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Dark side of environmental regulation: Wage inequality cost

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ABSTRACT

Environmental regulations have both bright and dark consequences, and understanding the dark side is critical for policymakers. This paper investigates whether and how environmental regulation exacerbates the wage inequality between skilled and unskilled labor. Employing a triple difference-in-differences (DDD) estimation method on Chinese urban household survey data, we find a 1.7% increase in the wage gap after the implementation of a regional-specific environmental regulation. We show that the enlarged wage gap is mainly due to the intensive margin's change and is dominated by the polluting sector rather than the non-polluting one. More importantly, the unappealing effect on wage inequality lasts in the long run and is not China-specific, according to our numerical simulation of a general equilibrium model. Finally, we also propose a non-environmental policy instrument to alleviate the negative impact. Overall, our work highlights that environmental regulation may have an unintended wage inequality cost, and our study is of generic policy implications to other economies.

1. Introduction

Environmental regulations are associated with benefits and costs. On the bright side, a stringent environmental policy could improve environmental quality and household life expectancy (Greenstone and Hanna, 2014; Tanaka, 2015). On the dark side, environmentally regulated firms would experience a recession, manifested as output reduction (Wang et al., 2018) and labor demand shrinkage (Kahn and Mansur, 2013; Liu et al., 2021). Yet, little is known about how different kinds of labor (*i.e.*, skilled and unskilled labor), especially their wage gap (inequality), respond to environmental regulations.

This paper attempts to fill this gap by studying the impact of an environmental policy on wage inequality between skilled and unskilled labor. Our study is of practical implications for policymakers, as the government strives for environmental and economic inequality issues when setting policy agendas. Previous studies have investigated environmental regulations' effect on income and health inequality (*e.g.*, Constant, 2019; Jha et al., 2019), while little attention has been paid to the causal relationship between environmental policy and skilled–unskilled wage inequality.[2] In this paper, we first establish the empirical relationship with short-run micro evidence in the context of China, and then generalize our findings to a long-run perspective and other countries with a general equilibrium framework.

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[2] For example, Jha et al. (2019) find National Ambient Air Quality standards enhance the market Gini coefficient of income distribution and affect the poor people more. Constant (2019) studies whether the environmental policy can mitigate inequalities in life expectancy.

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As one of the largest developing countries, China once experienced environmental deterioration for rapid production expansion but now makes great efforts in curbing environmental pollution. In 2005, the Chinese central government first put forward a province-varying reduction target on provincial sulfur dioxide (SO_2) emissions in the eleventh Five-Year Plan (*i.e.*, from 2006 to 2010). This policy effectively reduced pollution and has been used in studies about firms' responses (*e.g.*, labor demand and export decisions) to environmental regulation (*e.g.*, Liu et al., 2017; Shi and Xu, 2018).

In line with these works, we treat the provincial SO_2 reduction target policy as an exogenous shock, and employ a triple difference-in-differences (DDD) method to compare the wage gap between skilled and unskilled labor in highly and non-highly regulated regions before and after the policy shock. Our data are from the Chinese Urban Household Survey (UHS), a nationally representative dataset, which is used in many related studies (Han et al., 2012; Dai et al., 2021). Our DDD estimation finds that a one percentage point increase in the SO_2 reduction target would lead to an approximate 1.7% expansion in wage inequality. The result is persistent during the sample period (*i.e.*, from 2002 to 2009, with the shock period from 2006 to 2009).

To understand the economic mechanism of this enlarged wage inequality, we first investigate the dynamic pattern of the wage gap between the skilled and unskilled *workers* (*i.e.*, employed labor), and find the wage inequality still rises. Then, we look at the layoff propensity of the skilled and unskilled labor, and find no significant difference from the unemployment probability gap between the highly and non-highly regulated regions. Thus, our baseline result is mainly driven by the intensive margin (*i.e.*, change the relative wage of the skilled and unskilled workers) rather than the extensive margin (*i.e.*, relative high layoff probability). This result aligns with and complements the empirical findings in Berman and Bui (2001) and Liu et al. (2017), which examine the firm's *total* employment change in the wake of an environmental policy. In addition, we perform a subsample DDD analysis and show that the widened wage gap is from the polluting instead of the green sector.

Our empirical results are robust to the following specifications: (i) We perform a placebo test and show that the results are not led by the unobserved time-varying characteristics between the skilled and unskilled people. (ii) We take an instrumental variable (IV) approach to deal with the endogenous environmental regulation intensity. Concretely, we follow Hering and Poncet (2014) and Shi and Xu (2018) and use the provincial ventilation coefficient as the IV for policy intensity. Our IV results suggest an even more considerable increase in the wage gap. (iii) We exclude 2008 and 2009 to rule out the 2008 global financial crisis concurrent event, since the financial tsunami might also affect polluting firms' employment structure. (iv) We test the individual migration decision and find no evidence that unskilled labor tends to migrate to lower regulated regions after the policy implementation. That means the household's endogenous migration decision does not affect our findings. (v) We conduct a weighted regression analysis to show that the previous conclusions are robust to a weighting scheme incorporating the different number of interviewees in different provinces.

Based on the micro-level evidence, some further questions would be: whether the enlarged wage inequality caused by environmental regulations would last in the long run; or is specific to China; and moreover, how to deal with the unappealing rise in the wage gap. To answer these counterfactual questions, we construct a two-sector dynamic general equilibrium model. The model economy features differentiated skilled and unskilled labor, and differentiated firms in polluting and green sectors. The environmental regulation is modeled as the punitive penalties on firms' pollutant emissions, and its intensity is calibrated by matching the average provincial SO_2 reduction target outlined in the eleventh Five-Year Plan.

Our 40-year simulated transition path to this permanent exogenous regulatory shock also shows an increase in wage inequality after implementing the environmental policy. The transmission mechanism is consistent with our empirical findings that the polluting sector is more affected by the regulation. Both the skilled and unskilled workers who are squeezed out of the polluting firms seek opportunities in the green sector. Since the green sector is more skill-intensive than the polluting one, unskilled workers are relatively over-supplied in the green sector compared with the skilled ones, which explains the enlarged wage gap. The long-run effect and mechanism are qualitatively general, since the simulation results preserve when we relax model parameters to standard (non-China-specific) values in the literature (*e.g.*, Acemoglu et al., 2012; Angelopoulos et al., 2017).

To deal with the undesired wage inequality induced by the current environmental regulation, we also propose a non-environmental policy for regulators. The counterfactual experiment shows that boosting human capital investment plays a positive and effective role in preventing enlarged wage inequality, with the emission reduction target still fulfilled. This result implies that non-environmental policy aiming at reducing education gap together with environmental regulation could achieve both the environmental and equality goals.

Related literature. This paper is closely related to the literature studying wage inequality between skilled and unskilled workers. The main causes of wage premium in the literature are college attainment expansion, minimum wage rise, and skill-biased technical change (*e.g.*, Katz and Murphy, 1992; Krusell et al., 2000; Goldin and Katz, 2009; Acemoglu and Autor, 2011). However, the impact on wage inequality from the view of environmental regulation is less investigated. The only related work, to our best knowledge, is Ee et al. (2018) which report an ambiguous effect of a pollution tax on the wage gap in the short run but benefits for rural workers in the long run. Our study departs from them in three dimensions: First, we focus on the urban residents' wage inequality rather than the rural–urban wage gap. Second, we establish micro-level empirical evidence between existing China's environmental policy and the skilled–unskilled wage inequality using the UHS data, instead of using the Gini coefficient distinguishing the poor and rich's income distribution. Third, we study the policy's general long-run effect based on a calibrated dynamic general equilibrium model and propose non-environmental policy advice to alleviate the wage gap for regulators' references.

Our study also complements the empirical literature on the impact of China's environmental policy. Works in this literature using provincial SO_2 reduction policy as an exogenous shock mainly aim at firms' reactions in terms of export, FDI and labor demand (*e.g.*, Hering and Poncet, 2014; Cai et al., 2016; Liu et al., 2017, 2018; Shi and Xu, 2018; Liu et al., 2021), but abstract away from households' responses. It is worthy to note that Liu et al. (2017) focus on the firms' total labor demand in the printing and dyeing industries in Jiangsu province. Instead, we investigate how different kinds of labor respond to environmental regulation with extended geographical and industrial coverages. We further highlight that the deteriorated wage inequality consequence could persist in the short and long runs.

The remainder of this paper is organized as follows. Section 2 introduces the institutional background and describes the data. Section 3 presents the empirical results and Section 4 performs some robustness tests. Section 5 conducts counterfactual exercises to study the long-run effect and a remedial policy by a theoretical framework. The conclusion is made in Section 6.

2. Background, data source, and summary statistics

2.1. Provincial sulfur dioxide emission target

China, as the largest developing country, has suffered severe environmental pollution issues since 1980. In 2005, the State Council of China set forth a province-varying environmental regulation in the eleventh Five-Year Plan. It is the first time that each province has its reduction target of SO_2 pollutant emissions. Table A.1 lists the reduction percentage target of the provinces in our survey sample.

By linking the local officials' promotion with their performances in fulfilling the emission reduction target, the central government effectively curbed the SO_2 pollutant emissions.[3] According to Shi and Xu (2018), which illustrate the relationship between the provincial target and the actual SO_2 emission reduction, most provinces achieved their reduction targets.[4] Similarly, Chen et al. (2018) find that pollution-intensive activities in highly regulated areas declined significantly.

2.2. Household survey data

Our individual-level data are from the Urban Household Survey (UHS), conducted by the Urban Survey Organization of the Chinese National Bureau of Statistics (NBS). The UHS individual-level data are a representative sample of Chinese urban households based on the stratified random sampling process (Han et al., 2012). The data contain detailed information about individual wages and other demographic information, including birth year, education, employment, gender, and marital status. The UHS data are widely used in the literature studying various policies' impact on Chinese households (Han et al., 2012; Dai et al., 2021; Liu et al., 2021).

Our sample period spans from 2002 to 2009, covering both the pre- and post-shock periods as the environmental regulation was implemented in 2006.[5] The sample period ends in 2009 due to the UHS data availability. We select the sample data following the spirit of Han et al. (2012). First, we restrict our sample to full-time employed and unemployed labor between the ages of 18 and 60. Concretely, the non-full-time labor, such as disabled, retired, re-employed retired people and students, are excluded.[6] Second, we use 2002 as the base year and compute the real individual total wage. Specifically, we sum the salary, bonus, and subsidy income as the nominal wage, and deflate it by the corresponding provincial consumer price index (CPI). Thus, we preclude price changes and make data comparable between different years. The key variables (at the individual and province levels) used in this study are defined and listed in Table A.2.

Table 1 reports the summary statistics of the main variables. In Panel A of Table 1, there are 425,639 observations, 35.3% of which are skilled labor (*i.e.*, at least a junior college or technical institution graduate). Overall, people in the labor force have an average working experience of 22 years, with a mean age of around 40. Panel B shows the differences in wage and demographic factors between the skilled and the unskilled labor. As expected, there are fewer skilled labor than unskilled ones, and on average, skilled labor are younger and earn more. These systematical differences between the skilled and unskilled labor's characteristics validate our choice of control variables.

Before proceeding to a formal identification strategy, we first examine the changes in unconditional wage densities. Specifically, we split our sample into 8 ($2 \times 2 \times 2$) different sub-samples: for skilled and unskilled workers (2 groups) before and after (2 groups) the introduction of the SO2 targets in provinces above and below the median of the provincial reduction target (2 groups). In Fig. 1, we plot the kernel density curves of the unconditional log(Wage) before and after the regulation in high and low target provinces by stacking high-skilled and low-skilled workers together. Comparing the left and the right in Fig. 1(a), we find that the distance between the two curves widens in highly regulated regions, indicating an enlarged wage gap between the skilled and unskilled workers after introducing environmental restrictions in these regions. In contrast, Fig. 1(b) presents no significant changes in the wage gap in loosely regulated provinces. Motivated by the unconditional plots, we further conduct a more rigorous estimation in the next Section.

[3] If the local government achieved the reduction target, the leading group's promotion prospect would increase. Otherwise, the leaders would be confronted with administrative accountability and decruited from the office (Chen et al., 2018).

[4] Liu et al. (2017) also provide evidence that the policy resulted in a successful decline in SO_2 emissions.

[5] To exclude the possible confounding effects such as the 2008 global financial crisis, we conduct additional robustness check by dropping the last two years in Section 4.

[6] Note that the unemployment rate in our sample is around 7.465%, consistent with Feng et al. (2017).

Table 1
Descriptive statistics.

Panel A: Full sample					
Variables	Obs.	Mean	Std. Dev.	Min	Max
Wage	425,639	10 285.12	8882.817	0	67 729.7
Skill	425,639	0.353	0.478	0	1
Male	425,639	0.548	0.498	0	1
Age	425,639	39.874	9.827	18	60
Experience	425,639	21.547	10.784	0	54
Marital	425,639	0.867	0.339	0	1

Panel B: Subsamples of skilled and unskilled labor							
Variables	Unskilled labor			Skilled labor			Mean Diff.
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
Wage	275,460	7995.522	7257.745	150,179	14 484.716	9988.167	−6489.194***
Male	275,460	0.532	0.499	150,179	0.578	0.494	−0.046***
Age	275,460	40.890	10.019	150,179	38.011	9.177	2.879***
Male	275,460	162,432	0.546	150,179	96,615	0.59	−0.044***
Experience	275,460	24.239	10.614	150,179	16.608	9.236	7.631***
Marital	275,460	0.886	0.318	150,179	0.834	0.372	0.052***

Note: *, **, and *** denote significance at the 10%, 5% and 1% level from the t-test, respectively.

3. Identification and empirical results

3.1. Triple difference-in-differences approach

Following the spirit of Han et al. (2012) and Shi and Xu (2018), we employ a triple difference-in-differences (DDD) estimation strategy to evaluate the impact of environmental regulation on wage inequality between the skilled and unskilled labor. Specifically, we exploit three types of variation: (1) the time variation of the eleventh Five-Year Plan (*i.e.*, before and after 2006); (2) the provincial variation of the SO_2 reduction intensity; (3) the individual variation of being skilled labor or not. Our most preferred DDD model is specified as follows:

$$\ln(W_{ipt}) = \beta_0 + \beta_1 Post_t \times Reduction_p \times Skill_i + X_{it} + \delta_{pt} + \lambda_{dt} + \gamma_{it} + \kappa_{ip} + \mu_{pd} + \varepsilon_{ipt}, \tag{1}$$

where $\ln(W_{ipt})$ is the natural logarithm of the *real* total wage (adjusted by provincial CPI) of individual i from province p in the year t. $Post_t$ is a dummy variable equal to one if the survey year t is after 2005 and zero otherwise. $Reduction_p$ is a continuous treatment variable capturing the SO_2 reduction target percentage set for province p in the eleventh Five-Year Plan. $Skill_i$ is a dummy variable equal to one if individual i is at least a junior college or technical institution graduate and zero otherwise. We control for a vector of individual characteristics X_{it}, including gender, age (and its square), working experience (and its square), and marital status.[7]

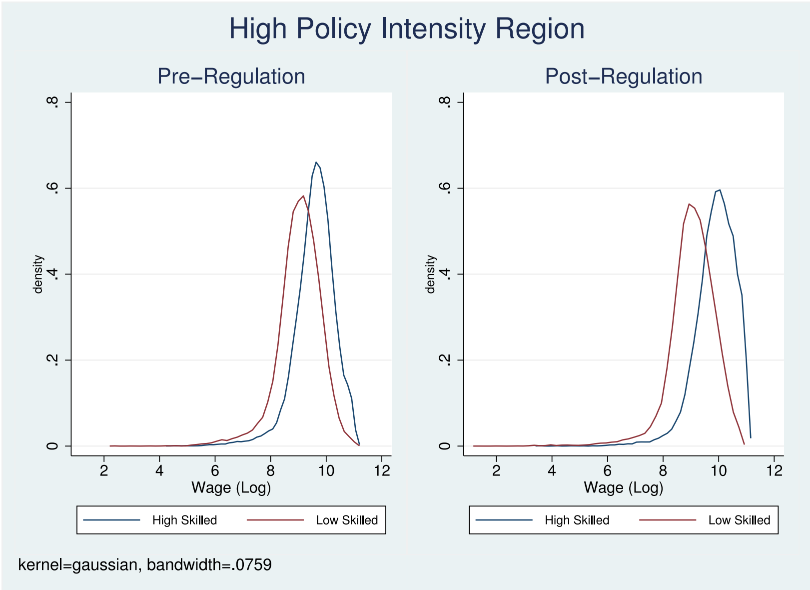
To control the time-varying provincial and industrial factors, we include the province × year fixed effect δ_{pt} and the industry × year fixed effect λ_{dt}, respectively. The industry refers to the industry that individual i works.[8] Also, we control for the skill × year (γ_{it}) as well as the province × skill (κ_{ip}) fixed effects. In addition, we add the province × industry fixed effect μ_{pd} to rule out the possibility of the time-invariant industrial characteristics in each province. By incorporating these fixed effects, our coefficient of interest, β_1, captures the wage gap change between the skilled and unskilled labor in provinces with different environmental policy intensities. We use the two-way clustered standard error at both the province and the year levels to account for the potential autocorrelation within a province and over time.

Table 2 presents the estimated DDD results based on Eq. (1). Column (1) shows the result pertaining to the province × year, skill × year, and province × skill fixed effects, and Column (2) includes individual characteristics affecting wage inequalities as the control variables. Column (3) further adds the industry × province fixed effect. Columns (1)-(3) show that the wage inequality between the skilled and unskilled labor exacerbates after implementing the eleventh Five-Year Plan. Column (4), our most preferred specification, adds the industry × year fixed effect to account for the time-varying unobservable industry characteristics, and the results remain consistent. Quantitatively, in Column (4), we find that a one percentage point increase in reduction target would enlarge the wage inequality between the skilled and the unskilled labor by 1.7 percent. Since the sample average real wage is around 10,285 yuan (1590 US dollars) per year, the regression result suggests that the wage gap is increased by about 175 yuan (27.03 US dollars).

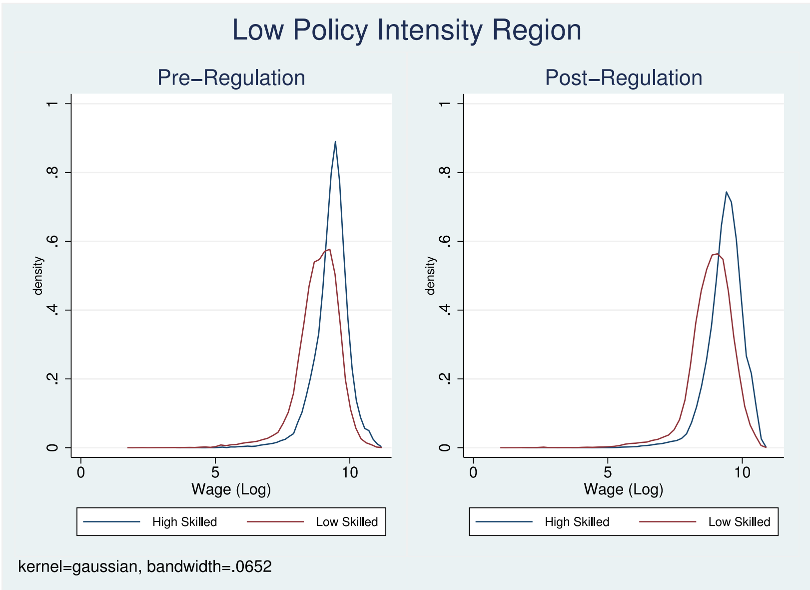
It is noticed in Table A.1 that provinces extracting coal and oil (e.g., Shanxi, Heilongjiang, etc.) are generally subject to weak environmental regulations. However, these provinces may experience a large wage gap change due to the extension margin change (job loss). Such concern could lead our main estimates in Table 2 to a downward bias. To assess the extent of this bias, we follow Minchener (2011) and exclude six provinces with intensive coal and oil production (*i.e.*, Anhui, Heilongjiang, Henan, Liaoning,

[7] Following Han et al. (2012), we define individual i's working experience as his/her age minus the schooling years minus six.

[8] For the unemployed (*i.e.*, zero wage) case, we create an artificial "industry" to capture job-less people's fixed effect.



(a) High Policy Intensity Region



(b) Low Policy Intensity Region

Fig. 1. Kernel density plots of log(Wage) between the high-skilled and the low-skilled. Notes: The figures show the kernel density plots of log(wage) between the high-skilled and low-skilled workers before and after the regulation. Panel (a) plots the subsample of the provinces subject to above-the-median reduction targets, while Panel (b) plots the subsample of the provinces subject to below-the-median reduction targets.

Shandong, and Shanxi). Based on the new sample, we re-estimate our DDD model and find slightly increased results shown in Table A.3, indicating that such bias is not a primary concern in our study.

3.2. Parallel trend and dynamic effect

To strengthen the validity of the DDD estimates, we further investigate the dynamic effect of the provincial environmental regulation on wage inequality between the high- and low-skilled labor from 2002 to 2009. We construct the dynamic version of the yearly DDD estimate by using 2005 as our base year. Concretely, we interact the skilled dummy and the reduction target with

Table 2
Impact of environmental regulations on wage inequality: DDD results.

Dependent variable	(1) $\ln(W)$	(2) $\ln(W)$	(3) $\ln(W)$	(4) $\ln(W)$
Post × Reduction × Skill	0.016**	0.018***	0.019***	0.017***
	(0.007)	(0.005)	(0.004)	(0.004)
Male		0.317***	−0.059	−0.056
		(0.081)	(0.050)	(0.046)
Age		0.904***	0.288***	0.219***
		(0.081)	(0.032)	(0.036)
Age^2		−0.007***	−0.001**	−0.001
		(0.001)	(0.000)	(0.000)
Experience		−0.300***	−0.212***	−0.201***
		(0.026)	(0.022)	(0.020)
Experience^2		0.001	0.001*	0.001
		(0.000)	(0.000)	(0.000)
Marital status		0.499**	−0.026	0.085*
		(0.149)	(0.048)	(0.043)
Province × Year FE	Yes	Yes	Yes	Yes
Skill × Year FE	Yes	Yes	Yes	Yes
Province × Skill FE	Yes	Yes	Yes	Yes
Industry × Province FE	No	No	Yes	Yes
Industry × Year FE	No	No	No	Yes
Observations	425,639	425,639	425,639	425,639
R-squared	0.069	0.219	0.520	0.529

Notes: The dependent variable is the natural logarithm of the real total wage of individual i from province p in the year t. $Post_t$ is a dummy variable equal to one if the survey year t is after 2005 and zero otherwise. $Reduction_p$ is a continuous treatment variable capturing the SO_2 emission reduction target percentage set for province p in the eleventh Five-Year Plan. $Skill_i$ is a dummy variable that equals to one if individual i is at least a junior college or technical institution graduate and zero otherwise. Robust standard errors in parentheses are by two-way clustering over province and year. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

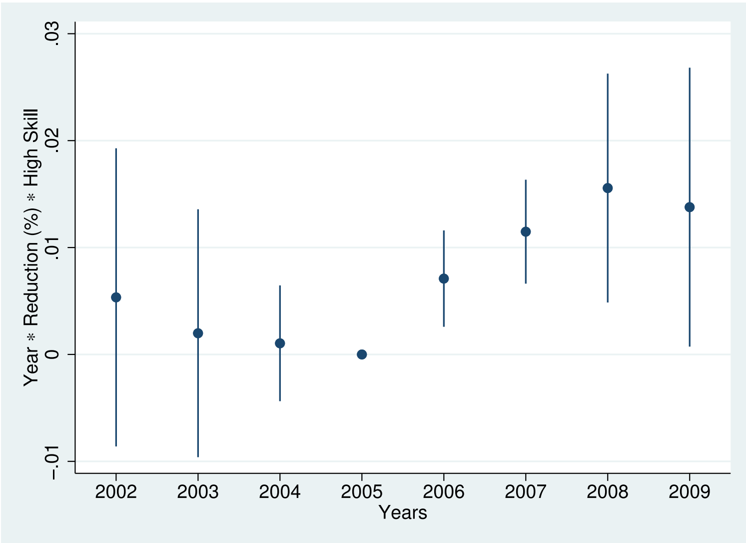
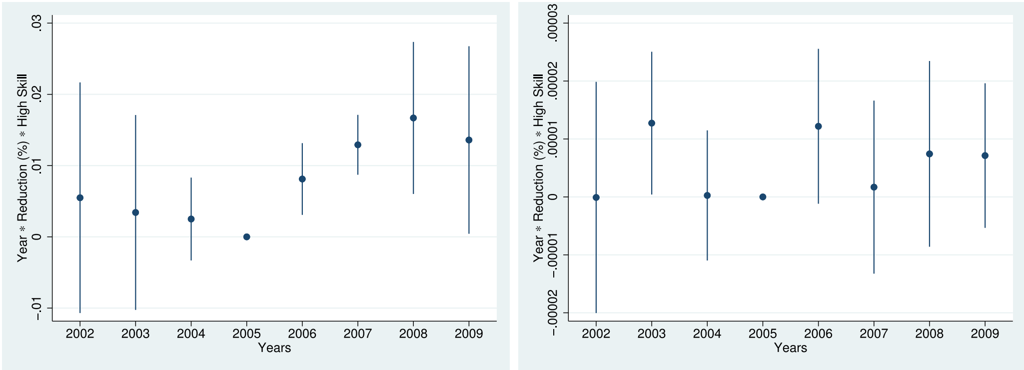


Fig. 2. The dynamic effect of environmental regulation on wage inequality. Notes: This figure illustrates the dynamic trends of environmental regulation on the individual's wage gap in the full sample. The vertical axis represents the dynamic DDD coefficients. The horizontal axis corresponds to the year from 2002 to 2009. The solid dot reports the DDD coefficient estimates before and after the policy implementation, using 2005 as the base year. The solid vertical lines depict the lower and upper bound of the 95% confidence interval, respectively.

a set of dummies of prior years (2002 to 2004) and post years (2006 to 2009) to see whether any pre- or post-trends existed for provinces with different environmental regulation intensities across time.

As Fig. 2 shows, there were no significant wage differences during the pre-trends (*i.e.*, before 2005) for the provinces with the high or low reduction targets, suggesting the parallel trend assumption is satisfied. In particular, the positive impact of reduction targets of SO_2 on wages emerged from 2006, when the eleventh Five-Year Plan was implemented. The magnitudes of the impacts became even more prominent for the years 2007, 2008, and 2009 respectively. Overall, we find the wage gaps between the high-



(a) Wage (b) Unemployment

Fig. 3. Economic mechanisms illustrations. Notes: This figure illustrates the dynamic trends of environmental regulation on (a) employed labor's wage gap and (b) unemployment propensity. In both figures, the vertical axis represents the dynamic DDD coefficients. The horizontal axis corresponds to the year from 2002 to 2009. The solid dot reports the DDD coefficient estimates before and after the policy implementation, using 2005 as the base year. The solid vertical lines depict the lower and upper bound of the 95% confidence interval, respectively.

and low-skilled labor in the highly and non-highly regulated regions are not systematically different but rise persistently after the occurrence of the policy.[9]

3.3. Economic mechanisms

Wage reduction or job loss. It is critical to understand the source of the enlarged wage inequality. The reason could be attributed to either (1) the relative wage adjustment between the skilled and unskilled labor (but they remain employed) or (2) the relative layoff propensity (*i.e.*, wage income drops to zero and being unemployed). In other words, our baseline results could be driven by the changes in the intensive margin (with a job) or the extensive margin (being dismissed). To examine whether the extensive margin dominates or not, we run the following two tests.

Firstly, we plot, in Fig. 3(a) that the dynamic effect using only the employed labor. The chart exhibits the same pattern as the baseline dynamic effect, *i.e.*, the wage inequality between the employed skilled and unskilled workers is getting larger. Secondly, we replace the outcome variable with the unemployment status, which is an indicator variable and equals one if an individual is unemployed in the year t. Other specifications are similarly defined as Eq. (1). We plot the dynamic effect in Fig. 3(b), and there is no significant effect on the skilled and unskilled labor's unemployment propensity gap after implementing the policy. In other words, our evidence suggests that firms do not respond to the policy by dismissing relatively more skilled or unskilled labor.

Taking together, the above findings indicate that the rising wage inequality is driven mainly by the relative earning gap between the high- and low-skilled labor (wage effect) but not by the relative employment reduction (unemployment effect). It is worth pointing out that our results do not contradict the conclusions in the related literature, such as Liu et al. (2017), which documents a statistically significant decline in polluting firms' *total* employment. Our work takes a step further to examine the workers' composition and to show that unemployment propensity between the skilled and unskilled labor does not alter substantially after the policy implementation.

Polluting vs. Green industries. The environmental regulation should no doubt have more impact on the polluting than the green industries. In other words, if the emission reduction pressure indeed causes the deterioration of wage inequality, we should observe that the enlarged wage gap is more salient in the polluting instead of the green industries. To test such heterogeneity, we re-estimate our baseline regressions based on the polluting and green industries subsamples. Following Wang and Zhang (2020), we define the polluting industry dummy variable as one when individual i works in mining and timber extraction, manufacturing, utilities, or construction industries, and zero otherwise. In our sample, we have 117, 709 workers serving in the polluting industries, approximately 29% of the total employed labor.

Table 3 presents the heterogeneous effects for workers in polluting and green industries. Column (1) of Table 3 shows that the wage gap between the high- and low-skilled workers in provinces with a higher reduction target experiences a more significant positive effect (1.9%) after the policy implementation. The economic magnitude is analog to our baseline results (*i.e.*, 1.7% in Table 2). In contrast, such relationship disappears for workers in the green industries, as reported in Column (2).

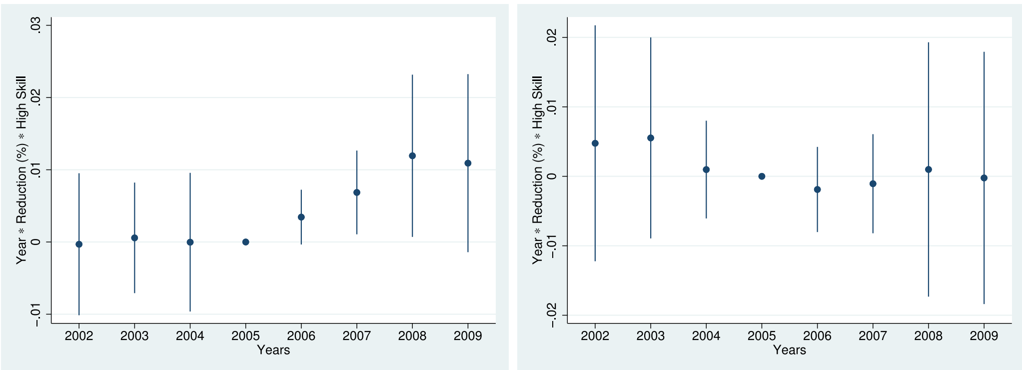
We further examine the dynamic effects of the environmental policy based on polluting and green industries separately to alleviate the parallel trend assumption concern. From Fig. 4(a), we find significantly positive effects of environmental policy on wage inequality since 2006. However, Fig. 4(b) indicates that there is no clear pattern for green industries. The findings suggest

[9] In Section 5, we would also perform the long-run (40-year) simulation analysis based on a theoretical model specified later.

Table 3
Impact of environmental regulation on wage inequality: Polluting vs. green industries.

Dependent variable	(1) Polluting $\ln(W)$	(2) Green $\ln(W)$
Post × Reduction × Skill	0.019*** (0.005)	0.001 (0.005)
Male	0.167*** (0.042)	−0.141** (0.051)
Age	0.169*** (0.028)	0.244*** (0.046)
Age^2	−0.001** (0.000)	0.000 (0.000)
Experience	−0.112*** (0.014)	−0.242*** (0.028)
Experience^2	0.001** (0.000)	0.001 (0.000)
Marital status	0.204*** (0.035)	0.159** (0.051)
Province × Year FE	Yes	Yes
Skill × Year FE	Yes	Yes
Province × Skill FE	Yes	Yes
Industry × Province FE	Yes	Yes
Industry × Year FE	Yes	Yes
Observations	117,709	276,156
R-squared	0.484	0.542

Notes: The dependent variable is the natural logarithm of the real total wage of individual i from province p in the year t. $Post_t$ is a dummy variable equal to one if the survey year t is after 2005 and zero otherwise. $Reduction_p$ is a continuous treatment variable capturing the SO_2 emission reduction target percentage set for province p in the eleventh Five-Year Plan. $Skill_i$ is a dummy variable that equals to one if individual i is at least a junior college or technical institution graduate and zero otherwise. Column (1) is based on polluting industries, and Column (2) is based on green industries. The polluting industry classification is from Wang and Zhang (2020), which is also released by the China Securities Regulatory Commission. Robust standard errors in parentheses are by two-way clustering over province and year. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.



(a) Polluting (b) Green

Fig. 4. Dynamic effects of environmental regulation: Polluting vs. Green Industries. Notes: This figure shows the dynamic trends of environmental regulation on wage inequality based on (a) the polluting industries and (b) the green industries, separately. In both figures, the vertical axis represents the dynamic DDD coefficients. The horizontal axis corresponds to the year from 2002 to 2009. The solid dot reports the DDD coefficient estimates before and after the policy implementation, using 2005 as the base year. The solid vertical lines depict the lower and upper bound of the 95% confidence interval, respectively.

there are relative wage adjustments of skilled and unskilled workers in the polluting industries in those highly regulated regions after the environmental policy.[10]

[10] We could not further infer whether the extensive margin plays a role or not in either the polluting or green industries. It is because the UHS is not an individual-level panel data. Once we know an individual belongs to the polluting or green industry, this person is automatically tagged as employed in the UHS data.

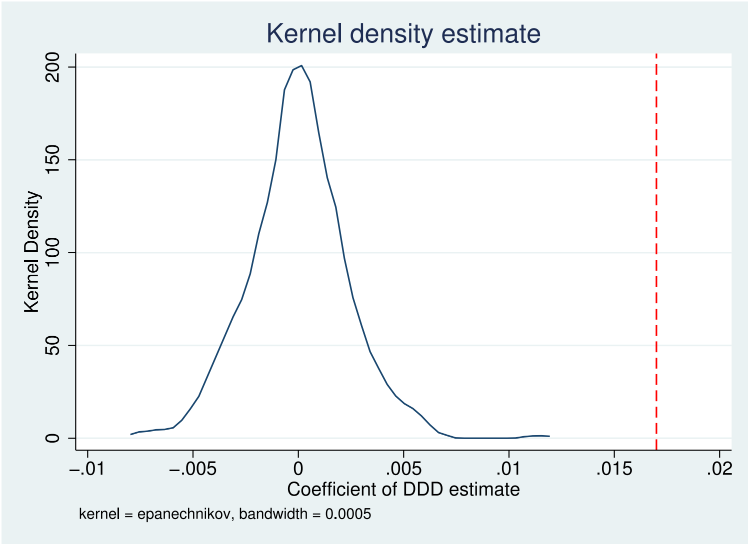


Fig. 5. Placebo test for the policy impact of environmental regulation.

4. Robustness

In this section, we perform several additional tests to further demonstrate the robustness of our baseline results. Specifically, we include (1) a placebo test; (2) an instrumental variable approach; (3) a concurrent event concern: the 2008 global financial crisis; (4) individual's migration concern; and (4) a weighted regression analysis.

4.1. Placebo test

While our DDD estimations control all the province and industry level time variations, it is still possible that some observed or unobserved province × year × skilled–unskilled labor's time-varying variables are not included and could bias the estimation results. Also, some omitted factors could simultaneously happen to the high- and the low-skilled labor in highly regulated regions.

To address this concern, we conduct a placebo test following Chetty et al. (2009), La Ferrara et al. (2012), and Cai et al. (2016). Specifically, we construct a new falsified treatment group based on three layers of random assignment (*i.e.*, skilled or unskilled, SO_2 reduction target, and the survey year). We then re-estimate Eq. (1) on this fully randomized sample 500 times and obtain a falsified estimated coefficient of $\hat{\beta}_1^{random}$.

The DDD kernel density curve of $\hat{\beta}_1^{random}$ is presented in Fig. 5. It indicates that the kernel density curve largely follows a normal distribution ranging from −0.01 to 0.015, and the coefficient estimates center around zero. Besides, our "true" point estimate (0.017) is far away from the center. Therefore, according to La Ferrara et al. (2012) and Cai et al. (2016), the placebo test result helps mitigate the concern on omitting potential unobserved variables and further validate our DDD identification assumption.

4.2. Instrumental variable approach

Though the DDD and its dynamic effect resolve the endogeneity concern arising from the parallel trend assumption, empiricists might still worry that the SO_2 emission target is never randomly set by policymakers. On the one hand, provinces with more polluting industries could lobby the central government to enact a laxer environmental policy. On the other hand, skilled labor in heavily polluted provinces might call for a stricter policy because pollution would affect their productivities (Graff Zivin and Neidell, 2012). Thus, our DDD results are possibly biased due to the endogeneity of provincial environmental regulation. For the sake of rigorousness, we use an instrumental variable (IV) method by exploiting the source of variation in environmental policy intensity that is not determined by the prevalence of polluting industries (exogenous) and does not affect wage inequality through other channels (the exclusive restriction).

Following Broner et al. (2012), Hering and Poncet (2014), and Shi and Xu (2018), we use the province-level ventilation coefficient as our IV candidate. The ventilation coefficient is defined as the product of wind speed and mixing height. Our rationale of this IV hinges on the assumption that the SO_2 regulation would be laxer in provinces where meteorological conditions facilitate pollutants' dispersion in the atmosphere (Broner et al., 2012).[11] Therefore, the ventilation coefficient is exogenously determined and serves as

[11] According to the Box model (Arya, 1998; Jacobson, 2002), two variables determine the horizontal and vertical dispersion of pollutants. The first one is wind speed, which eases pollutants' horizontal dispersion. The second variable is mixing height, which facilitates pollutants' vertical dispersion. The Box model predicts that regional pollution concentration would be inversely related to the product of wind speed and the mixing height (Broner et al., 2012).

Table 4
Endogeneity concern: Instrumental variable results.

Dependent variable	First stage	Second stage		
	(1)	(2)	(3)	(4)
		Full sample	Polluting	Green
	Post × Reduction × Skill	ln(W)	ln(W)	ln(W)
Post × Ventilation × Skill	−0.005*** (0.002)			
Post × Reduction × Skill (Predicted)		0.022*** (0.006)	0.030*** (0.003)	0.011 (0.007)
Male	−0.002 (0.003)	−0.056 (0.046)	0.168*** (0.042)	−0.141** (0.051)
Age	0.019 (0.011)	0.219*** (0.036)	0.169*** (0.028)	0.244*** (0.046)
Age^2	−0.000 (0.000)	−0.000 (0.000)	−0.001** (0.000)	0.000 (0.000)
Experience	−0.011 (0.006)	−0.201*** (0.020)	−0.112*** (0.014)	−0.242*** (0.028)
Experience^2	0.000 (0.000)	0.000 (0.000)	0.001** (0.000)	0.000 (0.000)
Marital status	0.015 (0.011)	−0.085* (0.043)	0.205*** (0.034)	−0.159** (0.051)
Province × Year FE	Yes	Yes	Yes	Yes
Skill × Year FE	Yes	Yes	Yes	Yes
Province × Skill FE	Yes	Yes	Yes	Yes
Industry × Province FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
F statistics	49.28			
Observations	425,639	425,639	117,709	276,156
R-squared	0.971	0.528	0.083	0.544

Notes: Column (1) reports the first stage 2SLS estimates and the remaining columns show the second stage 2SLS estimates. The dependent variable of Column (1) is Post × Reduction × Skill, and the dependent variables in Column (2)–(4) are the natural logarithm of the real total wage of individual i from province p in the year t. The independent variable of Columns (2)–(4) is Post × Reduction × Skill (Predicted). $Post_t$ is a dummy variable equal to one if the survey year t is after 2005 and zero otherwise. $Skill_i$ is a dummy variable equal to one if individual i is at least a junior college or technical institution graduate and zero otherwise. $Ventilation_p$ is the average provincial ventilation coefficient. Columns (1)–(2) are based on full sample and Columns (3)–(4) are based on polluting and green industries, respectively. The polluting industry classification is from Wang and Zhang (2020), which is also released by the China Securities Regulatory Commission. Robust standard errors in parentheses are by two-way clustering over province and year. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

a plausible instrument variable for environmental regulation but has no direct effect on wage inequality through other channels. We obtain the wind speed data from the European Center for Medium-Term Weather Forecasting EAR-interim dataset and use the average provincial ventilation coefficient from 2002 to 2005 as our IV, following Shi and Xu (2018).

The IV estimates are displayed in Table 4, and Columns (1) and (2) show the first- and the second-stage results, respectively. Our IV variable, the province-level ventilation coefficient, is statistically significant at a 1% level in the first stage, and the F-statistic is 49.28, which is consistent with Hering and Poncet (2014) and Shi and Xu (2018). Quantitatively, the second stage 2SLS estimate in Column (2) reports that a one percentage point increase in SO_2 reduction target enlarges the wage gap by 2.2%, slightly larger than the DDD estimate in Column (3) of Table 2. We also perform the analysis by the polluting and green firms and report the second stage results in Columns (3) and (4) of Table 4. Consistent with the DDD estimates, we could see the wage inequality in the polluting industries also increasing while no significant result for the green industries.

Note that one may still be concerned about the exclusion restriction of our IV, *i.e.*, regional economic agglomeration's creation and success presumably depend on climatic conditions. To alleviate the concern, we regress the provincial GDP and average wage on the ventilation coefficient, and find that the ventilation coefficient is not a significant predictor of regional economic growth or employment in our sample period (Table A.4). Furthermore, we conduct the same test as in Conley et al. (2012), and find robust DDD estimates in the second stage under the local to zero approach. Concretely, we show that a slightly positive perturbation of the IV (assuming a Gaussian prior) would slowly decrease our DDD estimates, with the statistical significance roughly ranging from 0 to 0.05. Fig. B.1 presents the estimates under the local to zero approach with a 95% confidence interval for the whole sample. It indicates that our IV results perform relatively well under the local to zero approach (Conley et al., 2012).

4.3. Concurrent event: 2008 global financial crisis

As the eleventh Five-Year Plan was implemented between 2006 and 2010, our findings may be biased if any other concurrent events simultaneously affect the wage gap between the high- and the low-skilled labor in highly polluted regions. A typical case could be the 2008 global financial crisis. Specifically, provinces subject to intensified environmental regulations are more economically

Table 5
Concurrent event concern: Exclude 2008 and 2009.

Dependent variable	(1) Full sample ln(W)	(2) Polluting ln(W)	(3) Green ln(W)
Post × Reduction × Skill	0.013** (0.005)	0.012** (0.004)	0.009 (0.005)
Male	−0.032 (0.042)	0.199*** (0.033)	−0.124* (0.048)
Age	0.255*** (0.033)	0.201*** (0.018)	0.286*** (0.047)
Age^2	−0.000 (0.000)	−0.001*** (0.000)	−0.000 (0.000)
Experience	−0.222*** (0.021)	−0.127*** (0.011)	−0.270*** (0.031)
Experience^2	0.000* (0.000)	0.001*** (0.000)	0.000 (0.000)
Marital status	−0.074 (0.055)	0.203*** (0.046)	−0.156* (0.067)
Province × Year FE	Yes	Yes	Yes
Skill × Year FE	Yes	Yes	Yes
Province × Skill FE	Yes	Yes	Yes
Industry × Province FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Observations	306,378	88,538	195,229
R-squared	0.570	0.088	0.586

Notes: The dependent variable is the natural logarithm of the real total wage of individual i from province p in the year t. $Post_t$ is a dummy variable equal to one if the survey year t is after 2005 and zero otherwise. $Reduction_p$ is a continuous treatment variable capturing the SO_2 emission target set for province p in the eleventh Five-Year Plan. $Skill_i$ is a dummy variable equal to one if individual i is at least a junior college or technical institution graduate and zero otherwise. Column (1) is based on full sample, and Columns (2)–(3) are based on polluting and green industries, respectively. The polluting industry classification is from Wang and Zhang (2020), which is also released by the China Securities Regulatory Commission. Robust standard errors in parentheses are by two-way clustering over province and year. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

prosperous and export-oriented, so that they bear the brunt of the financial crisis because firm exports dropped dramatically during this period (Shi and Xu, 2018). This is likely to hit firms hard and lead to a considerable amount of wage reduction, and this decrease could be specific to either skilled or unskilled labor. In other words, our DDD estimation on wage inequality could be biased because of the global demand contraction.

We drop the years 2008 and 2009 from our sample period to exclude this confounding factor and report the results in Table 5. The coefficient estimate of Column (1) declines but remains its sign and significance (0.013), suggesting that our main findings still hold when we rule out the influence of the 2008 global financial crisis. The polluting and green subsample analyses, shown in Columns (2) and (3), report consistent results as our baseline estimates. Therefore, we are confident that the 2008 global financial crisis does not affect our conclusions.

4.4. Migration concern

Another potential concern is the endogenous migration decision. It might affect the results because the unskilled labor in the highly regulated provinces may have the incentive to move to the less-regulated provinces in response to the environmental policy shock. Fortunately, the UHS data allow us to directly access the individual's migration decision to deal with this endogeneity issue.

Following Dai et al. (2021), we replace the outcome variable with a migration dummy variable, indicating whether or not an individual migrates to the current province in the survey years from 2006 to 2009. Specifically, we use the 2006–2009 sample, interact the reduction percentage with the skilled dummy, and run the OLS regression using the migration dummy as the dependent variable. The insignificant results for both the OLS and the 2SLS estimates in Table 6 suggest that the low-skilled labor residing in the highly-regulated areas do not move to less-regulated regions, relieving the migration concern.

4.5. Weighted regression

Lastly, we perform an additional test to show that our baseline results are robust to unequal weight scheme.

Concretely, we use the probability weights (PW), weighted by the number of respondents in each province. In other words, each individual would be weighted by the inverse of the probability that this observation is sampled. In the weighted regressions, these could be combined to produce estimates for unstratified cluster-sampled data. We re-run our baseline DDD and IV regressions and present the results in Table 7. We find consistent results with the preceding findings.

Table 6
Individual's migration concern.

Dependent variable	OLS		2SLS	
	(1) Migration decision	(2) Migration decision	(3) Migration decision	(4) Migration decision
Reduction × Skill	0.0003 (0.0002)	0.0003 (0.0002)		
Reduction × Skill (Predicted)			0.0003 (0.0005)	0.0004 (0.0006)
Individual controls	No	Yes	No	Yes
Skill × Year FE	Yes	Yes	Yes	Yes
Province × Skill FE	Yes	Yes	Yes	Yes
Industry × Skill FE	Yes	Yes	Yes	Yes
Industry × Province FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Observations	229,118	229,118	229,118	229,118
R-squared	0.013	0.023	0.013	0.023

Notes: The dependent variable is migration decision, a dummy variable indicating whether an individual i migrates to the current province during 2006 and 2009. $Reduction_p$ is a continuous treatment variable capturing the SO_2 emission target set for province p in the eleventh Five-Year Plan. $Skill_i$ is a dummy variable equal to one if individual i is at least a junior college or technical institution graduate and zero otherwise. Individual controls are included in all columns. Columns (1)–(2) show the OLS estimates, and Columns (3)–(4) represent the second stage 2SLS results. The first stage 2SLS estimates are not reported for brevity. Robust standard errors in parentheses are by two-way clustering over province and year. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 7
Impact of environmental regulation on wage inequality: Weighted regression.

Dependent variable	DDD			2SLS		
	(1) Full sample $\ln(W)$	(2) Polluting $\ln(W)$	(3) Green $\ln(W)$	(4) Full sample $\ln(W)$	(5) Polluting $\ln(W)$	(6) Green $\ln(W)$
Post × Reduction × Skill	0.020*** (0.005)	0.022*** (0.005)	0.001 (0.006)			
Post × Reduction × Skill (Predicted)				0.028*** (0.008)	0.039*** (0.004)	0.008 (0.009)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × Skill FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	425,639	117,709	276,156	425,639	117,709	276,156
R-squared	0.512	0.079	0.528	0.512	0.079	0.528

Notes: The dependent variable is wage inequality, measured by the natural logarithm of the real total wage of individual i from province p in the year t. $Post_t$ is a dummy variable equal to one if the survey year t is after 2005 and zero otherwise. $Reduction_p$ is a continuous treatment variable capturing the SO_2 emission target set for province p in the eleventh Five-Year Plan. $Skill_i$ is a dummy variable equal to one if individual i is at least a junior college or technical institution graduate and zero otherwise. Individual controls are included in all columns. All columns are adjusted using probability weights. Columns (1)–(3) are the DDD results and Columns (4)–(6) are the second stage of the 2SLS results. Columns (1) and (4) are based on full sample, and Columns (2)–(3) and (5)–(6) are based on polluting and green industries, respectively. The polluting industry classification is from Wang and Zhang (2020), which is also released by the China Securities Regulatory Commission. Robust standard errors in parentheses are by two-way clustering over province and year. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

5. Counterfactual discussions

Based on the short-run micro-level relationship between environmental regulations and wage inequality, policymakers might be further interested in the long-run regulatory impact and the way to remedy the unappealing wage gap consequence. This section addresses these counterfactual issues with a two-sector dynamic general equilibrium model.

5.1. Theoretical framework and simulation analysis

The model economy is populated by a representative household supplying differentiated skilled and unskilled labor, and differentiated firms in polluting and green sectors. Both types of labor can move freely across sectors. Under the environmental regulation, firms are directed to curb pollutant emissions and those who fail in the targets would endure punitive penalties on pollutant emissions. Hence, we model the regulation as firms' additional production costs for polluting output. The detailed model environment, agents' optimal decisions, and competitive equilibrium are elaborated in Appendices C.1–C.2.

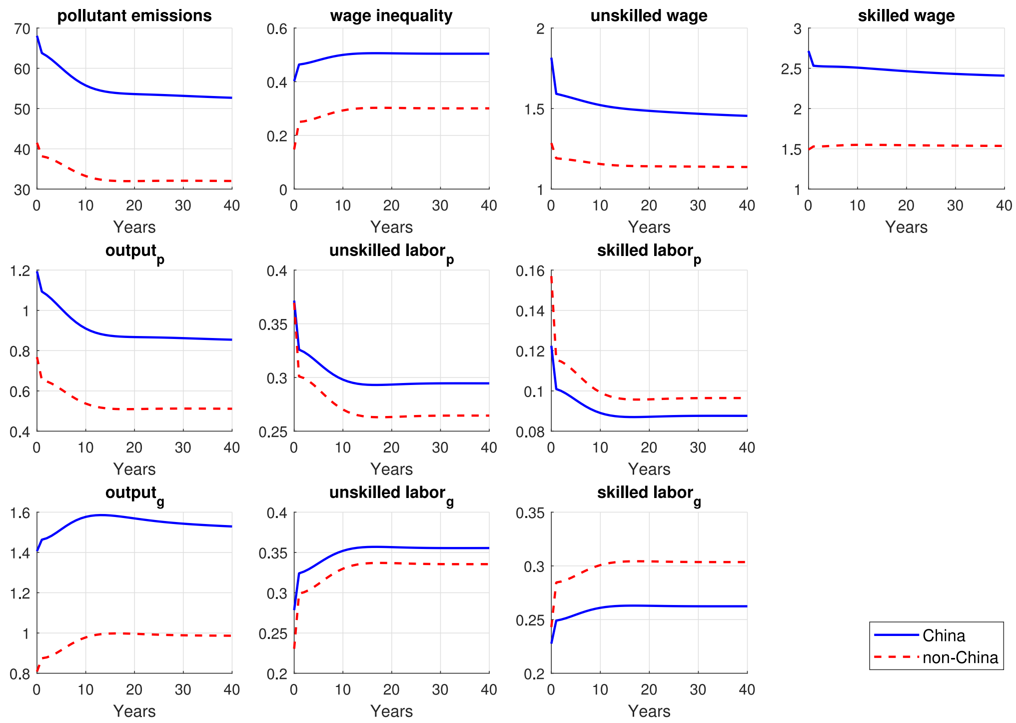


Fig. 6. Transition path to the environmental regulation. Notes: The subscripts "p" and "g" represent polluting sector and green sector, respectively.

Since the general equilibrium model does not admit a closed-form solution, we present the model results by numerical simulation. Parameters used in the simulation are calibrated to match Chinese macroeconomic statistics, which are described in Appendix C.3. It is worth mentioning that the environmental regulation related parameter, τ, is initially set at 0, indicating no regulation before 2006. We then adjust τ to 0.0046 as a final value to capture the provincial average SO_2 reduction target of 11.74% in five years after implementing the environmental policy.

The change of environmental regulation's intensity is treated as a permanent exogenous shock to the model economy. The solid blue lines in Fig. 6 plot the 40-year transition path from the pre-regulation (under $\tau = 0$, period 0) to the post-regulation (under $\tau = 0.0046$). The subscripts "p" and "g" represent polluting sector and green sector, respectively. The permanent regulatory shock hits in period 1, triggering the start of the economic transition.[12]

We find that our model well mimics the SO_2 reduction target since the pollutant emissions in the upper-left panel reduces by 11.74% (=1-60.07/68.06) in 5 years. This reduction is long-lasting, followed by gradually building responses, and reaches almost 23% in 40 years. However, this environmental policy enlarges the wage inequality between the skilled and unskilled labor, shown by the upper-middle panel. The increase in wage gap in 5 years is 7.8% (=0.480–0.402) and gets close to around 10% in the long run.[13] These results indicate that the policy's long-run impact is more considerable, in terms of cubing pollution and widening wage gap.

It is important to note that quantitative change of the simulated wage inequality could not be compared to the empirical result (1.7%) directly, since our empirical identification strategy uses the province-varying reduction target as the continuous treatment. In other words, the empirical result captures the relative wage inequality change between the highly and non-highly regulated regions, while the simulated result examine the country's average regulation impact.

The economic mechanism behind this long-run enlarged wage gap is similar to our empirical findings. For the regulated polluting firms, they could do nothing but contract output to curb pollutant emissions before they adjust to environmental-friendly machines (technology). A lower output reduces the marginal revenue of production inputs, and thus polluting firms demand less inputs including unskilled and skilled labor. As depicted by the middle panels, the unskilled workers are more severely affected than the skilled ones since the polluting sector is more unskill-intensive. These undesired unskilled workers can hardly get employed in the skill-intensive green sector unless they accept lower wage.

12 There are kinks between periods 0 and 1, meaning that the model economy jumps to a new equilibrium system.

13 Wage inequality is defined as the log difference of skilled wage and unskilled wage, so the change of wage inequality represents the percentage deviations from the initial steady state.

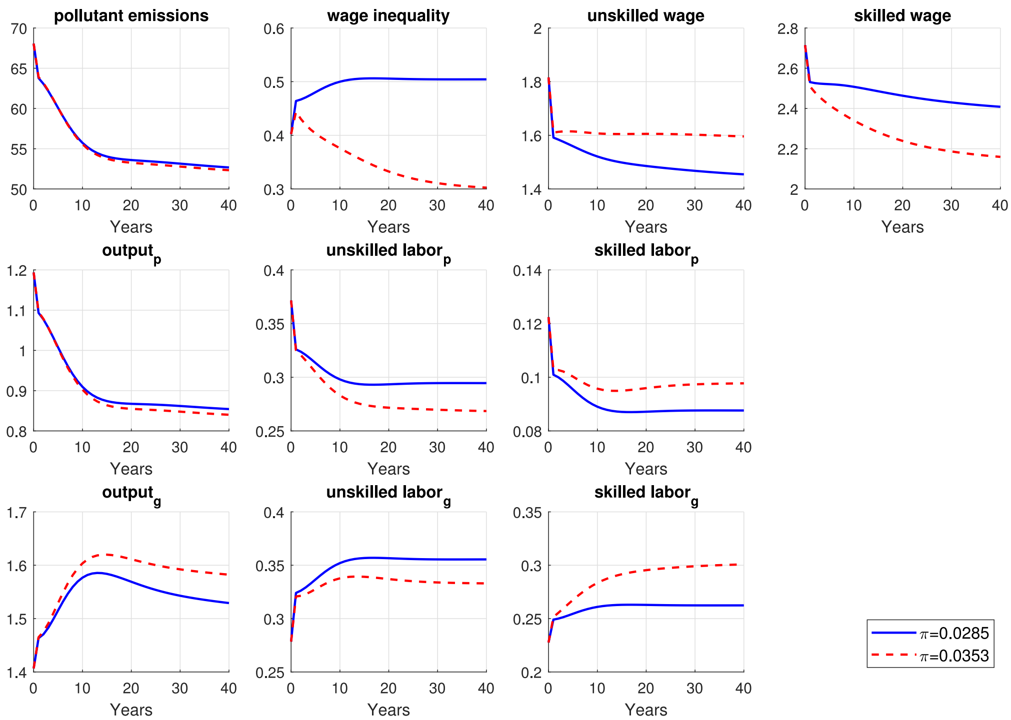


Fig. 7. Transition path to the environmental regulation: Human capital investment. Notes: The subscripts "p" and "g" represent polluting sector and green sector, respectively.

In our general equilibrium setup, household foresees the recession in the polluting sector, and switches investment to the green sector. Consequently, both the green output and the demand for both types of workers (the lower panels) are boosted. Hence, in equilibrium, the aggregate employment is nearly immune to the environmental regulation, while the wage for both workers decrease. The unskilled wage reduces more than the skilled wage due to the different skill intensity in both sectors, explaining the long-run rising wage inequality after the realization of environmental regulation.

The above long-run regulatory impact and economic mechanism are not restricted to the China context. The red dotted lines in Fig. 6 show that the simulation results are qualitatively similar if we relax model parameters to standard (non-China-specific) values in the literature (*e.g.*, Acemoglu et al., 2012; Angelopoulos et al., 2017).[14] In conclusion, our micro-level empirical evidence is not a special case linking environmental regulations and wage inequality, but is of general policy implications as the findings could be generalized to a long-run perspective and other countries.

5.2. Remedial policy

It seems a stringent environmental policy (and hence a better environmental quality) costs the wage inequality. Does there exist a non-environmental policy that balances the dark side of environmental regulations, without harming the fruit of it? In this section, we propose a possible remedial policy — human capital investment — for the regulators' reference.

Human capital accumulation usually refers to equipping the unskilled workers with skills through education. The transition proportion from the unskilled to the skilled is captured by the parameter π in our model. In this counterfactual exercise, we facilitate the transition by slightly raising π (from 0.0285 to 0.0353) such that the final steady-state share of skilled labor increases from 0.37 to 0.4. Other parameters remain the same except for the regulation intensity τ, which is re-calibrated to 0.0044 (close to 0.0046 in the benchmark) to keep the five-year SO_2 reduction target unchanged. The associated transition path is plotted in Fig. 7 with red dotted lines.

[14] In this exercise, we re-calibrate the parameters to match the U.S. statistics as an example. As there is no corresponding province-varying environmental policy in the U.S., we artificially set the regulation intensity as 0.0046, the same as the benchmark value, to study the qualitative results. The re-calibration procedure is described in detail in Appendix C.3. The wage inequality is lower than the benchmark because the U.S. has a higher skilled labor share.

Results show that a bit more human capital investment, such as improving educational attainment, would significantly offset the skilled and unskilled wage gap. The relative supply of skilled versus unskilled labor increases after the human capital investment, and consequently more skilled workers allocated in both sectors (in right lower panel). Hence, the oversupplied labor suppresses the wage compared to the benchmark, narrowing the enlarged wage gap from 7.8% (benchmark) to 0.1% (=0.403–0.402) in five years and even more in the long run. These findings are consistent with the literature on human capital (*e.g.*, Katz and Murphy, 1992; Goldin and Katz, 2009).

6. Conclusion

Under the backdrop of global warming, more and more developing countries start setting stricter environmental policies. It is thus critical for regulators to understand the policies' bright and dark consequences. Using nationally representative household survey data, we find that China's environmental policy regulating SO_2 emissions would exacerbate the wage inequality between skilled and unskilled labor. The worsen wage gap is due to the intensive margin rather than the extensive margin. Also, the enlarged wage inequality is primarily driven by the changes of workers in the polluting sector, as the environmental policy does not significantly impact the green sector. These findings are robust if excluding the 2008 financial crisis effect and considering individual migration decisions. Overall, our empirical evidence is persistent over the four years after the policy implementation.

The above micro-level relationship between environmental regulations and wage inequality is not specific to a short-run perspective or to China. We generalize our findings with a two-sector dynamic general equilibrium framework featuring heterogeneous labor. By numerically simulating the model economy, our 40-year transition path presents a general and long-run rise in wage inequality after the environmental policy implementation.

To remedy the undesired effect on wage inequality resulting from environmental regulation, we also propose a non-environmental policy based on the calibrated model. This counterfactual experiment finds that boosting human capital investment would alleviate the widening wage inequality while keeping the same level of environmental degradation. Therefore, our work is of general implications to regulators when setting up policies to balance the environmental and economic inequality issues.

While literature has focused on the output or total employment costs of environmental policy, our paper highlights that the skilled and unskilled wage inequality could be an non-negligible byproduct in both the short and long run. One limitation of this study is that the UHS household survey data is repeated cross-sectional, and we cannot control individual time-invariant characteristics or track an individual's employment change through time. We suggest that future research works use the individual-level panel data to empirically explore the general equilibrium effect induced by environmental regulation.

Appendix A. Tables

See Tables A.1–A.4.

Table A.1
SO_2 Controlling reduction target in the eleventh five-year plan.
Source: The provincial reduction target is from "Reply on the National Total Emission Control Plan for Major Pollutants during the eleventh Five-Year Plan", issued by the State Council of China in 2006.

Province	Sample Obs.	Reduction percentage
Anhui	26,516	4.0
Beijing	33,090	20.4
Chongqing	8056	11.9
Guangdong	28,749	15.0
Gansu	11,339	0
Heilongjiang	24,682	2.0
Henan	30,812	14.0
Hubei	24,318	7.8
Jiangsu	56,037	18.0
Jiangxi	16,908	7.0
Liaoning	45,859	12.0
Shandong	42,148	20.0
Shanghai	9913	25.9
Shanxi	22,598	14.0
Sichuan	26,152	11.9
Yunnan	18,462	4.0
Total	425,639	

Table A.2
Variable definitions.

Variable	Definition
Individual level variables:	
Wage	The sum of individual i's salary, bonus, and subsidy income deflated by the province CPI.
Skill	A dummy variable equal to one if individual i is at least a junior college or technical institution graduate and zero otherwise.
Male	A dummy variable equal to one if individual i is a male and zero otherwise.
Age	Individual i's age in the survey year.
Experience	Individual i's age minus the schooling years minus six.
Marital	A dummy variable equal to one if individual i is married and zero otherwise.
Province level variables:	
Reduction	A continuous treatment variable capturing the SO_2 emission reduction target percentage set for each province in the eleventh Five-Year Plan.
Ventilation	The average provincial ventilation coefficient, measured by the product of wind speed and mixing height from 2002 to 2005.

Table A.3
Impact of environmental regulations on wage inequality: Excluding provinces with concentrated coal and oil production.

Dependent variable	(1) $\ln(W)$	(2) $\ln(W)$	(3) $\ln(W)$	(4) $\ln(W)$
Post × Reduction × Skill	0.017**	0.021***	0.022***	0.021***
	(0.006)	(0.004)	(0.004)	(0.004)
Male		0.190**	−0.062	−0.063
		(0.066)	(0.062)	(0.060)
Age		0.900***	0.326***	0.255***
		(0.104)	(0.040)	(0.044)
Age^2		−0.007***	−0.001**	−0.001
		(0.001)	(0.001)	(0.001)
Experience		−0.322***	−0.242***	−0.230***
		(0.017)	(0.022)	(0.021)
Experience^2		0.001	0.001**	0.001
		(0.001)	(0.001)	(0.001)
Marital status		0.354*	−0.052	0.099*
		(0.185)	(0.046)	(0.044)
Province × Year FE	Yes	Yes	Yes	Yes
Skill × Year FE	Yes	Yes	Yes	Yes
Province × Skill FE	Yes	Yes	Yes	Yes
Industry × Province FE	No	No	Yes	Yes
Industry × Year FE	No	No	No	Yes
Observations	233,024	233,024	233,024	233,024
R-squared	0.078	0.210	0.506	0.514

Notes: The dependent variable is the natural logarithm of the real total wage of individual i from province p in the year t. $Post_t$ is a dummy variable equal to one if the survey year t is after 2005 and zero otherwise. $Reduction_p$ is a continuous treatment variable capturing the SO_2 emission reduction target percentage set for province p in the eleventh Five-Year Plan. $Skill_i$ is a dummy variable equal to one if individual i is at least a junior college or technical institution graduate and zero otherwise. We exclude six provinces with intensive coal and oil production (*i.e.*, Anhui, Heilongjiang, Henan, Liaoning, Shandong, Shanxi), according to Minchener (2011). Robust standard errors in parentheses are by two-way clustering over province and year. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table A.4
Validity of exclusion restriction: Impact of ventilation coefficient on local economic conditions.

Dependent variable	(1) $\ln(GDP)$	(2) $\ln(W)$
Ventilation	0.0001	0.0003
	(0.0001)	(0.0006)
Province FE	Yes	Yes
Year FE	Yes	Yes
Observations	128	128
R-squared	0.005	0.011

Notes: The dependent variable is the natural logarithm of provincial GDP and average wage. Province and year fixed effects are included in both columns. Robust standard errors in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Appendix B. Figure

See Fig. B.1.

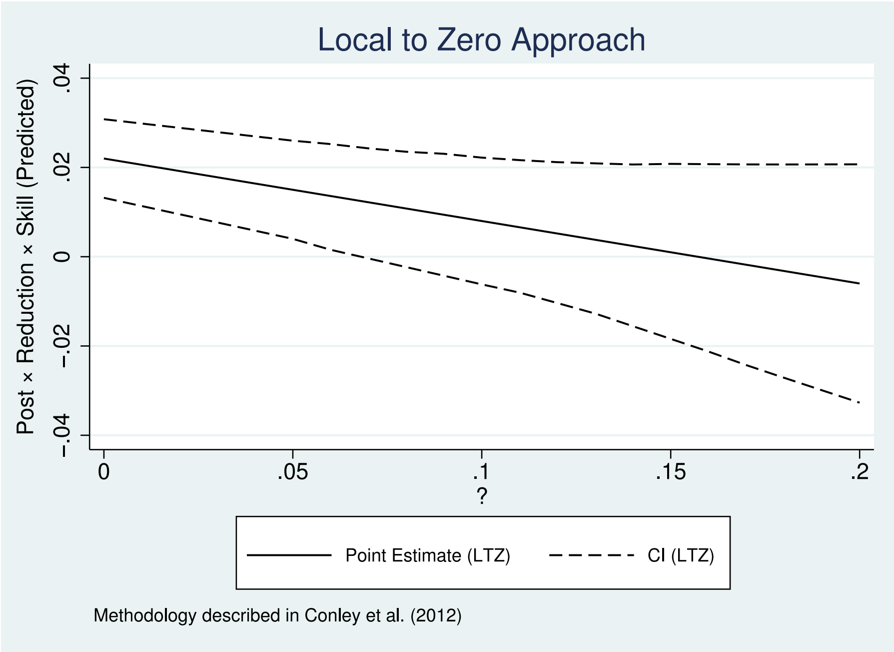


Fig. B.1. 95% interval estimates for IV estimates with positive Gaussian prior. Notes: This figure shows the 95% confidence intervals for the effect of provincial environmental regulation on wage inequality under the positive Gaussian prior.

Appendix C. Theoretical framework

The model economy is populated by a representative household supplying differentiated skilled and unskilled labor. There are two-sector intermediate goods firms constructed with polluting and green firms and a representative final goods firm producing the consumption and investment goods. Both types of labor can move freely across firms. The capitals (machines) used in each intermediate sector's production are also differentiated, denoted as polluting and green capital, respectively. Hereafter, We formally present the model environment, economic agents' optimal decisions, and define the competitive equilibrium.

C.1. Model environment

C.1.1. Household

We consider a representative household with CRRA preferences who maximizes its lifetime utility

$$\max_{c_t,k_{gt},k_{pt}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\eta}}{1-\eta}, \tag{C.1}$$

where $\mathbb{E}_0$ is the conditional expectation operator, $\beta > 0$ is the discount factor, $\eta \geq 0$ governs the household's risk aversion, and c_t is the consumption.

For the representative household, the numbers of skilled and unskilled members at the beginning of period t are denoted as S_{t-1} and U_{t-1}, respectively. Thus, the total size of the household (population) is $N_{t-1} = S_{t-1} + U_{t-1}$, which is assumed to grow at an exogenous net rate g_n. Following Angelopoulos et al. (2017), the new members joining the household is assumed unskilled, and in each period π proportion of unskilled labor accumulates enough knowledge and becomes skilled. Hence, the numbers of skilled and unskilled members change over time as follows: $S_t = S_{t-1} + \pi U_{t-1}$ and $U_t = U_{t-1} - \pi U_{t-1} + g_n N_{t-1}$. The respective population shares are given by

$$s_t = \frac{s_{t-1} + \pi u_{t-1}}{1 + g_n}, \tag{C.2}$$

$$u_t = \frac{u_{t-1} - \pi u_{t-1} + g_n}{1 + g_n}, \tag{C.3}$$

where $s_t = S_t / N_t$, $u_t = U_t / N_t$, and $s_t + u_t = 1$.

In each period t, the household inelastically supplies skilled and unskilled labor and, earns labor income at real wage w_t^s and w_t^u respectively. The household also rents polluting and green capital to firms and earns capital income at real rental rates r_{pt} and r_{gt}. Additionally, the household receives lump-sum income T_t from polluting firms to be defined in Appendix C.1.3. Meanwhile, the household spends its income on consumption and investment in polluting capital i_{pt} and green capital i_{gt}. The household budget constraint is given by

$$c_t + i_{pt} + i_{gt} = w_t^s s_t + w_t^u u_t + r_{pt} k_{pt-1} + r_{gt} k_{gt-1} + T_t, \tag{C.4}$$

where k_{pt-1} and k_{gt-1} are the stock of polluting and green capital owned by the household at the beginning of period t, accumulating as

$$k_{pt} = (1 - \delta_p) k_{pt-1} + i_{pt}, \tag{C.5}$$

$$k_{gt} = (1 - \delta_g) k_{gt-1} + \left[1 - \frac{\kappa}{2} \left(\frac{i_{gt}}{i_{gt-1}} - 1 \right)^2 \right] i_{gt}, \tag{C.6}$$

where δ_p and δ_g are the respective depreciation rate, and $\kappa > 0$ governs the curvature of the cost function. It is worth mentioning that Eq. (C.6) follows Christiano et al. (2005) and captures that dynamically it is more costly to install green capital than polluting capital. This specification is natural as green capital is more environmental-friendly and usually requires more research and development costs.[15]

C.1.2. Final goods firm

There exists a representative final goods firm producing output y competitively using green and polluting inputs y_g and y_p produced by the intermediate firms, according to the aggregate production function in Acemoglu et al. (2012)

$$y_t = \left(y_{pt}^{\frac{\epsilon-1}{\epsilon}} + y_{gt}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{C.7}$$

where $\epsilon > 1$ is the elasticity of substitution between the two sectors. We take the final goods as the numeraire and normalize its price to one. Accordingly, the prices of polluting and green inputs are denoted as p_p and p_g. The final goods firm, taking all intermediate goods prices as given, chooses the optimal demand for intermediate goods by maximizing its profits

$$\max_{y_{pt}, y_{gt}} y_t - p_{pt} y_{pt} - p_{gt} y_{gt}. \tag{C.8}$$

C.1.3. Intermediate goods firms

The inputs y_g and y_p are produced by the representative sectoral intermediate goods firms using skilled labor, unskilled labor, and sector-specific capital with the following Cobb–Douglas technology

$$y_{jt} = \left(k_{jt}^d \right)^{\alpha_j} \left(u_{jt}^{\gamma_j} s_{jt}^{1-\gamma_j} \right)^{1-\alpha_j}, \quad j = p, g \tag{C.9}$$

where k_{jt}^d is the capital demand from the firm. α_j, $(1-\alpha_j)\gamma_j$, and $(1-\alpha_j)(1-\gamma_j)$ measure factor income share of capital, unskilled labor, and skilled labor, respectively. In our subsequent calibration, we have $\gamma_p > \gamma_g$ as the green sector is relatively more skill-intensive than the polluting sector, suggested by the empirical evidence. This is natural since the green capital is usually high-tech machines with skill-biased technology.

Each sectoral firm chooses optimal demand for factor inputs and maximizes its profits

$$\max_{k_{jt}^d, u_{jt}, s_{jt}} p_{jt} y_{jt} - r_{jt} k_{jt}^d - w_t^s s_{jt} - w_t^u u_{jt} - \tau \xi_j p_{jt} y_{jt}, \quad j = p, g \tag{C.10}$$

where τ governs the intensity of environmental regulation, and ξ_j follows the interpretation in Acemoglu et al. (2012). Concretely, ξ_j measures the rate of environmental degradation resulting from the production of dirty inputs, *i.e.*, $\xi_p > 0$ while $\xi_g = 0$. According to the targets for reducing pollutant emissions set forth in the eleventh Five-Year Plan, firms are directed to curb pollutant emissions and those who fail in the targets would endure punitive penalties on pollutant emissions, which raises firms' production costs. In our model, we simply assume these penalties are transferred to the household as a lump-sum income, that is, $T_t = \tau \xi_p p_{pt} y_{pt}$.

[15] Dynamically, there needs more than one unit investment to accumulate one unit of green capital, suggesting its shadow price is larger than one. In the long run (*i.e.*, steady state), when the technology for installing green machines is mature, its shadow price converges to the price of one unit investment, just as the polluting capital.

C.1.4. Market clearing conditions and wage inequality

In a competitive equilibrium, the markets for final goods, skilled labor, unskilled labor and sector-specific capital are all clear. The clearing conditions in a sequence are given by

$$c_t + i_{pt} + i_{gt} = y_t, \tag{C.11}$$

$$s_t = s_{pt} + s_{gt}, \tag{C.12}$$

$$u_t = u_{pt} + u_{gt}, \tag{C.13}$$

$$k_{pt-1} = k^d_{pt}, \tag{C.14}$$

$$k_{gt-1} = k^d_{gt}. \tag{C.15}$$

A competitive equilibrium consists of sequences of prices and allocations such that (i) taking the prices as given, the allocations solve the optimizing problems for the household and the firms, and (ii) all markets clear.

Under the competitive equilibrium framework, we define the *wage inequality* as the log difference of the skilled-labor wage w^s_t and the unskilled-labor wage w^u_t, *i.e.*, $\ln\left(\frac{w^s_t}{w^u_t}\right)$, which is consistent with our empirical specification.

C.2. Equilibrium

Household's problem. In an equilibrium, the household's optimal decisions on $\{c_t, i_{pt}, i_{gt}, k_{pt}, k_{gt}\}$ by maximizing expected utility are

$$c_t^{-\eta} = \lambda_t, \tag{C.16}$$

$$\lambda_t = q_{pt}, \tag{C.17}$$

$$\lambda_t = q_{gt}\left\{\left[1 - \frac{\kappa}{2}\left(\frac{i_{gt}}{i_{gt-1}} - 1\right)^2\right] - \kappa\left(\frac{i_{gt}}{i_{gt-1}} - 1\right)\frac{i_{gt}}{i_{gt-1}}\right\} + \beta\mathbb{E}_t q_{gt+1}\kappa\left(\frac{i_{gt+1}}{i_{gt}} - 1\right)\frac{i^2_{gt+1}}{i^2_{gt}}, \tag{C.18}$$

$$q_{pt} = \beta\mathbb{E}_t\left[q_{pt+1}(1-\delta_p) + \lambda_{t+1}r_{pt+1}\right], \tag{C.19}$$

$$q_{gt} = \beta\mathbb{E}_t\left[q_{gt+1}(1-\delta_g) + \lambda_{t+1}r_{gt+1}\right]. \tag{C.20}$$

Above, λ_t is the Lagrange multiplier associated with the budget constraint and q_{pt} and q_{gt} are the marginal Tobin's Q for polluting capital and green capital respectively.

Laws of motion of two types of capital stocks are

$$k_{pt} = (1-\delta_p)k_{pt-1} + i_{pt}, \tag{C.21}$$

$$k_{gt} = (1-\delta_g)k_{gt-1} + \left[1 - \frac{\kappa}{2}\left(\frac{i_{gt}}{i_{gt-1}} - 1\right)^2\right]i_{gt}. \tag{C.22}$$

Laws of motion of two types of labor are

$$s_t = \frac{s_{t-1} + \pi u_{t-1}}{1+g_n}, \tag{C.23}$$

$$u_t = \frac{u_{t-1} - \pi u_{t-1} + g_n}{1+g_n}. \tag{C.24}$$

Final goods firm's problem. In an equilibrium, the final goods firm's optimal decisions on $\{y_{pt}, y_{gt}\}$ by maximizing profit are

$$p_{jt} = \left(\frac{y_t}{y_{jt}}\right)^{-\frac{1}{\epsilon}}, \quad j = p, g. \tag{C.25}$$

The production function is

$$y_t = \left(y_{pt}^{\frac{\epsilon-1}{\epsilon}} + y_{gt}^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}. \tag{C.26}$$

Intermediate goods firms' problem. In an equilibrium, the intermediate goods firms' optimal decisions on $\{k_{jt}^d, s_{jt}, u_{jt}\}$ where $j = p, g$ by maximizing profit are

$$r_{jt} = (1 - \tau\xi_j)p_{jt}\alpha_j \frac{y_{jt}}{k_{jt}^d}, \tag{C.27}$$

$$w_t^u = (1 - \tau\xi_j)p_{jt}\gamma_j(1 - \alpha_j)\frac{y_{jt}}{u_{jt}}, \tag{C.28}$$

$$w_t^s = (1 - \tau\xi_j)p_{jt}(1 - \gamma_j)(1 - \alpha_j)\frac{y_{jt}}{s_{jt}}. \tag{C.29}$$

The production function is

$$y_{jt} = \left(k_{jt}^d\right)^{\alpha_j} \left(u_{jt}^{\gamma_j} s_{jt}^{1-\gamma_j}\right)^{1-\alpha_j}, \quad j = p, g \tag{C.30}$$

Market clearing conditions. The market clearing conditions for final goods, skilled labor, unskilled labor and sector-specific capital markets are

$$c_t + i_{pt} + i_{gt} = y_t, \tag{C.31}$$

$$s_t = s_{pt} + s_{gt}, \tag{C.32}$$

$$u_t = u_{pt} + u_{gt}, \tag{C.33}$$

$$k_{jt-1} = k_{jt}^d, \quad j = p, g. \tag{C.34}$$

C.3. Parameterization for simulation

We calibrate the model parameters at an annual frequency to match the Chinese macroeconomic statistics over the sample period from 2002 to 2009.

On the household's side, the discount factor β is set to 0.978 to capture an average 2.25% real annual interest rate in China during the sample period. The household risk aversion η is fixed at 2, which is standard in the literature (*e.g.*, Fernández-Villaverde et al. (2015)). The depreciation rates for polluting capital δ_p and green capital δ_g are chosen to in line with the average annual capital depreciation rate of 5.1% obtained from Feenstra et al. (2015). Installing green capital is moderately costly, as indicated by the curvature $\kappa = 1$, an intermediate position between the 0.75 estimated in Fernández-Villaverde et al. (2015) and the 1.6 estimated in Born and Pfeifer (2014). The following data used in the labor-related calibration is from the Urban Household Survey (UHS). The household (labor population) size grows at 5.31% per year, which determines g_n. The annual proportion of unskilled labor becoming skilled π is pinned down at 0.0285 such that the sample average shares of skilled and unskilled labor are 0.37 and 0.63, respectively.

On the firms' side, the elasticity of substitution between the two intermediate sectors ϵ is set to 3, following Acemoglu et al. (2012). The average labor income accounts for the same share in each sector according to Acemoglu et al. (2012), which is approximately 58% from Feenstra et al. (2015). In other words, the capital shares $\alpha_g = \alpha_p = 0.42$. Among the total labor income, the unskilled labor income shares in the polluting and green sectors γ_p and γ_g are respectively calibrated to meet the average skilled-to-unskilled labor ratios of 0.24 and 0.44 by the UHS. As to the rate of environmental degradation ξ_p for polluting firms, we estimate ξ_p as the annual sulfur dioxide emissions (gram per Yuan of GDP) conducted by the Ministry of Environmental Protection, which is 32.9 on average before the environmental regulation.

In terms of the intensity of environmental regulation τ, we set the initial value at 0, indicating no regulation before 2006. We then adjust τ to 0.0046 as a final value to capture the target provincial average reduction of sulfur dioxide emissions of 11.74% in five years after implementing the environmental policy.

For an counterfactual exercise, we re-calibrate the parameters to match the U.S. statistics as an example. The discount factor β is set to 0.99 and the capital shares α_g and α_p are set to 0.33, all are standard values for the U.S. in the real business cycle literature (e.g., Acemoglu et al., 2012). The depreciation rates δ_p and δ_g are set to 0.048, according to Feenstra et al. (2015). The growth rate g_n is set to match the U.S. annual population growth rate of 0.93% from the World Bank dataset. Other parameters such as risk aversion η, curvature κ, and elasticity of substitution ϵ remains the standard values adopted from the above relevant literature. The annual proportion of unskilled labor becoming skilled π is pinned down such that the skilled labor share in the U.S. is 0.42 according to Angelopoulos et al. (2017). As there is no corresponding province-varying environmental policy in the U.S., we artificially set the regulation intensity as 0.0046, the same as the benchmark value, to study the qualitative results.

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