

Online Appendix for
“From Employer Responsibility to Environmental Irresponsibility:
Unintended Impacts of Social Insurance Law on Pollution Emissions”

Appendix A1: Details on Sample Construction

Appendix A2: Theoretical Model

Appendix A3: A Robustness Check: PSM-DID

Appendix A4: Exogeneity of Environmental Regulation

Appendix Figure A1: Density of Labor Intensity (log)

Appendix Figure A2: Standardized Bias across Matching Covariates before and after Matching

Appendix Figure A3: Dynamic Effects Using the Propensity Score Matched Sample

Appendix Figure A4: A Permutation Test

Appendix Figure A5: Balance of City Characteristics before and after Matching

Appendix Table A1: Summary Statistics Across Data Merging and Cleaning Steps

Appendix Table A2: Pattern of Missing Values in Emission Data

Appendix Table A3: Balance Test for Covariates Used in the Regression

Appendix Table A4: Results Based on a PSM-DID Model

Appendix Table A5: Controlling for the Impact of 12th Five-Year Plan

Appendix Table A6: Controlling for Time-Varying Environmental Enforcement

Appendix Table A7: Robustness Checks: Alternative Measures for Labor Intensity

Appendix Table A8: Impacts of the Social Insurance Law on SO₂ Emission Intensity

Appendix Table A9: Balance Test for City-level Variables

Appendix Table A10: The Role of Environmental Regulation: PSM-DID Analysis

Appendix Table A11: Robustness: The Mitigating Effect of Peer Pressure

Appendix References

Appendix A1. Details on Sample Construction

We follow five steps to clean the merged dataset (351,367 firm-year observations).

Step 1. We drop firms that have observations only before or after the implementation of the Social Insurance Law. This step removes 23.72% of the observations in the merged sample.

Step 2. We restrict the sample to the manufacturing industry and drop firms in non-manufacturing industries. This step drops 7.80% of the observations in the merged sample.

Step 3. We keep only above-scale firms, defined as those with annual sales greater than or equal to 5 million CNY during 2008-2010 and at least 20 million CNY after 2011. This step drops 0.10% of the observations in the merged sample.

Step 4. We drop observations with missing information on COD emission intensity, and trim the remaining values at the 1st and 99th percentiles. This step removes 16.22% of the firm-year observations in the merged sample.

Step 5. We drop firm-year observations that are missing one or more control variables or have missing information on industry or location. This step further removes 12.98% of the observations in the merged sample.

After applying steps 1-5, our final analysis sample consists of 137,669 observations, accounting for 39.18% of the number of observations in the merged sample. Table A1 reports the summary statistics at each intermediate step. The means and standard deviations at each step remain broadly consistent with those in the original datasets, indicating that the data cleaning process does not materially distort the distributions of key variables.

Appendix A2. Theoretical Model

We develop a simple theoretical model that integrates the social insurance policy shock into firms' pollution emission strategies. Inspired by the model proposed by Shapiro and Walker (2018), we formulate a firm's maximization problem in which the firm simultaneously chooses its production level and emission abatement activities. This model demonstrates how an exogenous labor cost shock stemming from higher social insurance contributions induces firms to reallocate resources away from pollution abatement, consequently increasing their pollution intensity.

A2.1 Setup

Following Shapiro and Walker (2018), we consider a firm that produces output Q using only labor. The firm chooses labor for two distinct activities:

- Production labor L_p : directly used in manufacturing output.
- Abatement labor L_a : used to operate pollution control equipment, monitor emissions, and maintain treatment facilities.

Total labor is given by:

$$L = L_p + L_a \tag{A1}$$

Production function. Output is produced using only production labor:

$$Q = f(L_p), f' > 0, f'' < 0. \tag{A2}$$

We abstract from capital for simplicity, as it does not affect the core mechanism.

Pollution generation.

Without abatement, each unit of output generates θ units of pollution. Abatement investments reduce the pollution intensity: the more labor allocated to abatement, the lower the pollution per unit of output. Following the environmental economics literature (e.g., Shapiro and Walker, 2018), we specify the pollution intensity (emissions per unit of output) as a function of abatement investments:

$$e = \theta \cdot g(L_a), \tag{A3}$$

where $g(L_a)$ is a decreasing function: $g'(L_a) < 0$ and $g''(L_a) > 0$ (diminishing returns to abatement labor). To ensure an interior solution for abatement labor, we also assume $g'(0) = -\infty$, so that the marginal benefit of the first unit of abatement labor is infinite, preventing the corner solution $L_a = 0$.

Total emissions are therefore an increasing function of output and a decreasing function of abatement investments:

$$E = e \cdot Q = \theta \cdot g(L_a) \cdot f(L_p) \quad (\text{A4})$$

From this equation, changes in total emissions are driven by two factors: changes in pollution intensity (e) and changes in total output (Q). Following Shapiro and Walker (2018), we term the contribution of pollution intensity changes to total emissions the **technique effect**, and the output contribution the **scale effect**.

Pollution tax. The firm pays a tax t per unit of emission, so total pollution-related cost is:

$$tE = t\theta \cdot g(L_a) \cdot f(L_p) \quad (\text{A5})$$

Labor costs. The firm pays wage W per worker plus social insurance contributions at rate τ , so the cost per worker is $W(1 + \tau)$. Total labor cost is:

$$W(1 + \tau)(L_p + L_a) \quad (\text{A6})$$

Pure fixed costs. In addition to variable labor costs, the firm incurs pure fixed costs $C > 0$ that do not vary with output or τ . Crucially:

$$\frac{\partial C}{\partial \tau} = 0 \quad (\text{A7})$$

A2.2 The Firm's Profit Maximization Problem

The firm chooses L_p and L_a to maximize profit:

$$\pi(L_p, L_a) = P \cdot f(L_p) - W(1 + \tau)(L_p + L_a) - t\theta \cdot g(L_a) \cdot f(L_p) - C \quad (\text{A8})$$

A2.2.1 First-Order Conditions

The first-order condition with respect to L_p is:

$$\frac{\partial \pi}{\partial L_p} = P f'(L_p) - W(1 + \tau) - t\theta \cdot g(L_a) \cdot f'(L_p) = 0,$$

which can be written as

$$[P - t\theta \cdot g(L_a)] f'(L_p) = W(1 + \tau). \quad (\text{A9})$$

The first-order condition with respect to L_a is:

$$\frac{\partial \pi}{\partial L_a} = -W(1 + \tau) - t\theta \cdot g'(L_a) \cdot f(L_p) = 0,$$

or equivalently,

$$-t\theta \cdot g'(L_a) \cdot f(L_p) = W(1 + \tau) \quad (\text{A10})$$

A2.2.2 Second-Order Conditions

The Hessian matrix of the profit function is given by:

$$H = \begin{bmatrix} \frac{\partial^2 \pi}{\partial L_p^2} & \frac{\partial^2 \pi}{\partial L_p \partial L_a} \\ \frac{\partial^2 \pi}{\partial L_p \partial L_a} & \frac{\partial^2 \pi}{\partial L_a^2} \end{bmatrix} = \begin{bmatrix} [P - t\theta g(L_a)]f''(L_p) & -t\theta g'(L_a)f'(L_p) \\ -t\theta g'(L_a)f'(L_p) & -t\theta g''(L_a)f(L_p) \end{bmatrix}. \quad (\text{A11})$$

For a local maximum, the Hessian must be negative definite, which requires:

$$\frac{\partial^2 \pi}{\partial L_p^2} < 0, \text{ and } |H| > 0.$$

Given $f'' < 0$ and $g'' > 0$, we have $\partial^2 \pi / \partial L_p^2 < 0$ and $\partial^2 \pi / \partial L_a^2 < 0$. The determinant condition is:

$$|H| = [P - t\theta g]f''(L_p) \cdot [-t\theta g''f(L_p)] - [-t\theta g'f'(L_p)]^2 > 0 \quad (\text{A12})$$

A2.3 Economic Interpretation

Equation (A9) shows that the marginal revenue product of production labor, net of the pollution tax liability it generates, equals the marginal cost of labor $W(1 + \tau)$. Equation (A10) shows that the marginal benefit of abatement labor (reduced pollution tax payments) equals its marginal cost $W(1 + \tau)$. These two conditions jointly determine the optimal choice of labor used in production and abatement.

A2.4 Comparative Statics: Effect of Social Insurance Contribution Rate τ

We examine how an increase in τ affects firms' input choices (L_p, L_a) , output Q , emission intensity e , and total emissions E .

A2.4.1 Effects on Labor Inputs and Firms' Output

Totally differentiating the first-order conditions (A9) and (A10) with respect to τ yields:

$$[P - t\theta g]f''(L_p) \frac{dL_p}{d\tau} - t\theta g'(L_a)f'(L_p) \frac{dL_a}{d\tau} = W, \quad (\text{A13})$$

$$-t\theta g'(L_a)f'(L_p) \frac{dL_p}{d\tau} - t\theta g''(L_a)f(L_p) \frac{dL_a}{d\tau} = W. \quad (\text{A14})$$

In matrix form:

$$\begin{bmatrix} [P - t\theta g]f''(L_p) & -t\theta g'(L_a)f'(L_p) \\ -t\theta g'(L_a)f'(L_p) & -t\theta g''(L_a)f(L_p) \end{bmatrix} \begin{bmatrix} dL_p/d\tau \\ dL_a/d\tau \end{bmatrix} = \begin{bmatrix} W \\ W \end{bmatrix}. \quad (\text{A15})$$

Let $D = |H|$ denote the determinant of the Hessian matrix. Solving using Cramer's Rule and noting that $|H| > 0$ (Equation A12), we have:

$$\begin{aligned} \frac{dL_p}{d\tau} &= \frac{\det \begin{bmatrix} W & -t\theta g'f' \\ W & -t\theta g''f \end{bmatrix}}{D} = \frac{W(-t\theta g''f) - (-t\theta g'f')W}{D} \\ &= \frac{Wt\theta[g'f' - g''f]}{D}. \end{aligned} \quad (\text{A16})$$

Given $g' < 0$, $f' > 0$, $g'' > 0$, $f > 0$, the numerator is negative. Since $D > 0$, we obtain:

$$\frac{dL_p}{d\tau} < 0. \quad (\text{A17})$$

Likewise, we have:

$$\begin{aligned} \frac{dL_a}{d\tau} &= \frac{\det \begin{bmatrix} [P - t\theta g]f'' & W \\ -t\theta g'f' & W \end{bmatrix}}{D} = \frac{[P - t\theta g]f'' \cdot W - W \cdot (-t\theta g'f')}{D} \\ &= \frac{W\{[P - t\theta g]f'' + t\theta g'f'\}}{D}. \end{aligned} \quad (\text{A18})$$

Since $f'' < 0$ and $g'f' < 0$, the numerator is negative. With $D > 0$, we obtain:

$$\frac{dL_a}{d\tau} < 0. \quad (\text{A19})$$

Output is given by $Q = f(L_p)$. Since $f' > 0$, it follows that:

$$\frac{dQ}{d\tau} = f'(L_p) \frac{dL_p}{d\tau} < 0. \quad (\text{A20})$$

Proposition 1: An increase in the social insurance contribution rate τ decreases production labor (L_p) and hence firms' output (Q).

Proof: This follows directly from Equation (A17) and Equation (A20).

A2.4.2 Effects on Abatement Investments and Emission Intensity

Proposition 2: An increase in the social insurance contribution rate (τ) reduces firms' abatement labor (L_a) and thereby increases emission intensity (e).

Proof: The decrease in abatement labor follows directly from Equation (A19). Next, we examine the effect on emission intensity.

Emission intensity is given by:

$$e = \frac{E}{Q} = \theta \cdot g(L_a). \quad (\text{A21})$$

Differentiating yields:

$$\frac{de}{d\tau} = \theta \cdot g'(L_a) \cdot \frac{dL_a}{d\tau} > 0, \quad (\text{A22})$$

where the inequality follows from $g'(L_a) < 0$ and $dL_a/d\tau < 0$.

Thus, higher social insurance contribution rates increase pollution emission intensity by reducing abatement investments.

A2.4.3 Effect on Total Emissions

Proposition 3: An increase in the social insurance contribution rate has an ambiguous effect on total emissions. The net impact depends on the relative strength of two opposing forces: the **technique effect** (which raises total emissions by increasing emissions intensity) and the **scale effect** (which lowers total emissions by reducing output).

Proof. Total emissions are given by $E = e \cdot Q = \theta \cdot g(L_a) \cdot f(L_p)$. Differentiating with respect to τ yields:

$$\begin{aligned} \frac{dE}{d\tau} &= \frac{de}{d\tau} \cdot Q + \frac{dQ}{d\tau} \cdot e \\ &= \underbrace{\theta g'(L_a) \frac{dL_a}{d\tau} \cdot f(L_p)}_{(1) \text{Technique Effect} > 0} + \underbrace{\theta g(L_a) \cdot f'(L_p) \frac{dL_p}{d\tau}}_{(2) \text{Scale Effect} < 0}. \end{aligned} \quad (\text{A23})$$

This expression consists of two competing effects. Following Shapiro and Walker (2018), the first term captures the **technique (or intensity) effect**, that is, the change in total emissions due to emission intensity, or emissions per unit of output. Since $g' < 0$ and $dL_a/d\tau < 0$, this term is positive, implying that reduced abatement investments increase emissions. This effect captures the impact of all abatement activities, including both end-of-pipe treatment and production process adjustments, that firms undertake in response to regulatory or cost pressures.

The second term captures the **scale effect**. Because $dL_p/d\tau < 0$, the second term is negative, implying that a contraction in output reduces total emissions.

Taken together, these two opposing forces imply that the overall effect of τ on total emissions is theoretically ambiguous. The net effect depends on the relative magnitudes of the technique (intensity) effect and the scale effect. If the technique effect dominates, total emissions rise; if the scale effect dominates, total emissions fall.

A2.4.4 Implications for Empirical Analysis

This framework yields two key insights that guide our empirical strategy.

(1) Emission intensity (e) is the preferred outcome variable for identifying the firm's behavioral response to labor cost shocks. It cleanly captures the **abatement effort channel** ($\partial L_a / \partial \tau$) without contamination from scale changes ($\partial Q / \partial \tau$).

(2) Total emissions (E) confound two opposing forces. Finding that total emissions decline after a labor cost increase does not necessarily indicate greener production. It may simply reflect output contraction. This distinction is crucial for interpreting our results and for policy discussions about whether environmental improvements are driven by genuine abatement or by output contraction.

A2.5 Extension: Effect of τ on Operating Leverage

Proposition 4: An increase in the social insurance contribution rate τ increases firms' operating leverage.

Proof: To analyze the financial distress channel, we decompose the firm's cost structure as follows.

Revenue is given by:

$$R = PQ = Pf(L_p). \quad (\text{A24})$$

Variable costs (all costs that vary with output or current labor allocation):

$$VC = W(1 + \tau)(L_p + L_a) + t\theta \cdot g(L_a) \cdot f(L_p) \quad (\text{A25})$$

Fixed costs:

$$FC = C \quad (\text{A26})$$

Contribution margin (revenue minus variable costs):

$$G = R - VC = Pf(L_p) - W(1 + \tau)(L_p + L_a) - t\theta \cdot g(L_a) \cdot f(L_p) \quad (\text{A27})$$

Note that G is exactly the firm's profit before subtracting fixed costs: $\pi = G - C$.

Earnings before interest and taxes (EBIT):

$$EBIT = G - C \quad (A28)$$

Degree of operating leverage (DOL) measures the sensitivity of EBIT to changes in revenue:

$$DOL = \frac{G}{G - C} = \frac{G}{EBIT} \quad (A29)$$

First, by the envelope theorem, the direct effect of τ on profit (and thus on contribution margin) is:

$$\frac{\partial \pi}{\partial \tau} = \frac{\partial G}{\partial \tau} = -W(L_p + L_a) < 0 \quad (A30)$$

Now differentiate DOL with respect to τ :

$$\frac{\partial DOL}{\partial \tau} = \frac{\frac{\partial G}{\partial \tau}(G - C) - G \cdot \frac{\partial G}{\partial \tau}}{(G - C)^2} \quad (A31)$$

Simplify the numerator:

$$\frac{\partial G}{\partial \tau}[(G - C) - G] = \frac{\partial G}{\partial \tau} \cdot (-C) \quad (A32)$$

Thus:

$$\frac{\partial DOL}{\partial \tau} = -C \cdot \frac{\frac{\partial G}{\partial \tau}}{(G - C)^2} \quad (A33)$$

Given that:

- $C > 0$
- $(G - C)^2 > 0$ (assuming the firm is profitable, i.e., $G > C$)
- $\frac{\partial G}{\partial \tau} = -W(L_p + L_a) < 0$, from A30

We obtain:

$$\frac{\partial DOL}{\partial \tau} = -C \cdot \frac{(\text{negative})}{(\text{positive})} > 0. \quad (A34)$$

Thus, an increase in the social insurance contribution rate τ increases the firm's operating leverage. The intuition is that higher labor costs reduce the contribution margin G , but fixed costs C remain unchanged. This makes the firm's profits more sensitive to revenue fluctuations, increasing financial distress risk, which is a key mechanism linking increases in labor costs to subsequent abatement decisions.

Appendix A3. A Robustness Check: PSM-DID

We complement our main analysis with a PSM-DID design that defines the treatment variable as a binary indicator. This approach helps mitigate some of the interpretational difficulties inherent in the continuous treatment setting.

Following prior studies (e.g., Cui et al. 2021), we conduct a propensity score matching (PSM) procedure using only pre-treatment variables in 2010 to avoid any potential post-treatment bias. The matching covariates include four firm-level variables measured in the immediate year before the 2011 Social Insurance Law (i.e., in 2010)—financial leverage (*Lev*), tangibles (*Tangibles*), export share (*Export*), and return on assets (*ROA*), along with COD emissions. We drop firm size from the matching variables, since including it led to poor matching quality and reduced common support.

Balance diagnostics are essential for assessing the quality of the PSM procedure. We first follow Imbens (2015) and Benzarti et al. (2020) to use normalized differences to assess the overlap in covariates. Figure A2 displays the standardized bias for all matching covariates before and after matching, based on 1:3 nearest-neighbor matching (results are similar using other matching ratios). The results show that the standardized biases across all variables are reduced to within 1%. While there is no formal threshold for normalized differences, they are well in line with those in other studies (Imbens, 2015; Benzarti et al. 2020).

We also follow Cui et al. (2021) to include a balance table (Table A3) that reports for each covariate used in the regression (i) the mean values of treated and control groups, and (ii) the corresponding t-tests for differences in means before and after matching. Results show that the matching procedure has improved the balance between the treated and comparison groups. After matching, most control variables (four out of five) show p -values greater than 0.10, indicating no statistically significant differences between treated and control groups on those variables. The only remaining imbalanced variable is firm size, reflecting the inherent tendency of labor-intensive firms to be smaller.

Overall, these balance tests demonstrate that the matching procedure effectively creates comparable treatment and control groups, which is crucial for unbiased estimation of PSM-based treatment effects.

Based on the PSM-matched sample, we re-estimate our DID regression model. As shown in Table A4, the results are robust to using different matching specifications, including 1:1, 1:3, 1:5 nearest-

neighbor matching, and kernel matching. All approaches yield highly similar treatment effects, supporting the robustness of our findings.

We further estimate the dynamic effect of the Social Insurance Law on corporate pollution emissions using the matched sample. As shown in Figure A3, the confidence intervals for the pre-treatment years (2008-2011) comfortably include zero for both COD and wastewater, confirming parallel pre-trends. Subsequently, the coefficients for both series jump in 2012 and remain elevated in 2013, indicating an increase in emission intensity following the law.

Appendix A4. Exogeneity of Environmental Regulation

In Section 7.1, we employ two environmental regulation measures to capture the stringency of local environmental regulation and study its role in mitigating the emission effect of a labor cost shock. Both measures satisfy the critical condition of being determined at the city or higher government level before the treatment, and beyond the influence of individual firms. This mitigates the concern that our regulatory strictness variable was itself a consequence of the 2011 Social Insurance Law, hence eliminating post-treatment bias in our heterogeneity analysis. Nevertheless, one may still be concerned about the exogeneity of the regulatory treatment. For example, stricter environmental enforcement may correlate with other local characteristics, such as economic conditions and baseline pollution levels, which could themselves affect firms' response to the Social Insurance Law. To address this concern, we use a propensity score matching (PSM) approach to construct two comparable groups, and then re-estimate the model.

We implement a PSM approach at the city level. Specifically, we estimate a logistic regression, in which the dependent variable is equal to one if a city is designated as a “key city” (our proxy for stricter environmental enforcement), and zero otherwise. The independent variables consist of pre-policy city characteristics that might correlate with regulation stringency: GDP per capita, population, and sulfur dioxide emission. Cities are matched with their nearest neighbors (ratio=1:2) based on propensity scores.

After matching treated and control cities based on city-level characteristics, we obtain 71 treated cities with 65 matched untreated cities. Balance tests indicate substantial reductions in pre-treatment differences between the two groups. The standardized bias of the matching variables (GDP per capita, population, SO₂ emission) decreases substantially after matching (see Figure A5) and post-matching differences are statistically insignificant (p -value > 0.5). Additionally, balance also improves for a non-matching variable, city-level wastewater emissions, providing reassurance that the matched sample is comparable along relevant dimensions, as reported in Table A9.

We re-estimate the main specifications on the matched samples. Table A10 reports quantitatively similar results as in Section 7.1. This check increases our confidence that the differential effects we observe are driven by the intensity of environmental monitoring rather than systematic cross-city differences in economic conditions or baseline pollution levels.

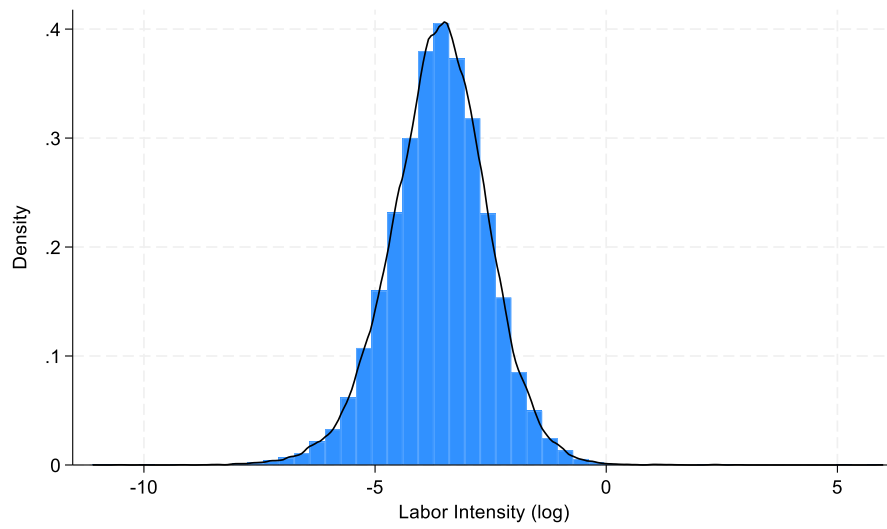


Figure A1. Density of Labor Intensity (log)

Note: This figure depicts the probability distribution of the logarithm of labor intensity at the end of 2010 for the sample in our empirical analysis.

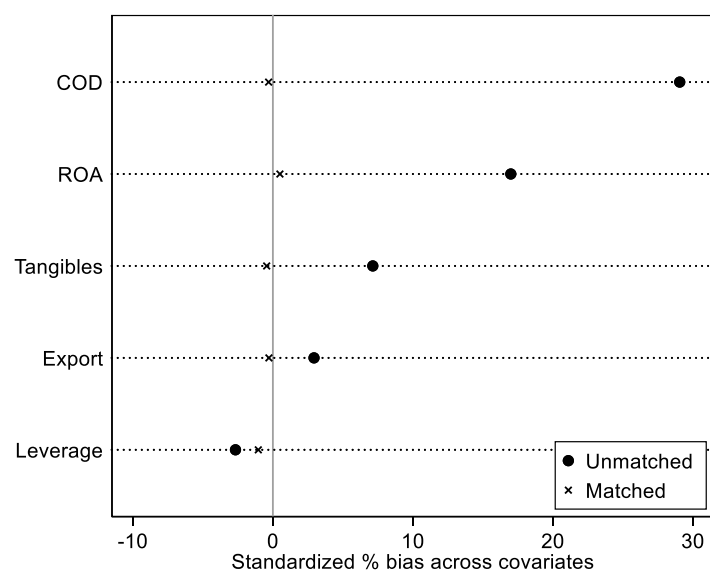


Figure A2. The Standardized Bias across Matching Covariates before and after Matching
 Note: Matching is performed using the nearest neighbor algorithm with a 1:3 matching ratio.

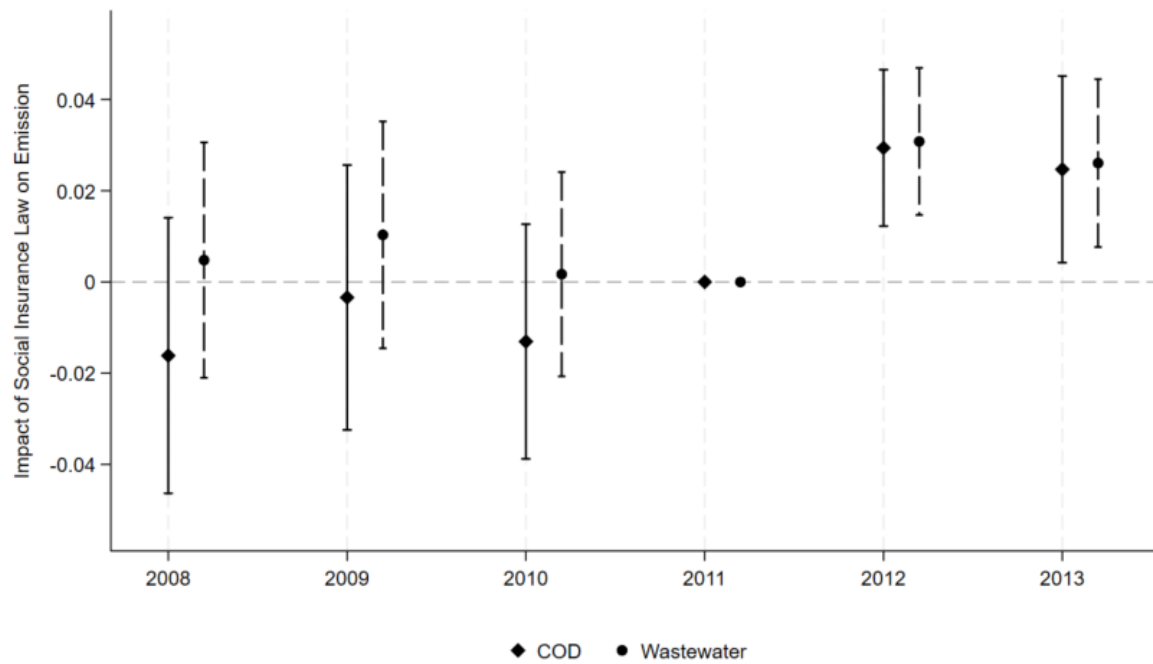


Figure A3. Dynamic Effects Using the Propensity Score Matched Sample

Note: This figure illustrates the estimated coefficients and 95% confidence intervals based on Equation 2, using the propensity score-matched sample. Matching is performed using the nearest neighbor algorithm with a 1:3 matching ratio. We control for the same set of firm-level covariates as in Table 2.

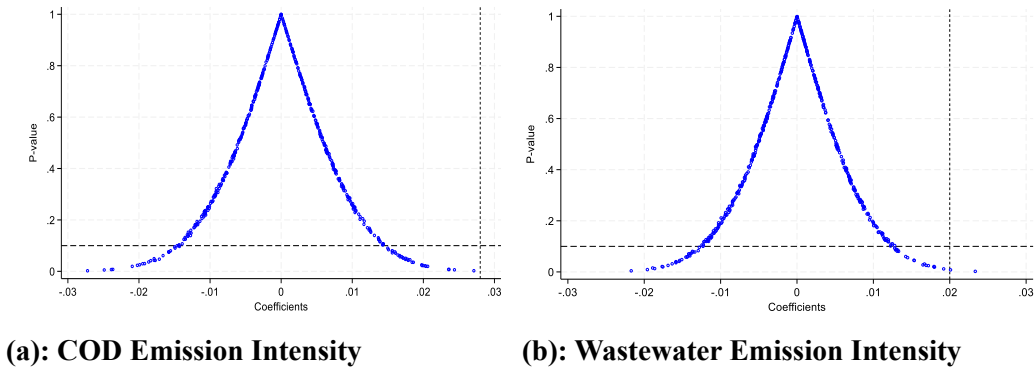


Figure A4. A Permutation Test

Notes: These figures display the estimated effects derived from re-estimating Equation 1 using 500 random permutations of the labor intensity variable. We randomize the labor intensity variable (as of the end of 2010) across firms to create a simulated policy exposure variable, then we re-estimate the DID regression (Equation 1) using this pseudo exposure variable. Figures (a) and (b) report results for COD and wastewater emission intensity, respectively. The blue hollow circle marks the point estimate on the x -axis, with the corresponding p -value shown on the y -axis. The vertical red line indicates the estimate magnitude from the actual data, while the horizontal red line denotes the 10% significance level.

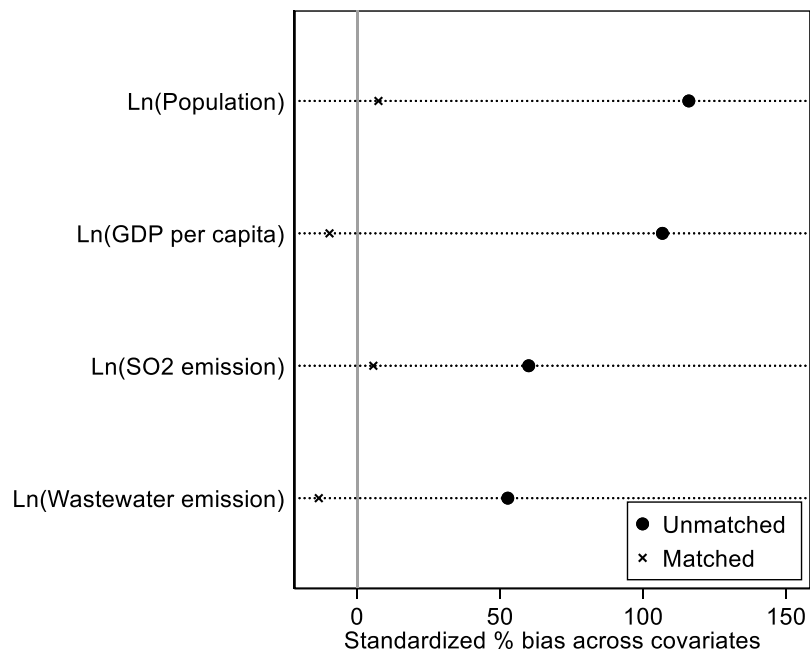


Figure A5. Balance of City Characteristics before and after Matching

Notes: This figure illustrates the balance of city characteristics between key cities and non-key cities before and after matching. The characteristics considered include GDP per capita, population size, sulfur dioxide emissions, and wastewater emissions.

Table A1. Summary Statistics Across Data Merging and Cleaning Steps

	Step 5 (Final Sample)	Step 4	Step 3	Step 2	Step 1	Merged Sample (No Restriction)	ASIF	ESR
No. Of Obs.	137,669	183,268	240,252	240,598	268,012	351,367	2,192,953	777,554
Output	54,220 (322,342)	47,831 (291,607)	48,484 (1,208,825)	48,464 (1,207,989)	46,899 (1,158,526)	39,451 (1,017,107)		24,966 (699,388)
COD Emission	50,163 (266,787)	44,058 (248,604)	49,883 (363,092)	49,870 (362,892)	47,456 (348,543)	44,023 (340,334)		38,052 (300,936)
Wastewater Emission	374,741 (2,092,197)	320,259 (1,847,254)	304,606 (1,802,409)	304,505 (1,801,486)	309,131 (2,603,044)	275,823 (2,342,043)		217,551 (1,794,691)
Labor Intensity (log)	-3.61 (1.06)	-3.61 (1.07)	-3.61 (1.07)	-3.51 (1.26)	-3.54 (1.29)	-3.47 (1.28)	-3.08 (1.23)	- -
Firm Size	9.29 (1.59)	9.20 (1.58)	9.13 (1.57)	9.13 (1.57)	9.15 (1.59)	8.90 (1.64)	7.85 (1.54)	- -
Financial Leverage	0.56 (0.28)	0.55 (0.29)	0.55 (0.29)	0.55 (0.30)	0.56 (0.32)	0.57 (4.57)	0.53 (1.88)	- -
Tangibles	0.38 (0.22)	0.38 (0.23)	0.38 (0.23)	0.38 (0.23)	0.39 (0.23)	0.39 (0.23)	0.37 (0.25)	- -
Share of Export	0.17 (0.32)	0.17 (0.32)	0.15 (0.31)	0.15 (0.31)	0.14 (0.30)	0.13 (0.30)	0.15 (0.34)	- -
Return on Assets	0.11 (0.26)	0.13 (1.85)	0.14 (1.63)	0.14 (1.63)	0.14 (1.57)	0.13 (1.41)	0.17 (11.59)	- -

Notes: Standard deviations are in parentheses. Step 1 drops firms with observations only before or only after the Social Insurance Law implementation. Step 2 restricts to firms in the manufacturing industry. Step 3 keeps above-scale firms. Step 4 drops missing COD emission and trims COD emission at the 1st and 99th percentiles. Step 5 drops missing controls and industry/location information. ASIF = Annual Survey of Industrial Firms. ESR = Environmental Survey Reporting.

Table A2. Pattern of Missing Values in Emission Data

	<i>Missing SO2</i>	<i>Missing COD</i>	<i>Missing Wastewater</i>
	(1)	(2)	(3)
Labor Intensity $\times$ Post	0.0053*** (0.0015)	0.0002 (0.0014)	0.0014 (0.0014)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes
Observations	174,452	174,452	174,452
Adjusted R-squared	0.764	0.696	0.700

Notes: This table assesses the impact of the Social Insurance Law on the likelihood of missing pollution data. The dependent variable in each column is a binary indicator for whether emission information is missing for the firm-year observation and zero otherwise. *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.

Table A3. Balance Test for Covariates Used in the Regression

	Unmatched Sample			Matched Sample		
	Treated	Control	P-value	Treated	Control	P-value
Leverage	0.554	0.561	0.052	0.554	0.556	0.541
Tangibles	0.394	0.379	0.000	0.394	0.395	0.795
Export	0.168	0.158	0.030	0.169	0.169	0.998
ROA	0.120	0.077	0.000	0.116	0.115	0.811
Size	8.466	9.959	0.000	8.467	9.798	0.000

Note: Matching is performed using the nearest neighbor algorithm with a 1:3 matching ratio. The column “P-value” reports the t-test for the covariate difference between treated and control firms in the pre-policy year (2010).

Table A4. Results Based on a PSM-DID Model

	(1) COD NN 1:1	(2) Wastewater NN 1:1	(3) COD NN 1:3	(4) Wastewater NN 1:3	(5) COD NN 1:5	(6) Wastewater NN 1:5	(7) COD Kernel	(8) Wastewater Kernel
High Labor Intensity × Post	0.097*** (0.024)	0.062*** (0.020)	0.065*** (0.021)	0.042** (0.018)	0.052*** (0.020)	0.034* (0.017)	0.049** (0.020)	0.030* (0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87,167	86,984	107,146	106,931	111,859	111,638	113,494	113,272
Adjusted R-squared	0.754	0.763	0.760	0.770	0.761	0.770	0.761	0.771

Note: This table reports treatment effect estimates under different matching specifications. Columns (1)-(2) use 1:1 nearest neighbor matching. Columns (3)-(4) use 1:3 nearest neighbor matching. Columns (5)-(6) use 1:5 nearest neighbor matching. Columns (7)-(8) use kernel matching. All matching variables are measured in 2010 (the pre-treatment period) to avoid potential post-treatment bias.

Table A5. Controlling for the Impact of 12th Five-Year Plan

	<i>Ln</i> (COD)	<i>Ln</i> (Wastewater)
	(1)	(2)
Labor Intensity × Post	0.026*** (0.008)	0.016** (0.007)
Exposure × FYP	-0.024*** (0.005)	-0.005 (0.004)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Province FE	Yes	Yes
Observations	137,669	137,237
Adjusted R-squared	0.767	0.775

Notes: This table reports the results controlling for the impact of the 12th Five-Year Plan (2011-2015). The dependent variable in columns (1)-(2) is the natural logarithm of COD emission intensity and wastewater emission intensity, respectively. *Post* is an indicator that equals zero in 2008-2011 and one in 2012-2013. *Labor Intensity* is firm-level labor intensity at the end of 2010 (in logarithm). *Exposure* captures provincial-level environmental regulation stringency, measured as the total COD reduction target mandated by the 12th Five-Year Plan. *FYP* is a policy indicator that equals one for the years 2011 onward and zero otherwise. Standard errors, presented in parentheses, are clustered at the firm level. Asterisks (*, **, ***) represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A6. Controlling for Time-Varying Environmental Enforcement

	<i>Ln</i> (COD)		<i>Ln</i> (Wastewater)	
	(1)	(2)	(3)	(4)
Labor Intensity $\times$ Post	0.029*** (0.009)	0.026*** (0.009)	0.020** (0.008)	0.018** (0.008)
Key Monitoring Enterprise	0.022 (0.019)		0.022 (0.016)	
Key Monitoring Enterprise-Year FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Observations	137,669	137,669	137,237	137,237
Adjusted R-squared	0.769	0.769	0.777	0.777

Notes: The dependent variable in columns (1)-(2) is the natural logarithm of COD emission intensity, while the dependent variable in columns (3)-(4) is the natural logarithm of wastewater emission intensity. *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). *Key Monitoring Enterprise* takes the value of one if a firm is designated as a key monitoring enterprise in a given year, and zero otherwise. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A7. Robustness Checks: Alternative Measures for Labor Intensity

	<i>Ln</i> (COD)		<i>Ln</i> (Wastewater)	
	(1)	(2)	(3)	(4)
High Labor Intensity $\times$ Post	0.059*** (0.018)		0.045*** (0.015)	
Labor Intensity before 2010 $\times$ Post		0.028*** (0.009)		0.018** (0.008)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Observations	137,669	136,896	137,237	136,468
Adjusted R-squared	0.769	0.768	0.777	0.776

Note: In columns (1)-(2), the dependent variable is the natural logarithm of COD emission intensity, while in columns (3)-(4), the dependent variable is the natural logarithm of wastewater emission intensity. *High Labor Intensity* is a dummy variable which equals one if a firm's labor intensity at the end of 2010 is greater than the median of its distribution, and zero otherwise. *Labor Intensity Before 2010* is the firm's average labor intensity during 2008-2010. *Post* is an indicator that equals zero in 2008-2011 and one in 2012-2013. Standard errors, presented in parentheses, are clustered at the firm level. Asterisks (*, **, ***) represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A8. Impacts of the Social Insurance Law on SO2 Emission Intensity

	<i>Ln</i> (SO2)	
	(1)	(2)
Labor Intensity × Post	0.025** (0.011)	0.028*** (0.011)
Firm Size		-0.067*** (0.013)
Financial Leverage		-0.039 (0.031)
Tangibles		0.037 (0.036)
Share of Export		-0.038 (0.033)
Return on Assets		-0.009 (0.016)
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Province-Year FE	Yes	Yes
Observations	93,287	93,287
Adjusted R-squared	0.818	0.819

Notes: This table reports the results for our baseline regression. The dependent variable is the emission intensity of sulfur dioxide (in 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, presented in parentheses, are clustered at the firm level. Asterisks (*, **, ***) represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A9. Balance Test for City-level Variables

	Unmatched Sample			Matched Sample		
	Treated	Control	P-value	Treated	Control	P-value
Ln(GDP)	10.865	10.321	0	10.703	10.752	0.532
Ln(Population)	5.049	4.267	0	4.659	4.609	0.549
Ln(SO2)	10.997	10.345	0	10.783	10.721	0.737
Ln(Wastewater)	8.795	8.214	0	8.457	8.604	0.357

Note: Matching is performed using the nearest neighbor algorithm with a 1:2 matching ratio. The column “P-value” reports the t-test for the covariate difference between treated and control cities in the year 2010.

Table A10. The Role of Environmental Regulation: PSM-DID Analysis

	<i>Ln(COD)</i>		<i>Ln(Wastewater)</i>	
	(1)	(2)	(3)	(4)
	Key City	Non-key City	Key City	Non-key City
Labor Intensity $\times$ Post	0.004 (0.018)	0.051** (0.020)	0.0002 (0.015)	0.039** (0.018)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Observations	27,403	20,600	27,308	20,533
Adjusted R-squared	0.797	0.772	0.812	0.780

Notes: The dependent variable in columns (1)-(2) is the natural log of COD emission intensity; in columns (3)-(4) it is the natural log of wastewater emission intensity. Columns (1)-(2) (and columns (3)-(4)) divide the sample based on whether firms are headquartered in “key cities” designated for pollution control in 2007. Standard errors, presented in parentheses, are clustered at the firm level. Asterisks (*, **, ***) represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A11. Robustness: The Mitigating Effect of Peer Pressure

Panel A: COD	Key City		Non-Key City	
	High-ESG	Low-ESG	High-ESG	Low-ESG
	Province	Province	Province	Province
	(1)	(2)	(3)	(4)
Labor Intensity $\times$ Post	0.017 (0.012)	0.019 (0.021)	0.006 (0.018)	0.117*** (0.030)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Observations	56,440	17,302	38,287	14,966
Adjusted R-squared	0.805	0.768	0.751	0.710
Panel B: Wastewater	Key City		Non-Key City	
	High-ESG	Low-ESG	High-ESG	Low-ESG
	Province	Province	Province	Province
	(1)	(2)	(3)	(4)
Labor Intensity $\times$ Post	0.009 (0.010)	0.024 (0.017)	-0.001 (0.016)	0.089*** (0.025)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Observations	56,310	17,244	38,154	14,868
Adjusted R-squared	0.817	0.793	0.753	0.703

Note: This analysis identifies the peer effect within regulatory regimes, rather than across them. The key idea is to compare firms that face similar formal environmental enforcement but differ in their exposure to ESG-sensitive peers. We first divide the sample based on whether firms are headquartered in “key cities” designated for pollution control in 2007. Within each group, we further divide the firms based on whether they operate in provinces with above-median average ESG scores. We test whether, within the same regulatory environment, firms with higher exposure to ESG-sensitive peers exhibit a smaller increase in pollution following the Social Insurance Law, relative to their low-exposure peers.

Appendix References

Benzarti, Youssef, Dorian Carloni, Jarkko Harju, and Tuomas Kosonen. "What goes up may not come down: asymmetric incidence of value-added taxes." *Journal of Political Economy* 128, no. 12 (2020): 4438-4474.

Cui, Jingbo, Chunhua Wang, Junjie Zhang, and Yang Zheng. "The effectiveness of China's regional carbon market pilots in reducing firm emissions." *Proceedings of the National Academy of Sciences* 118, no. 52 (2021): e2109912118.

Imbens, Guido W. "Matching methods in practice: Three examples." *Journal of Human Resources* 50, no. 2 (2015): 373-419.

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.