4)}$]			0.024			
p-value [$\beta^{(5)} < \beta^{(6)}$]					0.001	
Observations	15,510	103,350	54,374	78,048	56,762	75,679
R-squared	0.772	0.772	0.744	0.729	0.765	0.783

Notes: The dependent variable is the natural logarithm of COD emission intensity. In Panel A, we divide the sample into two subgroups, namely, an SOE subgroup and a non-SOE subgroup. In Panel B, we use the average COD emission intensities in 2010 for firms in the industry as a proxy for the the industry average emission intensity. A firm is included in a high (low) polluting industry if its industry average emission intensity is above (below) the median of the distribution. In Panel C, we use the frequency of environmental-related terms in provincial government work reports as a proxy for the stringency of environmental regulation. A firm is included in the strict (lax) enforcement group if it is located in a region with reduction target above the sample median. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, using a one-tailed when indicating a prediction.

5 Mechanism analysis

The above analysis has found that more labor-intensive firms exhibit a considerably higher pollution emission compared to their less labor-intensive counterparts following the 2011 Social Insurance Law. Now we investigate plausible channels that could explain this observed effect. We start by analyzing how the law impacts firms' labor costs and financial stress. Next, we explore the mechanisms through which firms implement emission reduction strategies in response to the increased costs. Specifically, we examine both end-of-pipe reduction strategies and production process reduction strategies to better understand the complex interplay between regulatory compliance and pollution control practices.

5.1 Labor cost and financial distress

We start by investigating the impact of the 2011 Social Insurance Law on firm-level costs and financial distress. The association between corporate financial distress and emission activities has been well documented by prior literature. For example, Bartram et al. (2022) and Zhang et al. (2023) have shown that financial distress and earning pressures can exacerbate corporate pollution intensity. Conversely, other studies suggest that easing financial constraints may lead to reduced emissions (Chen et al., 2023; Xu and Kim, 2022). The 2011 Social Insurance Law mandated timely and sufficient contributions to social insurance schemes, introducing stricter enforcement and penalties for non-compliance. Given the downward rigidity of wages, it is hard for firms to fully offset increased labor costs through wage reductions (Nielsen and Smyth, 2008). Thus, we hypothesize that the law substantially raised corporate labor expenses and financial distress, which may potentially constrain firms' capacity to invest in pollution abatement measures and lead to an increase in emission intensity.

We employ a difference-in-differences (DID) estimation framework to probe the role of financial distress as a possible mediator of the observed effect. We examine various financial outcomes, including labor cost, production cost and corporate operating leverage. The results presented in Table 8 provide empirical support for our hypothesis. Column (1) examines the impact of the policy on corporate labor cost, measured by total payroll expenses divided by total industrial output. The positive and significant coefficient on the interaction terms indicates a notable increase in labor costs among firms following the law's enactment. Given that labor constitutes a significant component of total production costs, we further examine the policy's impact on production costs, calculated as the cost of goods sold divided by total industrial output. Results in column (2) suggest a substantial rise in production costs after the law.

Next, we assess the impact of the law on corporate operating leverage, a proxy for financial distress (Serfling, 2016; Dang et al., 2023). Following Novy-Marx (2011) and Chen et al. (2019), we define operating leverage as the ratio of selling, general, and administrative expenses (SG&A) divided by total industrial output. The results in column (3) indicate a significant rise in firms' operating leverage, indicating that the increase in labor costs has translated into a greater financial burden for firms. This finding aligns with prior studies –labor costs are often fixed within a firm's production and operational framework, so any exogenous increase in these fixed costs is likely to elevate operating leverage, thereby amplifying firms' exposure to financial distress (Mandelker and Rhee, 1984; Serfling, 2016; Kahl et al., 2019; Chen et al., 2022; Dang et al., 2023).

Table 8 Labor Cost and Operating Leverage

	Labor Cost	Production Cost	Operating Leverage
VARIABLES	(1)	(2)	(3)
Labor Intensity × Post	0.005***	1.689***	0.113***
	(0.001)	(0.235)	(0.018)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-Year Fixed	Yes	Yes	Yes
Province-Year Fixed	Yes	Yes	Yes
Observations	69,394	108,363	106,731
R-squared	0.684	0.599	0.521

Notes: The table presents the estimated effects of the Social Insurance Law on various firm-level financial outcomes. Column (1) reports the impact on labor costs, measured as the ratio of total payroll expenses to total industrial output. Column (2) assesses the effect on production costs, using the ratio of the cost of goods sold to total assets as a proxy. Column (3) evaluates changes in operating leverage, proxied by the ratio of selling, general, and administrative expenses (SG&A) to total industrial output. Standard errors, reported in parentheses, are clustered at the firm level. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

We further examine the impact of the Social Insurance Law on firms' operating leverage through alternative tests. Drawing on the methodologies established by Serfling (2016) and Cui et al. (2018), we can utilize the elasticity of a firm's operating income with respect to total sales as a proxy for operating leverage. This approach allows us to rigorously investigate changes in operating leverage following the enactment of the Social Insurance Law.

$$\Delta Ln(EBIT_{it}) = \gamma_0 + \gamma_1 \Delta Ln(Sales_{it}) \times Post_t + \gamma_2 \Delta Ln(Sales_{it}) + \gamma_3 X_{it} + \kappa_i + \delta_{st} + \varphi_{pt} + \varepsilon_{it} \quad (3)$$

where $\Delta Ln(EBIT_{it})$ represents the change in natural logarithm of a firm's earnings before interest and taxes (EBIT), $\Delta Ln(Sales_{it})$ is the change in natural logarithm of a firm's total sales revenue. Both of these variables have been winsorized at the 1% and 99% levels. The variable $Post_t$ and X_{it} maintain the same definitions as outlined in our baseline regression. κ_i is firm-level fixed effect, δ_{st} is industry-year fixed effect, φ_{pt} is province-year fixed effect, ε_{it} is error term clustered at the firm level.

In Table 9, Column (1) presents the results of the regression analysis, where the coefficient associated with the interaction term is positive and statistically significant at the 1% level. This finding suggests that the enactment of the Social Insurance Law has heightened the sensitivity of earnings before interest and taxes (EBIT) to changes in sales revenue. Prior to 2011, a 1% increase in sales revenue resulted in a 0.772% increase in EBIT, as indicated by an elasticity coefficient of 0.772. Post-enforcement of the Social Insurance Law, this elasticity coefficient increased by an additional 0.185, indicating that, on average, the law has led to a 23.96% increase in firms' operating leverage (calculated as 0.185/0.772). This result indicates that the law has significantly heightened financial distress for firms on average.

Columns (2) and (3) provide further analysis through subsample estimates. The coefficient for the interaction term is notably larger for firms in the treatment group (those with initial labor intensity above the median), compared to those in the control group. The difference in coefficients is statistically significant (p-value = 0.031), indicating that firms with greater labor intensity experienced a more substantial increase in operating leverage following the implementation of the Social Insurance Law, thereby facing a higher risk of financial distress. Put together, the above analysis demonstrates that the Social Insurance Law increased pollution emissions by elevating the likelihood of financial distress among firms.

Table 9 Impact of Social Insurance Law on Firm's Operating Leverage

Variables	ΔLn(EBIT)		
	Full sample	Treatment group	Control group
	(1)	(2)	(3)
$\Delta Ln(Sales) \times Post$	0.185***	0.251***	0.110**
	(0.032)	(0.048)	(0.046)
$\Delta Ln(Sales)$	0.772***	0.719***	0.831***
	(0.029)	(0.041)	(0.042)
Controls	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes
Industry-year fixed	Yes	Yes	Yes
Province-year fixed	Yes	Yes	Yes
P-value[$\beta^{(1)} > \beta^{(2)}$]		0.031	
Observations	57,183	25,925	27,520
Adjusted R^2	0.104	0.109	0.100

Note: The dependent variable $\Delta Ln(EBIT_{it})$ is the change in natural logarithm of a firm's earnings before interest and taxes (EBIT). $\Delta Ln(Sales_{it})$ is the change in natural logarithm of a firm's total sales revenue. *Post* is an indicator that equals zero in 2008-2011 and one in 2012-2013. Treatment group refers to firms with initial labor intensity above the median of the distribution. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.2 End-of-pipe reduction strategy

The implementation of the Social Insurance Law results in an increase in firm's labor cost and the associated financial burden, which in turn creates a disincentive for firms to invest in efforts aimed at reducing pollutant emissions. We undertake an empirical examination of this mechanism, by scrutinizing the end-of-pipe reduction strategies (Chen et al., 2021; Chen et al., 2023; Qi et al., 2023). End-of-pipe reduction strategy denotes the activity in which firms allocate resources towards pollution abatement after the production process. We use four metrics to measure firms' effort in end-of-pipe reduction, following Chen et al. (2023) and Qi et al. (2023). The first is removal ratio, calculated as the ratio of the removal amount to the yield amount of COD. The removal ratio serves as a direct indicator for the efficiency of abatement efforts on COD emission. The second is the natural logarithm of the amount of abated industrial wastewater, of which COD is the key pollutant. The third is the number of treatment facilities for industrial wastewater employed by the firm (log transformation). .

The results are reported in Table 10. In column (1), the interaction term *Labor×Post* has a negative and significant coefficient, which indicates that treated firms exhibit considerable reduction in COD removal ratio following the implementation of the Social Insurance Law. It implies that firms decreased their pollution abatement efforts to mitigate the higher labor costs incurred from the law. In column (2), the coefficient on the interaction term is also significantly negative, demonstrating that labor intensive firms reduced the abatement for industrial wastewater after the law. In column (3), we further examine the impact on the quantity of the firms' treatment facilities, and observe significantly negative coefficient on the metric. End-of-pipe reduction activity consumes a large volume of electricity (Liu et al., 2021b), providing incentives for firms to save cash flow by reducing the operation time of pollution control equipment and cutting down treatment facilities, to partially offset the impact of cost escalation from strengthened social insurance contributions. Taken together, the regression results lend support to the mechanism of end-of-pipe reduction activities.

Table 10 Mechanism Tests: Reduction in End-of-Pipeline Treatment T

VARIABLES	Removal Ratio (1)	Wastewater Treatment Capacity (2)	# Abatement Facility (3)
Labor Intensity × Post	-0.005***	-0.029***	-0.005***
	(0.001)	(0.010)	(0.002)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-Year Fixed	Yes	Yes	Yes
Province-Year Fixed	Yes	Yes	Yes
Observations	132,121	132,445	132,445
R-squared	0.724	0.857	0.793

Notes: This table investigates how the introduction of the Social Insurance Law affect manufacturing firms' end-of-pipeline reduction efforts. In column (1), the dependent variable is the removal ratio, defined as the ratio of the removal amount to the yield amount of wastewater. In column (2), the dependent variable is the natural logarithm of one plus the capacity of firm's facilities to abate wastewater. In column (3), the dependent variable is the natural logarithm of one plus the quantity of wastewater abatement facilities. All standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.3 Pollution reduction in the production process

We also explore the impact of the social insurance reform on firms' pollution reduction in the production processes before any abatement activities are taken place (Chen et al., 2021; Chen et al., 2023; Qi et al., 2023). If a firm adopts advanced technology in the production process, it will lead to a simultaneous decrease in abatement expenditure and pollution emissions (Andersen, 2016; Gutiérrez and Teshima, 2018). In contrast, a less efficient technology leads to more pollution emissions.

In line with previous research (Gutiérrez and Teshima, 2018; He et al., 2020; Chen et al., 2023), we employ three metrics to represent technological advancements in the production process. First, we examine whether there was an increase in COD yield intensity during firms' production but before their abatement activities. The COD yield intensity is calculated as absolute COD yields (yields = emissions + removals) divided by industrial output (with log transformation). Second, we consider the natural logarithm of fresh water consumption per unit of output during the manufacturing process. A greater use of fresh water in the production process indicates a less reliance on clean technology (He et al., 2020). Third, we use green patent applications to measure green technology innovation, which is calculated by the natural logarithm of the number of green patent applications plus one.[10]

Table 11 reports the estimation results. In column (1), the coefficient on the interaction term *Labor×Post* is positive and statistically significant. It indicates that firms opt for less clean technology in their production process and use greater fresh water. In column (2)-(3), the coefficients of our interest are significantly negative. It suggests that after the implementation of the Social Insurance Law, firms have adopted less green technology for cleaner production.

The regression outcomes, therefore, lend support to the mechanism of pollution reduction in the production process. Collectively, the findings suggest that both the channels of pollution reduction in end-of-pipe and production process are plausible and consistent with our inference.

[10] The data source for the patent information comes from State Intellectual Property Office (SIPO) in China. Green patents are identified using the International Patent Classification Index and we apply the aggregated number of (green) patent applications to measure the (green) technology innovation.

Table 11 Mechanism Tests: Reduction from Production Process

VARIABLES	COD Yields (1)	Fresh Water (2)	Green Patent (3)
Labor Intensity × Post	0.021**	0.019***	-0.009***
	(0.010)	(0.007)	(0.001)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-Year Fixed	Yes	Yes	Yes
Province-Year Fixed	Yes	Yes	Yes
Observations	96,502	132,363	132,445
R-squared	0.862	0.827	0.654

Notes: This table investigates how the introduction of the Social Insurance Law affect manufacturing firms' production process. In column (1), the dependent variable is COD yields, measured as the absolute COD yields divided by industrial output (with log transformation); In column (2), the dependent variable is fresh water, measured as fresh water consumption per unit of output during the manufacturing process (with log transformation); in column (3), the dependent variable is green patent, measured as the number of green patent applications plus one (with log transformation). All standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6 Conclusion

The current literature provides limited understanding of how labor market policies affect corporate environmental behavior. This study aims to address this gap by investigating the impacts of the 2011 Social Insurance Law reforms on pollution emissions among Chinese manufacturers. Our findings indicate that firms with higher pre-existing labor intensity exhibit a substantial increase in COD emission intensity compared to less labor-intensive firms subsequent to the enactment of the law's implementation. We establish that this result is primarily attributable to the rise in firms' labor cost and financial distress imposed by heightened social insurance contributions. Consequently, firms reduce their expenditures on pollution abatement, including both end-of-pipe treatment and process-based interventions, leading to higher levels of corporate pollution intensity. Our findings highlight the potential trade-off between employment-related and environmental ESG factors.

We subject our results to several robustness checks, including parallel trend validation, propensity score matching, permutation tests, and alternate measures for the independent and dependent variables, and our findings remain consistent. Heterogeneous analysis reveals that the influence of the Social Insurance Law on firm emission intensity is more marked in non-SOE firms, firms operating in heavy-polluting industries, and those situated in areas with lenient environmental regulations.

Our study offers important policy implications. First, it underscores the need for policymakers to account for potential environmental responses when designing employee-protection regulations. Stringent employment protection measures may inadvertently lead to increased pollution emissions by firms, complicating the evaluation of their overall impact. Second, our findings suggest that the development of green financing could be enhanced by refining Environmental, Social, and Governance (ESG) criteria to include more specific metrics related to employee well-being, such as social insurance contributions. For example, financial institutions could then offer sustainability-linked loans with interest rates tied to a company's performance on these employee-related CSR benchmarks. By providing lower borrowing costs for firms that meet these standards, sustainable finance could incentivize better employee-related CSR practices while also advancing environmental sustainability (De la Orden and De Calonje, 2022). Lastly, the government could enhance the enforcement of environmental regulations to prevent companies from resorting to pollution abatement reduction as a means to alleviate financial burden resulting from cost shocks. By doing so, the government can ensure that companies adhere to established environmental standards and do not compromise environmental performance for short-term financial gains.

Reference

Almaghrabi, Khadija S. "Non‐operating risk and cash holdings: Evidence from pension risk." *Journal of Banking & Finance* 152 (2023): 106878.

Andersen, Dana C. "Credit constraints, technology upgrading, and the environment." *Journal of the Association of Environmental and Resource Economists* 3, no. 2 (2016): 283-319.

Andersen, Dana C. "Do credit constraints favor dirty production? Theory and plant-level evidence." *Journal of Environmental Economics and Management* 84 (2017): 189-208.

Antweiler, Werner, Brian R. Copeland, and M. Scott Taylor. "Is free trade good for the environment?." *American Economic Review* 91.4 (2001): 877-908.

Aragon, Fernando M., Juan Jose Miranda, and Paulina Oliva. "Particulate matter and labor supply: The role of caregiving and non-linearities." *Journal of Environmental Economics and Management* 86 (2017): 295-309.

Bae, Kee-Hong, Jun-Koo Kang, and Jin Wang. "Employee treatment and firm leverage: A test of the stakeholder theory of capital structure." *Journal of Financial Economics* 100, no. 1 (2011): 130-153.

Bai, John, Douglas Fairhurst, and Matthew Serfling. "Employment protection, investment, and firm growth." *The Review of Financial Studies* 33, no. 2 (2020): 644-688.

Balachandran, Balasingham, and Huu Nhan Duong. "Pension deficits and the design of private debt contracts." *Journal of Financial and Quantitative Analysis* 54, no. 4 (2019): 1821-1854.

Bartram, Söhnke M. "Corporate post-retirement benefit plans and leverage." *Review of Finance* 20, no. 2 (2016): 575-629.

Bartram, Söhnke M. "Corporate postretirement benefit plans and real investment." *Management Science* 63, no. 2 (2017): 355-383.

Bartram, Söhnke M., Kewei Hou, and Sehoon Kim. "Real effects of climate policy: Financial constraints and spillovers." *Journal of Financial Economics* 143, no. 2 (2022): 668-696.

Becker, Randy, and Vernon Henderson. "Effects of air quality regulations on polluting industries." *Journal of Political Economy* 108, no. 2 (2000): 379-421.

Bedi, Arjun S., Admasu Shiferaw, Måns Söderbom, and Getnet Alemu Zewdu. "Social insurance reform and workers' compensation." *Labour Economics* 78 (2022): 102214.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna. “Difference-in-differences with a continuous treatment.” No. w32117. *National Bureau of Economic Research*, 2024.

Chen, Shiyi, Tao Chen, Pingyi Lou, Hong Song, and Chenyu Wu. "Bank deregulation and corporate environmental performance." *World Development* 161 (2023): 106106.

Chen, Shiyi, Hong Song, and Chenyu Wu. "Human capital investment and firms' industrial emissions: Evidence and mechanism." *Journal of Economic Behavior & Organization* 182 (2021): 162-184.

Chen, Zhao, Matthew E. Kahn, Yu Liu, and Zhi Wang. "The consequences of spatially differentiated water pollution regulation in China." *Journal of Environmental Economics and Management* 88 (2018): 468-485.

Chen, Zhiyao, Jarrad Harford, and Avraham Kamara. "Operating leverage, profitability, and capital structure." *Journal of Financial and Quantitative Analysis* 54, no. 1 (2019): 369-392.

Chen, Huafeng, Jason V. Chen, Feng Li, and Pengfei Li. "Measuring operating leverage." *The Review of Asset Pricing Studies* 12, no. 1 (2022): 112-154.

Chetty, Raj, Adam Looney, and Kory Kroft. "Salience and Taxation: Theory and Evidence." *American Economic Review* 99, no. 4 (2009): 1145–77.

Compagnie, Vincent, Kristof Struyfs, and Wouter Torsin. "Tax avoidance as an unintended consequence of environmental regulation: Evidence from the EU ETS." *Journal of Corporate Finance* 82 (2023): 102463.

Cui, Chenyu, Kose John, Jiaren Pang, and Haibin Wu. "Employment protection and corporate cash holdings: Evidence from China's labor contract law." *Journal of Banking & Finance* 92 (2018): 182-194.

Curtis, E. Mark. "Who loses under cap-and-trade programs? The labor market effects of the NOx budget trading program." *Review of Economics and Statistics* 100.1 (2018): 151-166.

Dang, Viet Anh, Ning Gao, and Tiancheng Yu. "Climate policy risk and corporate financial decisions: Evidence from the NOx budget trading program." *Management Science* 69, no. 12 (2023): 7517-7539.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. "Two-way fixed effects estimators with heterogeneous treatment effects." *American economic review* 110.9 (2020): 2964-2996.

De la Orden, Raquel; De Calonje, Ignacio. 2022. Sustainability-Linked Finance: Mobilizing Capital for Sustainability in Emerging Markets. International Finance Corporation, Washington, DC.

Devos, Erik, and Shofiqur Rahman. "Does labor unemployment insurance affect corporate tax aggressiveness?." *International Review of Financial Analysis* 90 (2023): 102917.

Fowlie, Meredith. "Emissions trading, electricity restructuring, and investment in pollution abatement." *American Economic Review* 100.3 (2010): 837-869.

Goodman-Bacon, Andrew. "Difference-in-differences with variation in treatment timing." *Journal of econometrics* 225.2 (2021): 254-277.

Graham, John R., Hyunseob Kim, Si Li, and Jiaping Qiu. "Employee costs of corporate bankruptcy." *The Journal of Finance* 78, no. 4 (2023): 2087-2137.

Gray, Wayne B., Ronald J. Shadbegian, Chunbei Wang, and Merve Meral. "Do EPA Regulations Affect Labor Demand? Evidence from the Pulp and Paper Industry." *Journal of Environmental Economics and Management* 68, no. 1 (2014): 188–202.

Grether, Jean-Marie, and Jaime De Melo. "Globalization and dirty industries: Do pollution havens matter?." (2003).

Gutiérrez, Emilio, and Kensuke Teshima. "Abatement expenditures, technology choice, and environmental performance: Evidence from firm responses to import competition in

Mexico." *Journal of Development Economics* 133 (2018): 264-274.

Han, Yi, Enying Zheng, and Minya Xu. "The influence from the past: Organizational imprinting and firms' compliance with social insurance policies in China." *Journal of Business Ethics* 122 (2014): 65-77.

He, Guojun, Shaoda Wang, and Bing Zhang. "Watering down environmental regulation in China." *The Quarterly Journal of Economics* 135, no. 4 (2020): 2135-2185.

Houde, Sebastien, and Wenjun Wang. "The incidence of the US-China solar trade war." Available at SSRN 4441906 (2023).

Hsu, Po-hsuan, Kai Li, and Chi-yang Tsou. "The pollution premium." *The Journal of Finance* 78, no. 3 (2023): 1343-1392.

Hu, Jun, Huiying Wu, and Sammy Xiaoyan Ying. "Environmental regulation, market forces, and corporate environmental responsibility: Evidence from the implementation of cleaner production standards in China." *Journal of Business Research* 150 (2022): 606-622.

Jacobson, Louis S., Robert John LaLonde, and Daniel Gerard Sullivan. "Earnings Losses of Displaced Workers," *American Economic Review* 83, (1993): 685–709.

Jiang, Liangliang, Chen Lin, and Ping Lin. "The determinants of pollution levels: Firm-level evidence from Chinese manufacturing." *Journal of Comparative Economics* 42, no. 1 (2014): 118-142.

Kathuria, Vinish. "Controlling water pollution in developing and transition countries—lessons from three successful cases." *Journal of Environmental Management* 78, no. 4 (2006): 405-426.

Li, Jie, Yi Lu, Hong Song, and Huihua Xie. "Long-term impact of trade liberalization on human capital formation." *Journal of Comparative Economics* 47, no. 4 (2019): 946-961.

Liu, Guanchun, Yuanyuan Liu, Chengsi Zhang, and Yueteng Zhu. "Social insurance law and corporate financing decisions in China." *Journal of Economic Behavior & Organization* 190 (2021a): 816-837.

Liu, Zheng, Hongtao Shen, Michael Welker, Ning Zhang, and Yang Zhao. "Gone with the wind: An externality of earnings pressure." *Journal of Accounting and Economics* 72, no. 1 (2021b): 101403.

Liu, Mengdi, Ruipeng Tan, and Bing Zhang. "The costs of "blue sky": Environmental regulation, technology upgrading, and labor demand in China." *Journal of Development Economics* 150 (2021c): 102610.

Nielsen, Ingrid, and Russell Smyth. "Who bears the burden of employer compliance with social security contributions? Evidence from Chinese firm level data." *China Economic Review* 19, no. 2 (2008): 230-244.

Novy-Marx, Robert. "Operating leverage." *Review of Finance* 15, no. 1 (2011): 103-134.

Mao, Jie, Chunhua Wang, and Haitao Yin. "Corporate responses to air quality regulation: Evidence from a regional environmental policy in China." *Regional Science and Urban Economics* 98 (2023): 103851.

Mastrobuoni, Giovanni, and Paolo Pinotti. "Legal Status and the Criminal Activity of Immigrants." *American Economic Journal: Applied Economics* 7, no. 2 (2015): 175–206.

Parker, Susan W., and Tom Vogl. "Do conditional cash transfers improve economic outcomes in the next generation? Evidence from Mexico." *The Economic Journal* 133.655 (2023): 2775-2806.

Qi, Yu, Jianshun Zhang, and Jianwei Chen. "Tax incentives, environmental regulation and firms' emission reduction strategies: Evidence from China." *Journal of Environmental Economics and Management* 117 (2023): 102750.

Rauh, Joshua D. "Investment and financing constraints: Evidence from the funding of corporate pension plans." *The Journal of Finance* 61, no. 1 (2006): 33-71.

Rickne, Johanna. "Labor market conditions and social insurance in China." *China Economic Review* 27 (2013): 52-68.

Rodrigue, Joel, Dan Sheng, and Yong Tan. "The curious case of the missing Chinese emissions." *Journal of the Association of Environmental and Resource Economists* 9, no. 4 (2022a): 755-805.

Rodrigue, Joel, Dan Sheng, and Yong Tan. "Exporting, Abatement, and Firm-Level Emissions: Evidence from China's Accession to the WTO." *The Review of Economics and Statistics* (2022b): 1-45.

Serfling, Matthew. "Firing costs and capital structure decisions." *The Journal of Finance* 71, no. 5 (2016): 2239-2286.

Shapira, Roy, and Luigi Zingales. Is pollution value-maximizing? The DuPont case. No. w23866. National Bureau of Economic Research, 2017.

Shapiro, Joseph S., and Reed Walker. "Why Is Pollution from US Manufacturing Declining? the Roles of Environmental Regulation, Productivity, and Trade." *American Economic Review* 108, no. 12 (2018): 3814–54.

Shivdasani, Anil, and Irina Stefanescu. "How do pensions affect corporate capital structure decisions?." *The Review of Financial Studies* 23, no. 3 (2010): 1287-1323.

Shleifer, Andrei. "Does competition destroy ethical behavior?." *American Economic Review* 94, no. 2 (2004): 414-418.

Tang, Tanya Y.H. "A Review of Tax Avoidance in China." *China Journal of Accounting Research* 13, no. 4 (2020): 327–38.

Walker, W. Reed. "Environmental regulation and labor reallocation: Evidence from the Clean Air Act." *American Economic Review* 101, no. 3 (2011): 442-447.

Wang, Hua, and David Wheeler. Endogenous enforcement and effectiveness of China's pollution levy system. Vol. 2336. World Bank Publications, 2000.

Wang, Wenjun. "You scratch my back and i scratch yours: evidence from relationship-based bidding in IPO auctions." *Review of Quantitative Finance and Accounting* (2024): 1-21.

Xu, Qiping, and Taehyun Kim. "Financial constraints and corporate environmental policies." *The Review of Financial Studies* 35, no. 2 (2022): 576-635.

Yang, Xue, Peng Zhang, Xiaobo Hu, and Ghulam Muhammad Qamri. "Environmental pollution and officials' promotion: How China's green attention matters." *Journal of Environmental Management* 365 (2024): 121590.

Zhang, Xin, Xi Chen, and Xiaobo Zhang. "The impact of exposure to air pollution on cognitive performance." *Proceedings of the National Academy of Sciences* 115, no. 37 (2018): 9193-9197.

Zhang, Ming-ang, Shuling Lu, Sihan Zhang, and Yanfeng Bai. "The unintended consequence of minimum wage hikes: Evidence based on firms' pollution emission." *Energy Economics* 125 (2023): 106857.

Appendix A

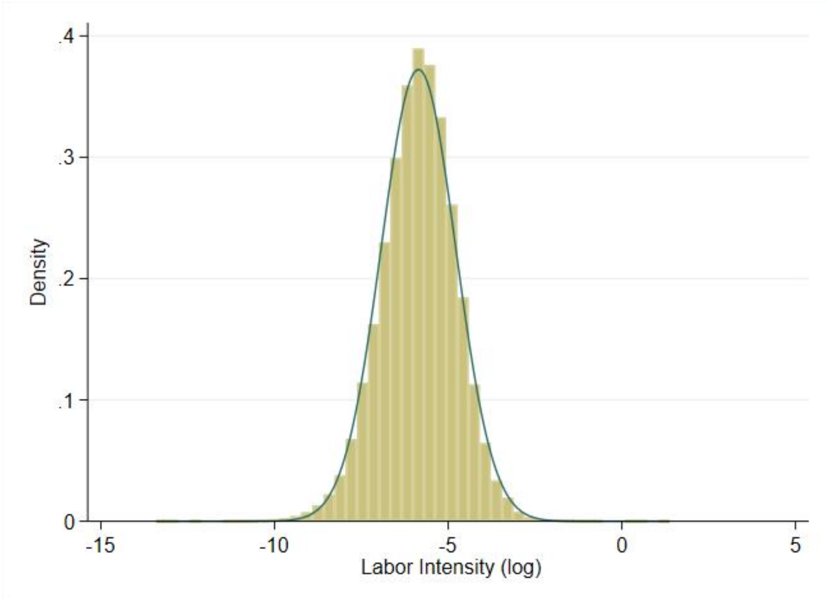


Figure A1 Density of Labor Intensity (log)

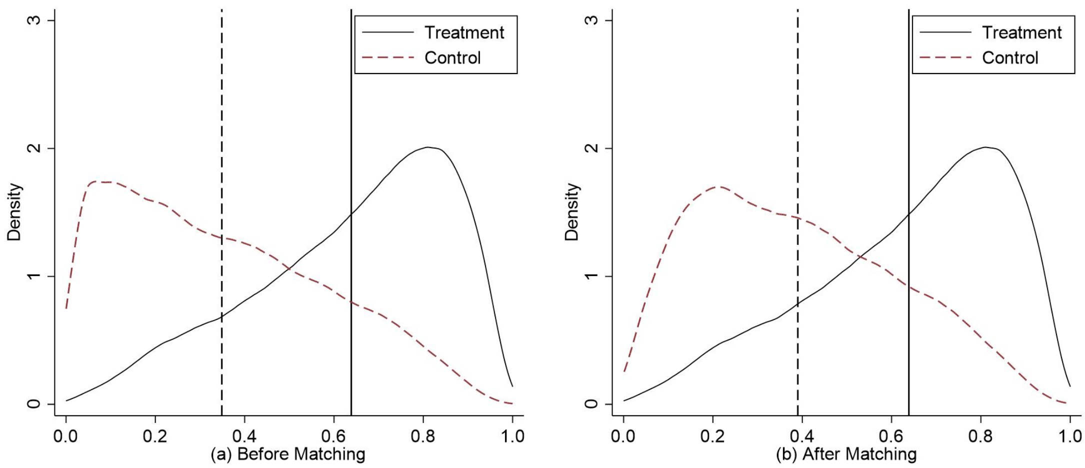


Figure A2 Propensity Score Distribution before and after matching

Note: The figure on the left displays the propensity score distribution before matching, while the figure on the right illustrates the propensity score distribution after matching. In both figures, the horizontal axis represents the propensity scores, and the vertical axis depicts the kernel density. The solid vertical line indicates the mean distribution value for the treatment group, whereas the dashed vertical line denotes the mean distribution value for the control group.

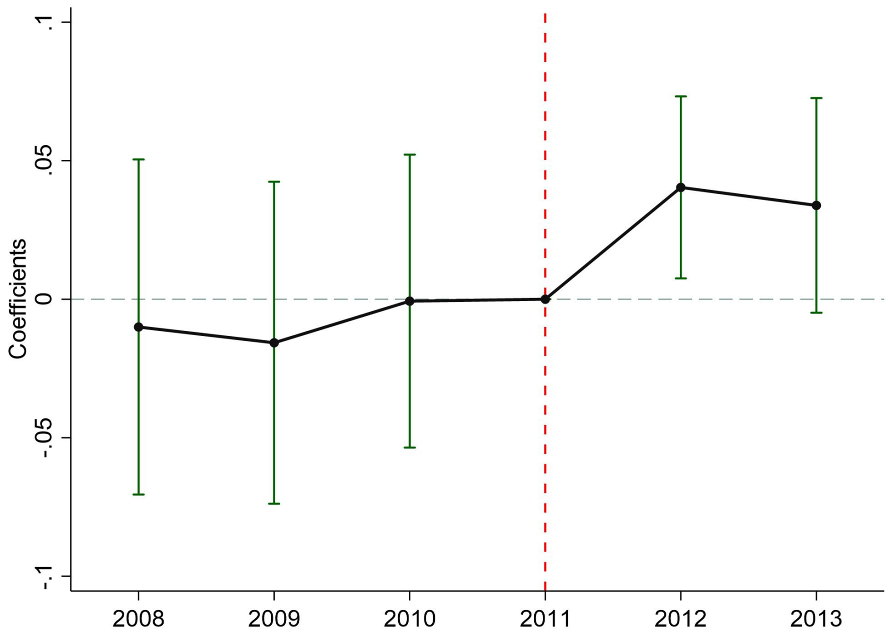
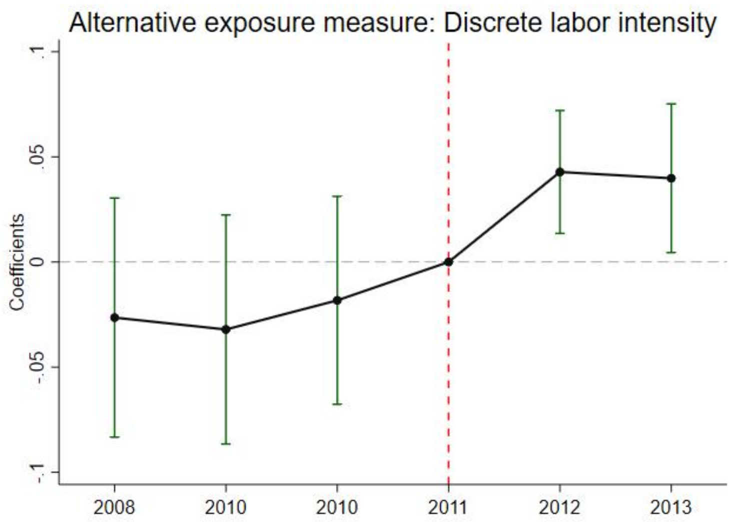
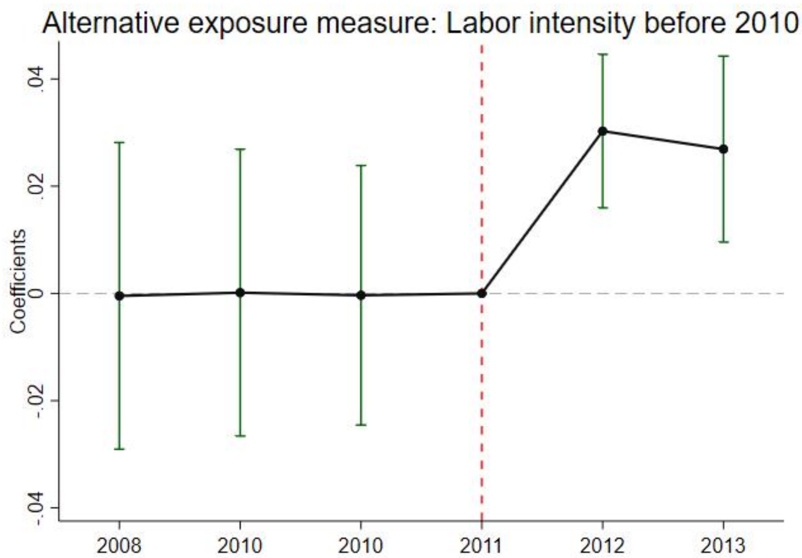


Figure A3 Dynamic Effects using the propensity score matched sample

Note: This figure plots the estimated coefficients (θ_t) and confidence intervals at the 95% level based on Equation 2, but uses the propensity score matched sample. The dependent variable is the natural logarithm of COD emission intensity. *Labor Intensity* is the firm's labor intensity at the end of 2010. We control for the same set of firm level covariates as in Table 2.



Panel A. Discrete labor intensity



Panel B. Average labor intensities before 2010

Figure A4. Dynamic Effects based on Alternative Labor Intensity Measures

Note: These two figures plot the estimated coefficients (θ_t) and confidence intervals at the 95% level based on Equation 2, but based on alternative measures of labor intensity. The dependent variable is the natural logarithm of COD emission intensity. In Panel A, labor intensity is a dummy variable which equals one if firm's labor intensity at the of 2010 is greater than the median of its distribution, and zero otherwise. In Panel B, the exposure variables is measured by a firm's average labor intensities during 2008-2010.