Environment for Development

Discussion Paper Series March 2024 ■ EfD DP 24-04

The Costs of ”Blue Sky”

Environmental Regulation, Technology Upgrading, and Labor Demand in China

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Bing Zhang* and Mengdi Liu†

Abstract

To cope with the stricter environmental regulation, manufacturing firms need to carry out pollution reduction activities and change their optimal production decisions, which may affect their labor demand. Using a ten-year firm-level panel dataset (1998-2007), we use an estimation technique pairing propensity score matching (PSM) with a difference-in-differences (DID) estimator to examine the impacts of a national air pollution control policy on employment in China. We find that China's Key Cities for Air Pollution Control (KCAPC) policy effectively lowered sulfur dioxide (SO2) emissions by approximately 26%. The new environmental regulation significantly reduced manufacturing labor demand by approximately 3%. Most importantly, firms reduce pollution emission mainly by upgrading production technology so the decline in labor is partly due to the increase in labor productivity brought about by technological progress. As a result of pollution reduction, low-skilled employees, female employees, and workers in domestic manufacturing firms are more affected by environmental regulation in China.

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To cope with the stricter environmental regulation, manufacturing firms need to carry out pollution reduction activities and change their optimal production decisions, which may affect their labor demand. Using a ten-year firm-level panel dataset (1998-2007), we use an estimation technique pairing propensity score matching (PSM) with a difference-in-differences (DID) estimator to examine the impacts of a national air pollution control policy on employment in China. We find that China's Key Cities for Air Pollution Control (KCAPC) policy effectively lowered sulfur dioxide (SO_2) emissions by approximately 26%. The new environmental regulation significantly reduced manufacturing labor demand by approximately 3%. Most importantly, firms reduce pollution emission mainly by upgrading production technology so the decline in labor is partly due to the increase in labor productivity brought about by technological progress. As a result of pollution reduction, low-skilled employees, female employees, and workers in domestic manufacturing firms are more affected by environmental regulation in China.

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I. Introduction

How to balance environmental protection and economic development has always been a key issue in policy formulation. Although environmental regulations can lead to improvements in environmental quality and associated declines in disease and mortality(Greenstone and Hanna, 2014; Tanaka, 2015), direct and indirect abatement costs are associated with corporate pollution reduction. As developing countries have gotten wealthier and pollution problem has emerged, pollution reduction has become the prime importance of their governments. Popular thinking is that the Chinese government is facing a hard tradeoff between developing economics and environmental protection when designing environmental policies. Recent studies examine the effect of China's stringent environmental regulations on firms' pollution emissions and their related economic outcomes(Fan et al., 2019; Chen et al., 2018; Liu, Shadbegian and Zhang, 2017; Cai et al., 2016). Among them, the impact on the employment of manufacturing enterprises is one of the most concerning influences. Particularly, given that there is a large amount of low-income and low-skilled employment in the manufacturing industry in China and other developing countries, their unemployment may further lead to social problems.

The dominant view in the literature is that stricter environmental policy may lead to higher production costs, causing firms to reduce their output and cut back on their inputs, resulting in a decrease in the demand for labor. To comply with more stringent environmental regulations, firms must either alter their production processes or install pollution abatement equipment to generate less pollution, which may need more or less labor depending on the pollution control strategies of firms. So the overall effect of environmental regulation on employment is uncertain from a purely theoretical perspective and thus requires empirical analyses (Berman and Bui, 2001).Therefore, identifying the emission reduction strategies of polluting companies and possible differential employment impacts will help explain the impact channels and make better policy impact assessments.

Most previous empirical studies focused on regulation-induced job effects in the United States and Western Europe using partial equilibrium empirical modeling. Greenstone (2002) found that in the first 15 years during which the Clean Air Act Amendments were enacted in the United States (1972-87), nonattainment counties lost approximately 600,000 jobs (3.4%) relative to attainment counties. Curtis (2017) found that the NOx budget trading program leads to a 1.3% decrease in the overall employment in the manufacturing sector. Similarly, several studies found that areas/industries that faced more stringent environmental regulations experienced lower employment growth (approximately 10%) than less regulated areas/industries (e.g.,Henderson et al. (1996); Kahn and Mansur (2013); Walker (2011, 2013)).

However, a range of empirical studies found no evidence that environmental regulation has such negative effects on labor demand (e.g., Berman and Bui (2001); Cole and Elliott (2007); Gray et al. (2014); Anger and Oberndorfer (2008); Abrell, Ndoye Faye and Zachmann (2011); Chan, Li and Zhang (2013)). Although environmental regulations in China have become increasingly stringent, the costs of those environmental regulations have not been fully analyzed. Most recently, using firms in the neighboring provinces as the control group, Liu, Shadbegian and Zhang (2017) found that the stricter water pollution emission standard in the Jiangsu Province led to a loss of jobs in the regulated area by approximately 7%, which is similar to the findings in developed countries. In contrast, this paper focus on the employment effect of a nationwide air pollution control policy in China, with a particular focus on the heterogeneous employment effects on different types of workers, which contributes to the existing literature by providing empirical evidence from developing countries.

Due to inexpensive labor and laxer environmental regulations, the concept of "Made in China" has been growing dramatically under China's economic transformation and growth since the end of the last century. In recent decades, however, as China has become wealthier and pollution problems have created large dissatisfaction among the public, pollution reduction has become a high priority for the government. In 2014, at the Communist party's annual congress, Premier Li Keqiang declared war on air pollution in China. At the party congress in 2017, he renewed his vow to "make our skies blue again." As China has published a series of policies and plans aimed at addressing environmental problems, the urgent question to answer is as follows: Who will bear the cost? Unlike developed countries where the cost and benefit analysis has long been considered in the policy design process, policymakers in developing countries such as China have only recently begun to pay attention to the potential costs of environmental policies. With the increasing intensity of environmental governance, China's already heavy burden under which it must constantly create new jobs simply to prevent unemployment from increasing may become even heavier. Therefore, estimating the potential impacts of air pollution control on employment, identifying vulnerable groups, and providing corresponding policy recommendations in China is particularly urgent.

In this paper, we estimate the impact of a nationwide target-based air pollution control policy, the KCAPC policy, on the environmental performances and labor demands of firms using two firm-level datasets: China's Environmental Statistics Database (CESD) and China's Industrial Enterprise Database (CIED), as well as other sources at both the city level and individual-level. In the 10th Five-Year Plan (FYP), 66 cities were designated as the second batch KCAPC and were thus required to show progress in improving the air quality of the city (see section 2 for detailed information). Since the KCAPC selection is not random, to alleviate the difference between treated cities and control cities, we first use PSM based on the pre-KCAPC attributes of the cities to select a statistically defensible comparison group from untreated cities. Then, we use a DID estimation to investigate how the KCAPC policy affected employment in the treated area compared with the untreated area. We find that the KCAPC policy is effective in terms of reducing SO_2 emissions (measured at 26%), mainly by leading to "changes in the production process" rather than "end-of-pipe" treatments or production reduction. Most importantly, our results show that the new environmental regulations have led to significantly lower levels of employment in the manufacturing sector in regulated areas: employment in treatment firms fell by 3% relative to similar firms in nonregulated areas, which is similar to the existing findings on the U.S. Clean Air Act Amendments (Greenstone, 2002). These results suggest that a 1% reduction in SO_2 emissions will lead to a 0.13% decrease in labor demand. Additionally, we find that low-skilled workers, female workers, and workers in domestic firms are more likely to lose their jobs under environmental regulation in China. Environmental regulations have also increased labor productivity, which may be due to the effects of improved technology. Using the WTO accession as the external shock, we further prove that technology upgrading could be skill increasing and thus labor-saving.

This paper contributes to the existing literature on the topic of environmental regulation and employment in three ways. First, the existing theoretical framework has suggested that different pollution reduction strategies of enterprises may have different effects on labor demand - "changes in the production process" will reduce labor demand due to technology substitution while "end-of-pipe" requires additional labor. This study provides new empirical evidence from the largest developing country for the impact of pollution control strategies on employment, which complements existing literature.Specifically, given that we have rich and detailed enterprise-level production and pollution information of each production process, including pollution generated during production, pollution removal from abatement facilities, and the number and cost of abatement facilities, etc., we can measure different corporate pollution control strategies. In contrast to Liu, Zhang and Geng (2018), which focuses on the relationship between corporate pollution control and labor demand, this study directly assesses the differential labor demand impact of enterprises with different emission reduction strategies under environmental regulation, and thus can provide direct policy implications. Moreover, this paper analyzes the impact of corporate emission reduction strategies on labor productivity, a previously unexplored topic by Liu, Zhang and Geng (2018). We found that technological innovation in the production process decreases the demand for labor but also boosts labor productivity. Thus, our study investigates the influence of environmental regulation on the labor market in a more comprehensive manner.

Second, unlike the research that has paid more attention to the average employment impact of environmental regulation, we explored the heterogeneity impact of environmental regulation on employment from the perspectives of different ownership types and different skill levels of employees, and contributed to the existing literature. The analysis of the heterogeneous employment impact of environmental regulation has theoretical and practical value. When discussing the long-term impact of environmental regulation on employment, it is often necessary to consider the re-employment of unemployed workers, while the difficulty of re-employment of high-skilled and low-skilled workers is different. In particular, low-skilled workers may need more re-employment training in this process, and it may take them a longer time to re-employ, which will result in greater social costs. In addition, the analysis of the impact of environmental regulation on heterogeneous employment effects also provides evidence for discussions on environmental protection and social equity.

Third, this study complements existing research mainly focusing on developed countries by providing new evidence from China, the world's second-largest economy with heavy reliance on the manufacturing sector that is now contending with environmental problems. We use the most comprehensive firm-level data, which has only recently become available to researchers in China, to examine the impact of a nationwide air pollution control policy on labor demand. The research results can provide support for the cost-benefit assessment of China's environmental policies.

In the next section, the institutional background of the KCAPC policy is outlined. In section 3 we illustrate the conceptual framework of the environmental regulation impact on employment as well as the main channels. In section 4 , we describe our empirical strategy, and in section 5 , we present our datasets. Our main empirical results, mechanism analyses, a set of heterogeneity analyses, and robustness checks are presented in section 6 . Finally, section 7 provides our conclusions and policy recommendations.

II. Policy Regime: KCAPC Policy

A. Background of the KCAPC

Under China's vertical performance appraisal system, top-down target-based environmental management is considered to be the fastest and most effective type of regulation due to the incentive of official promotion. The FYP is China's most important mandatory target system, in which the environmental requirements on unit pollution emissions and energy consumption are assigned to local governments. The first recognized target-based air pollution control policy in history, the Two Control Zones (TCZ) policy[1], has been widely examined in existing literature as a quasi-natural experiment to examine China's environmental regulations' impacts on pollution reduction, economic growth (Chen, Li and Lu, 2018), infant mortality (Tanaka, 2015), and foreign direct investment (Cai et al., 2016).

The KCAPC as the policy of interest of this paper is another important target-based air pollution control policy in China. The KCAPC concept was first proposed in 1998 in an official document (known as the "two compliance policy") of the Ministry of Environmental Protection (MEP)[2] with the intention to improve the air quality of some key cities. The central government designated 47 prefecture-level cities as the first batch of cities in the KCAPC, most of which were municipalities (i.e., Beijing, Shanghai, Chongqing, and Tianjin), provincial capital cities, cities in special economic zones, major tourist cities, and coastal open cities. All industrial pollution sources to comply with the corresponding emission standards for SO2 and TSP set by national or local environmental regulations by 2000, namely "two compliance policy". The

[1]In 1998, the central government issued a major policy initiative to establish control zones for sulfur emissions and acid rain, namely Two Control Zones.

[2]For the official document, see http://www.110.com/fagui/law_94153.html.

ranking of the key cities for the implementation of the "two compliance policy" was then released in the Environmental Status Bulletin of China in 2000[3].

To amplify the benefits of improved air quality on human health, an additional 66 cities were designated in the second batch of KCAPC in December 2001 in China's 10th FYP[4]. These cities were chosen based mainly on the Law for the Prevention and Treatment of Air Pollution. Specifically, after a comprehensive economic analysis and an assessment of contemporaneous air pollution levels in 2000, 66 cities were added to the KCAPC based mainly on the following considerations[5]':

a) Cities' comprehensive situation of economic development and environmental pollution.

b) Cities' TCZ status.

c) Cities with cultures that are in urgent need of protection.

In this paper, we focus on the newly designated KCAPC of December 2001. It would also be interesting to examine the impact on the first batch KCAPC. However, the data availability began in 1998[6]. In addition, as described above, cities in the first batch of KCAPC are the wealthiest cities in China and have special political tasks, which makes it difficult to find a similar control group among the untreated cities.

[3]The first three cities are Guilin, Ningbo, and Hangzhou. For the official document, see http://www.mee.gov.cn/hjzl/zghjzkgb/lssj/2000nzghjzkgb/201605/t20160522_341633.shtml.

[4]For the official document, see http://www.zhb.gov.cn/gkml/zj/wj/200910/t20091022_172232.htm. The distribution of cities in the list of KCAPCs is shown in Figure 1

[5]For the work report, see http://www.zhb.gov.cn/info/ldjh/200307/t20030703_86927.htm; For the selection scheme, see http://wfs.mep.gov.cn/dq/gzjz/200302/t20030213_84369.htm.

[6]In 1998, the China National Environmental Monitoring Center was established to be responsible for the collection, summary, review, and drafting of Environmental Statistics Annual Report (see http://www.cnemc.cn/jcbg/zghjtjnb/).

B. Requirements and Implementations of KCAPC

According to the policy, the prefecture-level cities listed in the KCAPC are required the key cities to comply with the National Ambient Air Quality Standard (GB3095-96) [7]. Specifically, they were required to improve the intensity of law enforcement, establish an environmental monitoring network, and need to be assessed by the MEP. The firms listed in the KCAPC were required to undertake clean production, mainly by updating production technology. Specifically, enterprises were required to promote the use of clean energy such as electricity, natural gas, and liquefied gas, reduce the consumption of raw coal, and promote clean coal technology[8]. Cities that do not meet the standard would be recorded by the MEP and may thus affect the comprehensive evaluation and promotion.

The KCAPC has received extensive attention from both upper-level governments and local-level governments. From a top-down perspective, one year after the first batch of KCAPC was released, the requirements for the KCAPC were included in the Air Pollution Prevention and Control Act, which is the strictest law among all air pollution policies showing the central government's special attention to the KCAPC. In addition, every year in China's annual environmental status report, there is a section dedicated to summarizing the KCAPC implementation of pollution control in key cities, which signifies continuous attention to KCAPC from the central government and thus creates continuous pressure on regulated cities. From the perspective of prefecture-level cities, the designated cities reported environmental conditions and improvements in pollution control to the public by holding regular press con-

[7]The requirements for the average annual concentration of SO2, TSP, PM10, and NOx are 0.02, 0.08, 0.04, and 0.05 mg/m3 respectively.

[8]For the official document, see http://www.mee.gov.cn/gkml/zj/wj/200910/t20091022_172141.htm

ferences. Being under the supervision of and subject to potential complaints from the public provided local governments with additional pressure to improve environmental performance.

III. Conceptual Framework

To help inform our empirical analysis, we adopt the Berman and Bui (2001) framework, which allows environmental regulations to operate via the following two separate mechanisms: (1) the output effect and (2) the substitution effect[9]. Notably, Berman and Bui (2001) developed their theoretical framework based on the partial static equilibrium, and the key insight from the partial static equilibrium model was that some factor inputs can be taken as "quasi-fixed" factors that are set by exogenous constraints rather than by cost minimization. In our case, "quasi-fixed" inputs include those treatment costs (e.g., investment in pollution abatement capital and operating costs associated with pollution abatement) that are incurred to comply with environmental policies. We allow all other "productive" factors to be variable (e.g., labor input and capital input).

Assume that a perfectly competitive firm minimizes costs by choosing the levels of variable inputs and "quasi-fixed" inputs. The variable cost function is as follows[10]:

$$CV = H(Y, P_1, ..., P_J, Z_1, ..., Z_K) \tag{1}$$

where Y represents output, P_j denotes the prices of the variable factors, and Z_k represents the levels of the "quasi-fixed" inputs. According to Shephard's

[9] Morgenstern, Pizer and Shih (2002) use a similar model but disaggregate the employment effect into three components: The demand effect, the cost effect, and the factor-shift effect.

[10] Our notations are largely adopted from Berman and Bui (2001).

lemma, the demand for labor input is a function of output, prices, and the level of "quasi-fixed" inputs and can be expressed as follows:

$$L = \alpha + \rho_y Y + \sum_{j=1}^{J} \gamma_j P_j + \sum_{k=1}^{K} \beta_k Z_k \tag{2}$$

Then, the direct effect of environmental regulations R on labor demand is as follows:

$$\frac{dL}{dR} = \rho_y \frac{dY}{dR} + \sum_{j=1}^{J} \gamma_j \frac{dP_j}{dR} + \sum_{k=1}^{K} \beta_k \frac{dZ_k}{dR} \tag{3}$$

Assume that input factor markets are perfectly competitive, and thus, any change in environmental regulation will not impact input factor costs. Therefore, the second term in Equation 3 will drop out, leaving the other two terms. The first term in Equation 3 refers to the effects of environmental regulations on labor demand by means of its effect on output, which is typically assumed to be negative; however, if firms comply with environmental regulations by investing in abatement capital that decreases marginal costs, then $\frac{dY}{dR}$ may be positive. The production reduction will lead to a decrease in labor demand. The third term shows the effects that environmental regulation have on employment through the impact on the demand for pollution abatement activities. The change in demand for quasi-fixed abatement activity caused by stricter environmental regulation, $\frac{dZ_k}{dR}$, is assumed to be positive. The signs of the β_k coefficients depend on whether pollution abatement activities and labor demand are complements or substitutes for one another. Abatement activities fall into two groups: "end-of-pipe" treatments and "changes in production processes". Therefore, Equation 3 can be written as follows:

$$\frac{dL}{dR} = \rho_y \frac{dY}{dR} + \beta_1 \frac{dZ_1}{dR} + \beta_2 \frac{dZ_2}{dR} \tag{4}$$

where Z_1 represents those inputs used in "end-of-pipe" treatments and Z_2 represents those inputs that are used in "changes in production processes". Firms must either reduce production or implement new pollution reduction activities to achieve the goal of reducing emissions. "End-of-pipe" refers to techniques applied at the end of the production process (e.g., installation of flue gas desulfurization units) aiming at reducing pollution released into the environment by eliminating those pollutants that have already been generated in the production process. To operate and maintain the "end-of-pipe" equipment, firms may increase their labor demand; thus, β_1 is assumed to be positive. In contrast, "changes in production processes" refer to those techniques that are used during the process of production that aim to reduce the amount of pollutants generated during production (e.g., installation of more efficient boilers that produce less pollution). A general skill bias of this technological change could reduce labor demand; thus, β_2 is assumed to be negative. Therefore, based on the theory alone, the overall effect of environmental regulation on labor demand, μ , is uncertain:

$$L = \delta + \mu R \tag{5}$$

IV. Empirical Framework

A. *PSM Strategy*

Our empirical analysis' main objective is to estimate the effect the KCAPC policy has had on employment. As described above, 66 cities were newly designated as the second batch of KCAPC in December 2001, which allows us to estimate the causal effect of environmental regulation on labor demand with good precision using the DID strategy. The DID method has the advantage of capturing pre-existing differences between firms in the 66 newly designated KCAPC cities and firms in non-KCAPC cities, thereby eliminating selection bias, while also controlling for possibly confounding variables that may have changed near the 10th FYP, which may have affected both sets of firms. DID estimation is most appropriate when the treatment is randomly set or at least when the observable characteristics can be used to control for the treatment. However, real-world policies do not easily meet the requirements of random experiments. In the absence of an experiment, people usually alternatively find or construct a comparable control group using matching techniques. Rosenbaum and Rubin (1983) suggest matching on the propensity score–the probability of receiving the treatment conditional on covariates. Dehejia and Wahba (2002) prove that the PSM approach succeeds in focusing attention on the small subset of comparison units, which are comparable to the treated units and thus succeed in taking the bias away because of the systematic differences between the treated and comparison units. Then, the PSM method is widely used in the field of policy analysis such as the research focusing on the U.S. Clean Air Act (see, e.g., Greenstone (2004); List et al. (2003)) and the research focusing on the U.S. Title IV SO_2 Trading Program (Ferris, Shadbegian and Wolverton, 2014).

Similarly, the assignment of the regulated cities in our case is not random but relies on the economic conditions and pollution levels of the cities. Therefore, we first use the PSM approach to construct a comparable control group. PSM uses a logistic regression (the dependent variable is equal to 1 for KCAPC and is 0 otherwise) in which the independent variables consist of pretreatment characteristics that may affect the "propensity" to be included in the KCAPC. Cities are matched with their nearest neighbor (NN) based on their propensity scores, which are scalar summaries of pretreatment characteristics from a logistic regression.

The propensity score predicts the probability that a city will be designated in the KCAPC, $P(X) \equiv Pr(D = 1|X)$, for a set of given observable characteristics (X). As discussed above, cities were chosen to be included in the KCAPC mainly based on a comprehensive economic analysis and an assessment of contemporaneous air pollution levels in 2000. Specifically, the selection criteria included cities' comprehensive situation of economic development, environmental pollution, and whether a city was in the TCZ. Thus, we replicate the policy rule using a city's population and GDP per capita as indicators of the comprehensive economic situation, and we use SO_2 concentration and abatement costs per unit of industrial SO_2 emission as indicators of the environmental performance. We also include a TCZ dummy (TCZ is equal to 1 if a city is in the TCZ and 0 otherwise). After matching treated and control cities based on pretreatment characteristics, we obtain 62 support-treated cities with 62 matched untreated cities[11]. We test the biases between treated and untreated cities before and after matching, and we find that the bias of most of the indicators in the two groups decreases substantially after matching (see Figure 2). Figure 3 shows the distribution of treatment cities and matched control cities.

[11]To make the control group comparable, 4 cities in the treatment group are dropped because their propensity score is higher than the maximum or less than the minimum propensity score of the controls (i.e., common support). We further add the ratio of the secondary industry and the change rate of industrial SO_2 emissions as robustness checks. To include all the 66 cities we also relax the common support restriction as robustness checks. The results are shown in Figure A1 in the appendix.

B. DID Estimation Equation

After assembling a matched sample that consists of cities designated as KCAPC and cities in the nearest untreated neighbors, we estimate the average treatment effect of the KCAPC policy on employment. Notably, environmental policy in China has long been considered unimportant (Alford, 1997). Adequate monitoring capacity has not been implemented as a basic regulatory element, and the cost of breaking environmental regulations remains quite low (Jin, Andersson and Zhang, 2016). For example, Wang et al. (2003) examined the factors affecting monitoring and enforcement of environmental regulation in China and found that certain types of firms in China have excessive bargaining power when negotiating with local environmental protection departments, which results in ineffective enforcement of environmental regulations. If the KCAPC is just an empty slogan without practical implementation, there is no need to estimate other effects (such as employment effects). Therefore, we should first examine whether the KCAPC policy has been effective at reducing pollution emissions before estimating the KCAPC policy impact on employment. We first examine the efficacy of the KCAPC policy using the following DID model for the log of SO_2 emissions[12]:

$$ln(SO_2)_{it} = \beta_1 KCAPC_i \times Post_t + \alpha_i + \gamma_t + \eta_{jt} + \epsilon_{it} \tag{6}$$

where i represents firms, j represents the 2-digit National Standard Industrial Classification (NSIC) industries (e.g., textiles, food manufacturing, paper and paper products, chemical fiber manufacturing, and so on), and t represents

[12]It is better to examine the impacts of more than one pollutant. However, for industrial pollution, the central government of China previously focused on only SO_2 for air pollutants and COD for water pollutants. We also use SO_2 emission per unit of output (i.e., SO_2 intensity) as a robustness check.

years. $ln(SO_2)_{it}$ is the logarithm of SO_2 emissions. $KCAPC_i$ equals 1 if a firm is listed in the KCAPC and otherwise equals 0. $Post_t$ equals 1 for all years after 2001 (policy period) and otherwise equals 0. $KCAPC_i \times Post_t$ is the interaction term between the $KCAPC_i$ and $Post_t$, which captures the average differential change in SO_2 emissions at KCAPC firms relative to the control group. Thus, the coefficient β_1 measures the DID effect as follows:

$$\begin{aligned} \beta_1 = &(ln(SO_2)_{KCAPC=1,Post=1} - ln(SO_2)_{KCAPC=1,Post=0}) \\ &-(ln(SO_2)_{KCAPC=0,Post=1} - ln(SO_2)_{KCAPC=0,Post=0}) \end{aligned} \tag{7}$$

If the coefficient β_1 is negative, we can infer that the new environmental regulation decreased SO_2 emissions effectively. We exploit the panel nature of our firm-level data by including firm fixed effects (α_i) and year fixed effects (γ_t) in our basic specification. The inclusion of year and firm fixed effects indicates that we capture the general macroeconomic factors which impact all firms over time as well as time-invariant firm-specific characteristics. We also include a set of industry-year interactions (η_{jt}), to control for industry-specific time trends. ϵ_{it} is the usual idiosyncratic error term. In some specifications, we further control for city-level characteristics, including average wage and industrial output as well as province-by-year fixed effects as a robustness check. Following Brandt et al. (2017), because the explanatory variables of interest vary only at city-year level, we clustered standard errors at that level to construct our confidence intervals for all models.

After we estimate the KCAPC policy effects on pollution reduction, we examine the KCAPC policy effects on our main outcome variable, employment, as measured by the logarithm of the number of employees using a similar DID model. The regression model for employment is as follows:

$$ln(Labor)_{it} = \beta_1 KCAPC_i \times Post_t + \alpha_i + \gamma_t + \eta_{jt} + \epsilon_{it} \tag{8}$$

where $ln(Labor)_{it}$ is the outcome variable of interest. The other variables' meaning is the same as in Equation 6. Similarly, the coefficient β_1 measures the DID effect of the air pollution control policy on labor demand, where

$$\begin{aligned} \beta_1 = &(ln(Labor)_{KCAPC=1,Post=1} - ln(Labor)_{KCAPC=1,Post=0}) \\ &-(ln(Labor)_{KCAPC=0,Post=1} - ln(Labor)_{KCAPC=0,Post=0}) \end{aligned} \tag{9}$$

V. Data

To analyze the KCAPC policy impact on environmental performance and employment, we merge two firm-level panel datasets from 1998 to 2007: CESD and CIED. We also use city-level data, including the China City Statistical Yearbook (CCSY) and city-level CESD, and the individual-level data Urban Household Survey (UHS).

A. Firm-level Environmental Data

The China's Environmental Statistics Database (CESD) is the most detailed environmental statistical data in China and covers nationwide data. The MEP established an environmental information system that covers all major emission sources. However, the CESD remained confidential for a long time and has only recently become available to researchers[13]. Each firm self-reports data seasonally, and then, the data are compiled by the MEP. Specifically,

[13]Wu et al. (2017) used these data to analyze the location choice of new polluting enterprises driven by the 11th FYP's water pollution mandates. Liu, Shadbegian and Zhang (2017) used data for Jiangsu province and nearby provinces to analyze the impact of water emission standards on labor demand.

local EPBs confirm data quality through unannounced inspections and other monitoring activities. Then, the local EPBs generate a final report that is sent to the provincial-level EPBs. After a thorough review, the certified information is sent to the MEP, and thereafter, environmental protection departments at all levels can use the microdata to release an annual environmental status report. According to an interview with local EPBs and polluting firms, both national and provincial environmental protection departments often review the statistical work of the local EPBs in various ways, including random spot checks. If problems are found, onsite inspections are carried out when necessary. Upper-level governments also directly conduct flight inspections, cross-checks, and onsite verifications of corporate pollution emissions. The CESD is the most comprehensive environmental microdata set in China and covers approximately 85% of the annual major pollutant emissions (e.g., SO_2 and COD) in each county and for each year. The CESD contains information on basic firm information (e.g., firm name, legal person code[14], region code and industry code), pollution emissions, environmental equipment (e.g., the number of waste gas treatment facilities and wastewater treatment facilities), and other firm-level environmental information (e.g., pollutant removal, pollutant removals, treatment capacity, and the operating costs of abatement facilities). For our empirical analysis, we use the CESD information regarding SO_2 emissions, SO_2 generation[15], COD discharge, the number of waste gas treatment facilities, statistical year, ownership type, region code and industry code.

[14]Legal person code is akin to a firm ID and is used to identify firms. Firm names are often long, and one or two words in a firm name may change over time, which makes the legal person code useful.

[15]SO_2 generation refers to the SO_2 produced before entering any "end-of-pipe" equipment. In the database, we have information on how much SO_2 is removed by the firm's equipment and how much SO_2 is eventually discharged into the environment. We add the two to calculate the amount of SO2 produced.

B. Firm-level Economic Data

The China's Industrial Enterprise Database (CIED) is another large dataset containing a substantial amount of information on the production and finances of all state-owned and nonstate-owned firms whose annual business income is greater than 5 million Chinese Yuan (CNY)[16]. The CIED covers more than 40 industries and more than 600 subindustries, and the total output from these firms accounts for roughly 90% of total industrial output of China. The CIED contains over one hundred variables that are related to financial and economic indicators, such as industrial output, ownership type, and the number of employees. In our paper, we extract the number of employees, output value, total wage, the year operations began, statistical year, ownership type, region code and industry code from the CIED.

C. Other Data Sources

In addition, we also use city-level and individual-level data from several sources. Specifically, we use information on population, GDP per capita, area, total employment, and unemployment from the CCSY, which is an annual city-level statistical publication produced by the National Bureau of Statistics of China and covers the main socioeconomic statistical data of 658 cities (including 289 cities at the prefecture-level and above and 369 cities at the county level). The aggregate of industrial SO_2 emissions, COD emissions, industrial output, and the number of industrial firms are from the city-level CESD. Information regarding whether a city is within the scope of the TCZ and whether a city is on the NFHCC list are from official documents. Individual-level information such as job status and educational level is from the UHS, which is

[16]The CIED has been widely used in the research on China problem (see, for example, Brandt, Van Biesebroeck and Zhang (2012); Brandt et al. (2017)).

a cross-sectional annual survey.

D. Descriptive Statistics

We obtained our manufacturing firm-level matched panel data from 1998 to 2007 using information for legal person code and firm name in the two datasets. First, we used legal person code to match the two datasets; 46% of the observations in the CESD are successfully matched. Then, we use the firm name to perform the matching, and another 6% of the observations in the CESD are matched[17]. We update industry code and region code in the raw data according to official documents. We drop observations that appear to violate accounting principles, i.e., where liquid assets, fixed assets, or net fixed assets are larger than total assets or where current depreciation is greater than cumulative depreciation. Finally, we arrive at 28,310 unique firms in the matched sample, leading to 97,106 firm-year observations from 1998 to 2007 in our baseline model (47,443 from KCAPC cities and 49,663 from non-KCAPC cities). Table 1 shows the summary statistics (mean value, standard deviation, and observations) of the main characteristics that we used. Each firm employs an average of 587 employees per year. The average annual SO_2 emissions amount to approximately 156,493 kilograms per firm, and the average annual COD emissions amount to approximately 86,696 kilograms per firm. On average, firms in our sample generate 329,047 kilograms SO_2 during the production process. On average, each firm has 3 sets of abatement facilities.

[17]Finally, we have successfully matched 52% of the CESD observations with those in the CIED, and 15% of the CIED observations with those in the CESD. There are several reasons explaining why some firms cannot be matched. First, the scopes of the two datasets are different. The CIED includes only industrial firms (e.g., manufacturing firms and power plants), while the CESD also includes mining firms and firms that discharge hazardous wastes (e.g., hospital). Second, the CIED dataset consists of only firms whose annual business income is greater than 5 million CNY, while some high-polluting firms in the CESD may have smaller annual business incomes.

The average output value is 149,609 thousand CNY, and the average wage per worker is 12.3 thousand CNY. On average, each city has 297 thousand workers employed and 18,585 workers unemployed. The total industrial SO_2 and COD emissions average 59,633 and 17,194 tons per city. Each city averages 241 industrial firms with a total industrial output of 24 billion CNY. Approximately 7% of the job statuses of interviewees were unemployed in our sample, and the average educational level was high school. Table 1 demonstrates that the observations in our sample exhibit great variations with regard to nearly every variable.

VI. Results

A. *Test on Policy Effectiveness*

We first test the policy effectiveness using information on firm-level SO_2 emissions. To ensure satisfaction with the strong identification hypothesis that the treatment group would have tracked the same trend as the control group in the absence of the KCAPC policy, we begin by checking on the identification assumption. Figure 4 presents coefficients and 95% confidence intervals on the KCAPC-year interactions from the regressions of $ln(SO_2)$ and on KCAPC-year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms from 1998 to 2007. As Figure 4 shows, before the policy was enacted, the coefficients of KCAPC-year interactions do not significantly differ from 0, indicating that KCAPC firms and non-KCAPC firms have similar pollution emission trends. Ideally, the pre-treatment test requires more pre-period information. Unfortunately, due to the unavailability of the data, we can only access firm-level data from 1998, which provide us only 4 pre-treatment years. After the policy was enacted, the coefficients of

KCAPC-year interactions are less than 0, which indicates a reduction in SO_2 emissions in the treatment group compared to the control group.

The DID results on the environmental performance corresponding to Equation 6 are shown in columns (1) and (2) in Table 2. The result in column (1) indicates the estimate for KCAPC×Post is significantly negative, implying that the KCAPC manufacturing firms are facing harsher environmental requirements after the policy change than the manufacturing firms in the matched control group, as shown by the significantly decreased SO_2 emissions. Given that most of China's policies were designed at the provincial-level, we also control for province-by-year fixed effects to capture the policy factors at the province level. To further alleviate the impact of the substitution process in response to the possible different growth factors, we control for city-level characteristics, including average wage and industrial output. As the result shows in column (2), we found little evidence that undermines the basic conclusions. These results offer evidence that the new air pollution control policy is effective at reducing firm-level SO_2 emissions in treated cities. The point estimates suggest that SO_2 emissions declined by 26% as a result of the KCAPC policy [18]. We also use SO_2 intensity as a robustness check [19]. After the policy, SO_2 intensity dropped by 25% more in the treatment group than in the control group (see columns (3) and (4) of Table 2 and Figure A2 in the online appendix).

B. The Main Results of Employment

The DID results of the new environmental regulation effects on employment, our main outcome of interest, corresponding to Equation 8 are reported

[18]Since we use a semilog model, we use Equation $e^{\beta} - 1$ to calculate the elasticity of all models.

[19]SO_2 intensity is defined as SO_2 emission per unit of output value.

in columns (5) and (6) of Table 2. As the pretrend shown in Figure 5, the coefficients of the KCAPC-year interactions before the policy are not significantly different from 0, indicating that KCAPC firms and non-KCAPC firms have similar employment trends. The estimates on KCAPC×Post, our main variable of interest, are significantly negative, implying that KCAPC manufacturing firms, who faced harsher environmental regulations after the policy change, employed significantly fewer workers than firms in the matched control group. These results provide evidence that the new air pollution control policy has led to significantly lower levels of employment in the manufacturing sector in cities subjected to the KCAPC policy. The point estimates suggest that employment fell by 3% more than the non-KCAPC firms. The combined results of pollution emissions and employment suggest that a 1% reduction in SO_2 emissions will lead to a 0.13% decrease in labor demand.

C. Checks on the Labor Reduction Channels

We further examine the channels for polluting firms to reduce labor demand for environmental compliance. As discussed above, firms must either reduce production or implement new pollution reduction activities to achieve the goal of reducing emissions. The reduction in production will lead to a decrease in labor demand. Abatement activities fall into two main categories: "end-of-pipe" treatments and "changes in production processes". "Changes in production processes" refers to any adjustment in the production process that impacts the amount of pollutants generated during the production process, such as the adoption of more advanced production technology or alterations to the input of production raw materials. "End-of-pipe" techniques, such as the installation of flue gas desulfurization units, may require more labor to install, operate and maintain, thereby positively effecting labor demand. By contrast, "changes in production processes", such as the installation of more efficient boilers that generate less pollution, may reduce labor demand due to the general skill bias inherent in this type of technological change, especially low-skilled labor demand. Liu, Zhang and Geng (2018) found that pollution reduction by pollution prevention has substitutive impacts on employment and that pollution reduction through "end-of-pipe" pollution control may require extra employees and thus has a positive but not significant effects on employment.

As we have detailed information on each production process, we can decompose the amount of pollutant emissions into the amount of pollutant generation minus the amount of pollutant removed. Then, we use the amount of SO_2 generated during the production process (before entering abatement facilities) per unit of real output value as the measure of "changes in production processes"[20] abatement and the number of abatement facilities as the measure of "end-of-pipe" treatments.

Table 3 reports the coefficients of the fixed effects models using the log real output value[21], log SO_2 generation per unit of real output, and log number of abatement facilities as the dependent variables. The estimated coefficients are found to be negative and statistically significant for only SO_2 generation per unit of real output (columns (3) and (4)) but are nonsignificant or only marginally statistically significant for real output value (columns (1) and (2)) and the number of abatement facilities (columns (5) and (6)). The results show that firms in the KCAPC mainly reduce pollution emissions by installing more efficient boilers that generate less pollution. The point estimates suggest that

[20] Unfortunately, we do not have information on the firm's production facilities to more precisely measure technical advancement.

[21] The real output value is calculated using the province-specific Producer Price Index (PPIs), where 1998 is considered to be the base year.

SO_2 generation intensity declines by 26% after the policy was enacted.

We further divided firms in the treatment group into two subgroups ("high change in production processes" and "low change in production processes") according to their pollution reduction strategies after the policy was enacted. Specifically, first, we calculate the average SO_2 generation intensity of each firm before and after the policy. Then, we calculate the changes before and after the policy. We classify firms with changes above the average as "high change in production processes", and the others as "low change in production processes". We found that the "high change in production processes" subgroup reduces labor demand more significantly than the "low change in production processes" group after enactment of the policy (see Table 4), which is consistent with the results of Liu, Zhang and Geng (2018). We further compare firms' characteristics between the two groups. As Table A1 shows, firms that adopt more processing control tend to behave lower output value, capital, and labor but relatively older and have more FDI. The two types of firms show no significant difference in average wage and SO_2 intensity.

We also find that after the policy was enacted, firms in the treatment group increased their labor productivity (see appendix Figure A5), which provides some evidence that part of the reason for the decline in labor is the increase in labor productivity brought about by technological progress. To further prove that technology upgrading could be skill increasing and thus labor-saving, we use the WTO accession as the external shock. A more relaxed environment for foreign investment promotes learning and technology spillovers. There is ample evidence that trade liberalization conducive to introducing new intermediate inputs (see e.g., Goldberg et al. (2010)), raising quality (see e.g. Amiti and Khandelwal (2013); Fan, Li and Yeaple (2018); Verhoogen (2008)) and productivity (see e.g., Topalova and Khandelwal (2011); Edmond, Midrigan and Xu (2015); Amiti and Konings (2007); Kasahara and Rodrigue (2008); Halpern, Koren and Szeidl (2015)), and adopting new technologies (see e.g., Atkeson and Burstein (2010); Bustos (2011)). As Figure A3 shows, there was a large reduction of input tariff at the industry level in 2001 when China entered WTO while decreases are more gradual before 2001[22]. In addition, according to the interquartile range, the reduction of tariffs in different industries is different, which allows us to carry out DID analysis.

Specifically, with reference to Sivadasan (2009)'s method, the industries with larger import tariff reductions are regarded as the sectors that are impacted by WTO accession, while others are regarded as the control group. We sort the industries according to the tariff reduction rates in 2007 compared to 1998 and set the industries that exceed the average value as the treatment group of the WTO accession, with a value of 1, otherwise, the value is 0. Then we multiply it with the year dummies to construct a series of interaction terms. Given that the decline in the labor force may also be attributable to the decrease in production resulting from the greater competition for local firms caused by tariff reductions, the model additionally accounts for the output value of enterprises. As Figure A4 shows, firms that are more impacted by lower tariffs have seen a significant decline in labor demand after controlling for output. This results further proves that technology upgrading could be skill increasing and thus labor-saving.

D. Who Bears the Costs?

Except for the average environmental regulation treatment effects on labor demand, policymakers are more concerned with who actually bears the costs and thus identify the group sensitive to environmental protection. In this

[22]We use the industry-level input tariffs data from Brandt et al. (2017).

section, we explore heterogeneous employment effects to show who bears the burden of regulation[23]. As the results of the mechanism analysis indicate, firms reduce SO_2 emissions mainly by "changes in production processes", which are assumed to reduce more low-skilled labor due to the general skill bias inherent in this type of technological change. Thus, we first directly estimate heterogeneous employment effects by workforce skill. Firms with different ownerships are likely to be different in many aspects, such as organizational form, production technology, and regulatory intensity. Then, we estimate the heterogeneous employment effects by firm ownership.

Workforce skill. Theoretically, highly skilled labor has higher labor productivity than low-skilled labor. The increase in labor productivity provides some indirect evidence that the proportion of highly skilled workers increased, which in turn led to a workforce upgrade. Then, we estimate the heterogeneous effects of workforce type using two methods. First, we separate firms into two groups (high and low) according to the ratio of high school or above workers for year 2004 (a census year) [24]. As the results shown in column (6) of Table 5, demand for workers in the low-skilled manufacturing firms (5.5%) decrease more compared to those in the high-skilled manufacturing firms (4.5%). These findings indicate that compared to skilled workers, unskilled workers are relatively more affected by the more stringent environmental regulation. Also, compared to high-skilled firms, low-skilled firms reduce more SO_2 emissions, SO_2 intensity, and SO_2 generation. Second, we use individual-level cross-sectional data from China's UHS to examine the probability of unemployment by different educational levels. As the results show in Figure A6 and Table 6, the probability of unemployment was very similar in the two groups prior

[23] Curtis (2017) found that young workers and workers in the energy-intensive industries experienced the largest employment declines.

[24] There is no education information in other years.

to the policy, and then increased for workers in the treatment group after the policy was enacted (see columns (1) and (2) of Table 6). These results are consistent with the results of the firm-level analysis. By further dividing the workers into two groups, we find a relatively stronger effect for low-skilled workers when using either a high school diploma or bachelor's degree as the cutoff but the difference between the high-skilled and low-skilled workers is statistically insignificant (see columns (3)-(6) of Table 6).

Workforce gender. We also investigate the heterogeneous policy effects across gender categories. In contrast to the U.S. study, which concludes that environmental taxes affect both male and female labor demand (Yip, 2018), we find that China's environmental rules have a greater effect on female workers. The results in Table 7 indicate that after the implementation of environmental regulations, the unemployment rate of women grew dramatically, whereas the unemployment rate of men did not change significantly. One possible explanation is that men are more likely to hold skilled occupations, whilst women are more likely to take unskilled jobs. Unfortunately, we only have cross-sectional data at the individual level, which prevents us from controlling individual characteristics that do not change over time to obtain more convincing results. In the future, further discussions are needed based on individual tracking data.

Firm ownership. Foreign firms are known to have better environmental performances than domestic firms, and thus, these firms may not have to alter their operations as much to comply with the new environmental regulations as either state-owned or privately owned domestic firms (Dean, Lovely and Wang, 2009). Using the intensity of SO_2 emissions as an indicator of cleaner production, we found that the SO_2 intensity by foreign-owned firms before the policy was significantly lower than that of state-owned and privately owned firms (see appendix Figure A7). Therefore, we expect that the KCAPC policy will have a more substantial impact on domestic firms than on foreign-owned firms. The results in Table 8 indicate that the KCAPC policy only significantly negatively impacts labor in state-owned firms (4%) and privately owned domestic firms (3%) . As expected, both the state-owned firms and the private firms reduce SO_2 emissions, SO_2 intensity, and SO_2 generation after the policy while there is no significant effect on environmental performance for foreign firms mainly because the foreign firms on average had better environmental performance before the policy [25], which helps explain the heterogeneous labor effects by ownership. Thus, the manufacturing workers in domestic firms are more likely to lose their jobs under environmental regulation than those in foreign-owned firms.

E. City-level Effects

The potential limitation of using survey data at the firm level is that we can observe only the presence of existing firms (i.e., intensive margin) [26]. However, if the cost of strengthening environmental regulations is large enough that a firm cannot continue to make profits, then environmental regulation may also lead to the closure of industrial firms and restrictions on entry (see, e.g., List et al. (2003)), thereby reducing labor demand (i.e., extensive margin). Therefore, we collected further data at the city level to examine the pollution effects and employment effects. Specifically, we use total industrial SO_2 emissions and intensity at the city level as the measure of air pollution, total employment and total unemployment at the city level to measure labor effects, and the number of industrial firms and total industrial output value to examine the effects on

[25] Another possibility is that the local government treats foreign firms, privately-owned domestic firms, and state-owned firms differently but it is hard to measure the enforcement of the regulation based on the available information.

[26] Since both CIED and CESD are not census data, we cannot accurately identify firm entry and exit from the market simply based on the entry and exit from the sample.

city-level manufacturing production and firm entry/exit. The results shown in Table 9 indicate that the KCAPC policy had significant effects on industrial air pollution, employment, and unemployment but had no effect on industrial output value, which is consistent with our firm-level findings. The results on the number of industrial firms is positive and nonsignificant, implying that the KCAPC had little effect on firm entry and exit[27]. Therefore, the interpretation of KCAPC policy labor loss based on our baseline firm-level analyses is reasonable[28].

F. Effects of the WTO Accession

As discussed above, China joined the WTO in the same year as the policy implementation. After that, both tariff barriers and non-tariff barriers reduced, which led to the large increase in increasing rate of import and export after 2002. One may raise the concern that the trade liberalization to be the confounding factor. Particularly, if there is a significant difference in whether the cities in the treatment group and the control group are coastal, there will be an endogeneity issue [29].

Since all the special economic zones and coastal open cities [30] were selected as

[27]To ensure satisfaction with the strong identification hypothesis that the treatment group would have tracked the same trend as the control group in the absence of the KCAPC policy, we begin by checking on the identification assumption. Figure A8 presents coefficients and 95% confidence intervals on the KCAPC-year interactions from the regressions of Y on KCAPC-year interactions, city fixed effects, and province-year fixed effects from 1998 to 2007. The results are consistent with our firm-level findings.

[28]The policy might affect both entry and exit and lead to insignificant effect on total numbers. We further create a dummy variable for entry and exit for each firm and conduct the analysis at the firm level using CIED. As Figure VII shows, both firm entry and exit show insignificant differences between the two groups after the policy.

[29]There is a large literature uses the trade exposure between inland and coastal regions before and after trade accession (Goldberg and Pavcnik, 2005; Verhoogen, 2008; Topalova, 2010)

[30]Special economic zones in mainland China are granted more free market-oriented economic policies and flexible governmental measures by the government of China. In 1984, China opened 14 other coastal cities to overseas investment including Dalian, Qinhuangdao,

the first batch of cities in the KCAPC (see Figure 1) and our estimation focus only on the second batch of cities in the KCAPC, the high trade exposure cities are excluded from both the treatment and the control groups theoretically. However, given that the selection scheme of the second batch includes the economic development, and more developed area and less developed area may experienced different trend after the WTO accession, the WTO accession may still have different effects on our treatment and control groups. To separate the WTO confunder we further conduct two tests.

First, we estimate the impact on trade exposure using two indicators - foreign direct investment (FDI) and export at the firm level to see if there is a significant difference between the treatment and the control group after the WTO accession. As shown in Figures A10 and A11 and Table A2, we find no evidence that the treatment group and the control group show different trends in trade exposure after the WTO accession.

Second, we added FDI variables to the PSM model, so as to select a control group with similar foreign capital exposure. As shown in Figure A12, after matching, the difference in foreign direct investment between the two cities is significantly reduced. We then use the newly matched sample as a robustness check. After alleviating the potential differential trend in trade exposure caused by the WTO, our main results for both environmental performance and labor demand are still robust (see Table A3).

G. Robustness Checks

Test on water pollution. Apart from examining the impact of the air pollution control policy on the target air pollutant SO_2 emissions, we further

Tianjin, Yantai, Qingdao, Lianyungang, Nantong, Shanghai, Ningbo, Wenzhou, Fuzhou, Guangzhou, Zhanjiang, and Beihai.

conduct a falsification test by analyzing the impact of such regulations on COD emissions (one of the most important water pollutants). Firms use different abatement techniques to reduce COD and SO_2 emissions; as a result, changes in the air pollution control regulations should not impact COD discharge levels. The results in Table 10 and Figure A13 show that the estimates regarding KCAPC×Post are nonsignificant in all models, showing that the KCAPC policy does not affect COD discharges. Thus, these results offer some evidence that the decreases in SO_2 emissions are the result of the new KCAPC policy and not other confounding factors such as economic recession, which supports the effectiveness of our DID estimator[31].

Clean and dirty firms. To directly prove that the reduction in employment is due to pollution reduction and not other factors, we first divide firms in the treatment group into two groups, clean and dirty, based on the pollution generation intensity (mean value is used as the cutoff). Then, we interact the clean/dirty dummy with the KCAPC×Post. As the results show in Table 11, dirty firms reduced their pollution emissions (70%) and labor demand (6%) after the policy was enacted, and as we expected, the coefficients are larger than our baseline results while clean firms were less affected by the environmental regulation. These results indicate that firms with high pollution levels are more severely affected than enterprises with low pollution levels.

Alternative samples. To directly compare the effects on SO_2 emissions and labor demand, we use matched data in our baseline analyses. We now use unmatched data as a robustness check. As the result shows in Table A5, the coefficient of KCAPC×Post, our main variable of interest, is significantly negative. The point estimates suggest that SO_2 emissions, SO_2 intensity, and

[31]We also conduct a falsification test at the city level (see Table A4 in the online appendix). The results are consistent with our firm-level findings.

labor demand declined by approximately 24%, 28%, and 3%, which is consistent with our baseline matched data.

Results without PSM. One may raise the concern that the results are sensitive to the PSM method. We reproduce the main firm-level results without PSM. As the results in Figure A14 shows. the coefficients of $KCAPC \times$year interactions show a declining trend after 2001 for SO_2 emissions, SO_2 intensity, and labor demand, while there is an increase in labor productivity. These results are generally consistent with our main conclusion using PSM. However, since the difference between the two groups at the city level was significantly reduced after matching, we prefer to use the results of our previous PSM-DID model as our main strategy.

Contemporaneous policies. Finally, there may be issues with the potential confounding effects of other environmental regulations from the same time period, the two most significant of which being the TCZ Policy and the FYP. To rule out the effects of TZC, we use the city's TCZ status as a covariate in our primary PSM approach. After matching, the distribution of TCZ cities is balanced between the treatment and control groups (see Figure 2). The 62 control cities contain 50 TCZ cities, while the 62 treatment cities contain 51 TCZ cities. Moreover, we conduct an additional analysis excluding all non-TCZ cities from our sample. In other words, the effects of KACPC policy inside the TCZ cities are compared. As illustrated in Figure A15 and Table A6, the results are robust when non-TCZ cities are excluded. For the Five-Year-Plan (FYP), the targets were primarily established at the provincial level, with only five cities having explicit reduction goals. Hence, our results controlling for province by year fixed effects can rule out the effects of FYP to a large extent. In addition, because the FYP went into effect in 2006, we restrict our sample to 1998 to 2005 as a robustness check. Table A7 demonstrates that the results hold.

VII. Conclusions

Manufacturing is a pillar sector in China, especially after joining the WTO, and one crucial reason is that labor costs and environmental regulation stringency in developing countries are lower than in developed countries, which creates competitive advantages in the global market. Therefore, the development of labor-intensive industries in developing countries plays a significant role in economic growth. In this paper, we find that the nationwide air pollution control policy, the KCAPC policy, significantly reduced labor demand by 3%. Most importantly, we found that low-skilled employees and workers in domestic firms are more affected by environmental regulation in China. Given that low-skilled workers have difficulties finding other jobs, the unemployment of this group of people may result in substantial social costs (e.g., job searching, training, social subsidy, and social relief). However, we certainly cannot assume that environmental regulation can only bring costs. These policies will lead to substantial improvements in environmental quality, and thus reduce related diseases and mortality, which in turn will bring social benefits.

The combined results of pollution emissions and employment suggest that a 1% reduction in SO_2 emissions will lead to a 0.13% decrease in labor demand. During China's 13th FYP (2016-2020), the central government set a target to reduce SO_2 emissions by approximately15%. According to our results, the reduction in SO_2 emissions during this period will reduce labor demand in polluting manufacturing firms by approximately 1.4% every year more than in 2015. Considering 2015 to be the baseline, approximately 7 hundred thousand manufacturing employees per year will lose their jobs due to air pollution control during China's 13th FYP, leading to a 0.38% increase in the unemployment rate compared to 2015's 4.05%.

However, we should interpret these results cautiously. First, it is possible for resources to shift from a regulated region (or industry) to an unregulated region (or industry), which sets an upper bound the use of DID estimations on the employment effect of our study as well as other existing studies using a similar approach (see, e.g., Greenstone (2002); Gray et al. (2014); Liu, Shadbegian and Zhang (2017)) (i.e., spillover effect). The extreme case is that the estimated regulation effects entirely reflect a relocation of manufacturing activity from key cities to nonkey cities, which means that the estimation of the employment effect is "double counting". However, according to Walker (2013), job transitions mostly occur from the regulated industries to unregulated industries within the same labor market rather than across labor markets. Additionally, we found that the total industrial output and number of firms did not change significantly, which dispels the possibility of movement. Thus, our use of other labor markets as the control group is an effective way to alleviate the spillover effect. Moreover, the KCAPC number has been increasing over the years: in China's 12th FYP, the number of cities comprising the KCAPC further expanded from 113 to 333; thus, firms may know it is unlikely for the control group to remain untreated in the future. Additionally, most polluting industries have substantially "sunk" costs that restrict relocation (Greenstone, 2002). Finally, although the workers could have found jobs from other sectors or regions, there are economic costs associated with this movement (Walker, 2013), especially in the cases where unskilled workers bear the costs.

Moreover, the recent literature showed that the reduction in pollution may have positive effects on labor supply (see, e.g., Hanna and Oliva (2015)), making our estimation an underestimated value. First, we alleviated the impact from the supply side by adding city-level characteristics (average wage and total industrial output) as control variables in some of our specifications. Our results are robust to the inclusion of supply-side controls. Second, highly skilled labor with high wages are often more likely to be able to transfer. However, our results showed that highly skilled workers were not significantly affected by environmental policy, which is consistent with the fact that the willingness of Chinese people to pay for clean air was low during that period.

China is in the midst of solving its overcapacity and air pollution problems through a series of supply-side reforms, such as closing certain steel companies, which may have a substantial impact on unemployment. Recently, China's 13th FYP (2016-2020) further promoted several ambitious targets, including both total amount control targets (e.g., a 15% reduction in SO_2 emissions and a 15% reduction in NOx emissions) and air quality improvement goals (e.g., the proportion of days with good air quality above 80% and an 18% reduction in PM2.5 concentrations). To fulfill the goal of making our skies blue again, China's government is expected to implement more stringent environmental regulation in the near future. As China continues to strengthen its environmental regulations, the potential negative effects on employment, especially on low-skilled, inexpensive, and female labor, should also be carefully considered when analyzing the economic impact of environmental regulations and when planning for sustainable economic growth. Based on our research, we suggest policymakers consider both benefits and costs under different environmental objectives when designing emission reduction targets. In addition, policymakers can also develop supporting policies to reduce the adverse effects on vulnerable firms and workers. Specifically, although the workers could have found jobs in other sectors or regions, there are economic costs associated with this movement, especially in cases where unskilled workers are more affected. Supporting policies such as reemployment training and financial support are needed. Most recently, Chinese governments have released several policies and government notices to deal with this problem. For example, starting in 2017, Chinese governments have placed the resettlement of the laid-off workers as a key task and made government funds available for rewards and subsidies in this regard.

In recent years, other developing countries in Southeast Asia and South Asia, such as India, Pakistan, Bangladesh, Thailand, and Vietnam, have faced similar situations as those faced by China. With China's labor costs increasing, the general trend is the shift in the manufacturing industries to these regions. Thus, understanding the types of firms and workers that bear more burden in terms of environmental protection and how to help these workers and firms survive in the tide of environmental protection is crucial to the future development of these low-income countries. Finally, we show some evidence that unskilled workers are more affected using the average wage levels at the firm level as a proxy but the ideal proxy for workforce skill is education level. We suggest that more heterogeneous labor effects should be explored in the near future. To identify the types of workers that may be more vulnerable to environmental regulation, it is particularly important to analyze the effects of pollution control on the demand for different types of workers.

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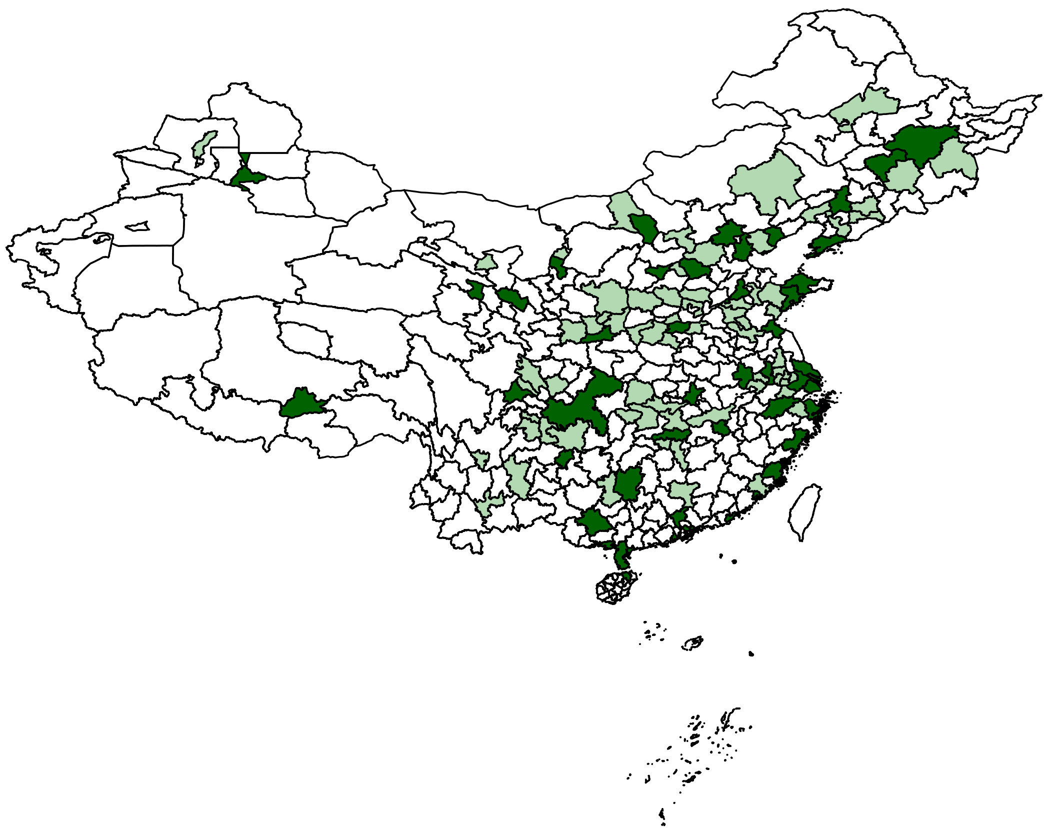

FIGURE 1. THE DISTRIBUTION OF CITIES IN KCAPC

Notes: The first batch of cities (marked in dark green) and second batch of cities (marked in green) are 47 prefecture-level cities designated KCAPC in 1998 and 66 cities designated KCAPC in 2001.

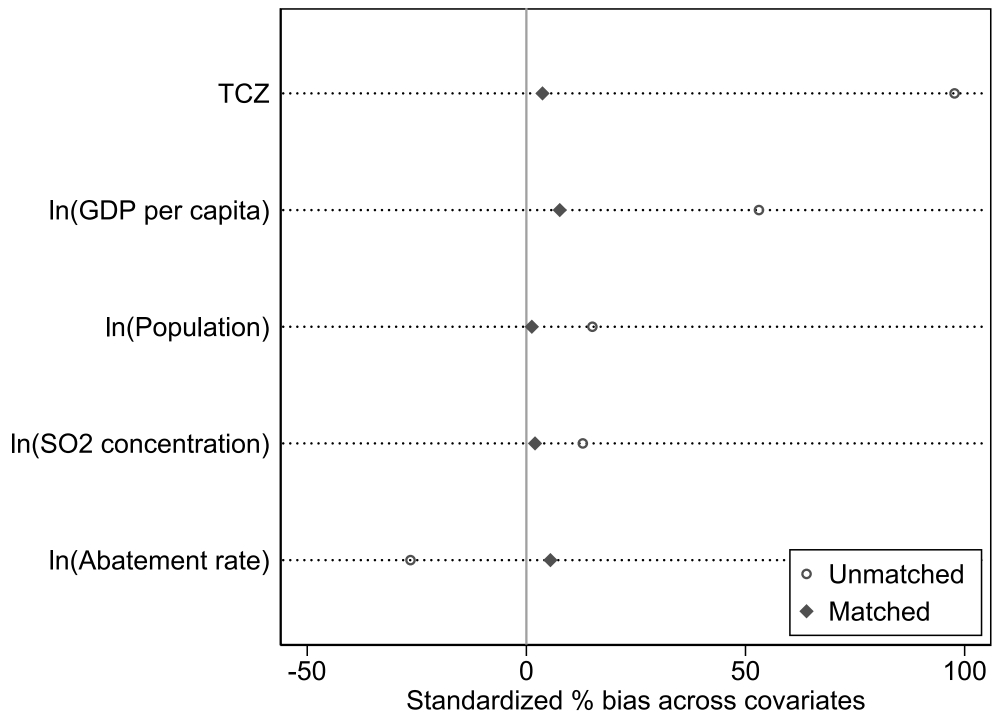

FIGURE 2. CITY CHARACTERISTICS BIAS BEFORE AND AFTER MATCHING

Notes: City characteristics bias between the second batch of cities and untreated cities before and after matching.

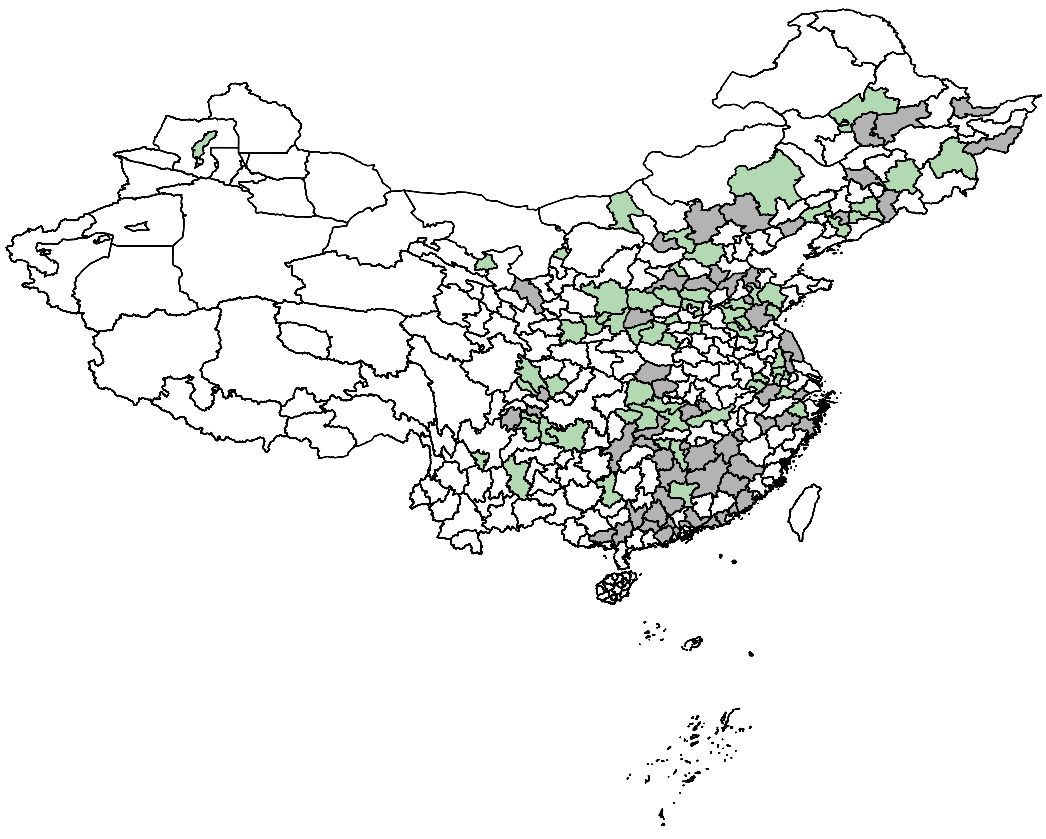

Figure 3. The distributions of treatment and matched control groups

Notes: 62 treatment cities (marked in green) and 62 control cities (marked in gray) are selected by PSM and used in our DID analysis.

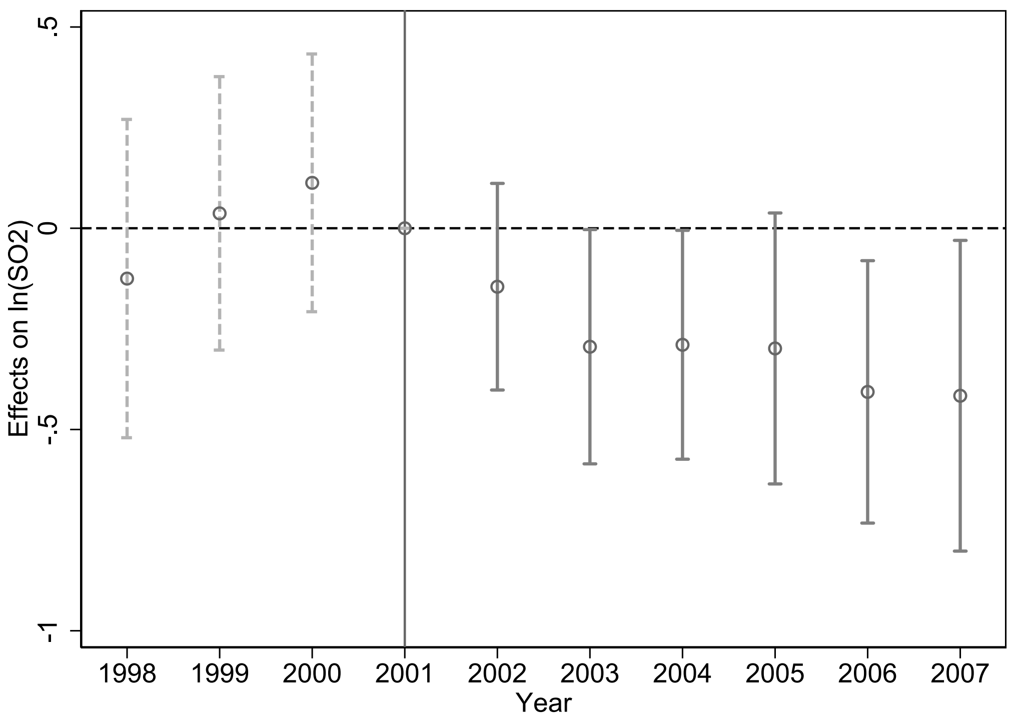

Figure 4. Treatment-year interaction coefficients for firm-level SO_2 emissions

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of ln(SO_2) on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-year level.

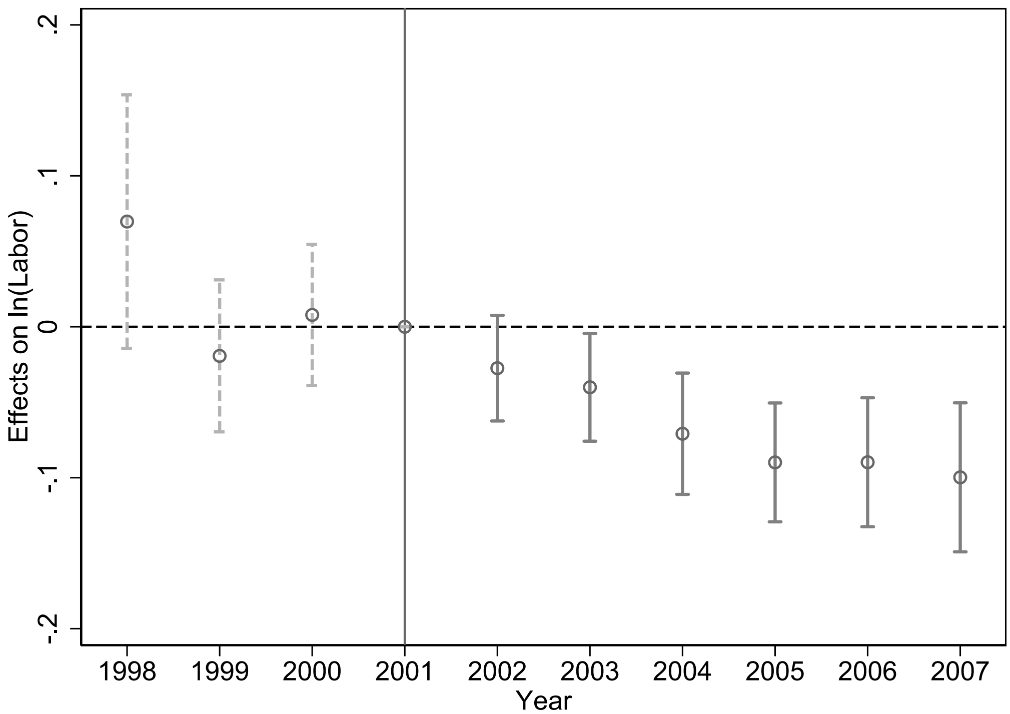

Figure 5. Treatment-year interaction coefficients for firm-level labor demand

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of ln(Labor) on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-year level.

Table 1—Summary statistics

Variable	Mean	Std.Dev	Obs	Data Source
SO_2 emission (kilograms)	156493.0	1501570.0	97,106	CESD
COD emission (kilograms)	86696.3	629864.7	97,106	
SO_2 generation (kilograms)	329047.3	6810347.0	97,106	
Number of facilities (unit)	2.8	9.6	97,106	
Labor (persons)	586.8	2219.0	97,106	CIED
Output (thousand CNY)	149609.8	795672.5	97,106	
Wage (thousand CNY)	12.3	241.1	97,106	
Total employment (ten thousand persons)	29.7	13.7	1,220	CCSY
Total unemployment (persons)	18584.8	12642.8	1,217	
Total SO_2 emission (tons)	59633.4	48588.4	1,240	CESD (city level)
Total COD emission (tons)	17194.4	16812.5	1,240	
Industrial output (ten thousand CNY)	2422448 .0	2749761.0	1,240	
Number of firms (unit)	240.9	186.1	1,240	
Unemployment dummy (%)	0.07	0.26	164,881	UHS
Educational level (category)	3.0	1.5	164,881	

Notes: Educational level 3 refers to high school. For 1998 and 1999, some variables have missing values in CCSY and CESD (city level) due to the incomplete statistical range of earlier years.

Table 2—Main results on air pollution and employment at the firm level

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(SO_2) FE	ln(SO_2) FE	ln(SO_2 intensity) FE	ln(SO_2 intensity) FE	ln(Labor) FE	ln(Labor) FE
KCAPC×Post	-0.304***	-0.296***	-0.299***	-0.292***	-0.067***	-0.035***
	(0.097)	(0.112)	(0.099)	(0.111)	(0.015)	(0.013)
ln(Average wage)		-0.545		-0.569		0.002
		(0.440)		(0.436)		(0.052)
ln(Industrial output)		0.191**		0.158*		0.022**
		(0.090)		(0.089)		(0.010)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions		YES		YES		YES
N	97106	97106	97106	97106	97106	97106
R^2	0.562	0.567	0.578	0.583	0.938	0.940

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

Table 3—Checks on the mechanisms

	(1) ln(Output) FE	(2) ln(Output) FE	(3) ln(SO_2 generation) FE	(4) ln(SO_2 generation) FE	(5) ln(Facility) FE	(6) ln(Facility) FE
KCAPC×Post	-0.006	-0.004	-0.296***	-0.304***	-0.024	-0.008
	(0.020)	(0.017)	(0.099)	(0.111)	(0.017)	(0.020)
ln(Average wage)		0.024		-0.452		0.086
		(0.071)		(0.434)		(0.091)
ln(Industrial output)		0.033**		0.163*		0.025
		(0.014)		(0.088)		(0.020)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions		YES		YES		YES
N	97106	97106	97106	97106	97106	97106
R^2	0.929	0.931	0.578	0.582	0.760	0.762

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Dependent variables in columns (1) and (2) are log real output values calculated using province-specific PPIs, considering 1998 to be the base year. Dependent variables in columns (3) and (4) are log SO_2 generated per unit of real output. Dependent variables in columns (5) and (6) are log number of abatement facilities. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

Table 4—Heterogeneous employment effects by pollution control strategies

	(1) ln(Labor) FE	(2) ln(Labor) FE
High processing control×KCAPC×Post	-0.094***	-0.060***
	(0.017)	(0.015)
Low processing control×KCAPC×Post	-0.043***	-0.013
	(0.016)	(0.014)
ln(Average wage)		0.002
		(0.052)
ln(Industrial output)		0.022**
		(0.010)
Year fixed effects	YES	YES
Firm fixed effects	YES	YES
Industry-year interactions	YES	YES
Province-year interactions		YES
N	97106	97106
R^2	0.938	0.940

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Firms in the treatment group are classified into two groups, high processing control and low processing control , according to the main pollution control strategies used after the policy is enacted. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

Table 5—Heterogeneous employment effects by workforce skills

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(SO2) FE	ln(SO2 intensity) FE	ln(Output) FE	ln(SO2 generation) FE	ln(Facility) FE	ln(Labor) FE
High-skilled×KCAPC×Post	-0.299**	-0.279**	-0.019	-0.303**	-0.004	-0.046**
	(0.128)	(0.127)	(0.023)	(0.127)	(0.023)	(0.020)
Low-skilled×KCAPC×Post	-0.436***	-0.418***	-0.019	-0.437***	-0.026	-0.057***
	(0.126)	(0.125)	(0.020)	(0.125)	(0.022)	(0.018)
High-skilled×Post	0.873	0.767	0.106	0.809	-0.365*	-0.258**
	(1.065)	(1.075)	(0.174)	(1.071)	(0.194)	(0.124)
Low-skilled×Post	1.040	0.800	0.240	0.844	-0.329*	-0.003
	(1.066)	(1.076)	(0.173)	(1.071)	(0.194)	(0.124)
ln(Average wage)	-0.009	-0.081	0.072	-0.022	0.221**	0.055
	(0.487)	(0.484)	(0.087)	(0.487)	(0.102)	(0.064)
ln(Industrial output)	0.219*	0.173	0.046**	0.182*	0.030	0.030**
	(0.112)	(0.109)	(0.018)	(0.108)	(0.025)	(0.013)
[1em] Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions	YES	YES	YES	YES	YES	YES
N	39372	39372	39372	39372	39372	39372
R^2	0.545	0.562	0.909	0.561	0.727	0.922

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Firms in the treatment group are classified into two groups, high-skill or low-skill, according to the ratio of high school or above workers for year 2004 (a census year). Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

Table 6—Effects on unemployment by workforce skills using individual-level data

	(1) Unemployment Probit	(2) Unemployment Probit	(3) Unemployment Probit	(4) Unemployment Probit	(5) Unemployment Probit	(6) Unemployment Probit
KCAPC×Post	0.0166*	0.0132*				
	(0.00977)	(0.00682)				
High-skilled×KCAPC×Post			0.0113	0.0105	0.0117	0.0108
			(0.0123)	(0.00804)	(0.0113)	(0.00719)
Low-skilled×KCAPC×Post			0.0181*	0.0142**	0.0187**	0.0144**
			(0.00932)	(0.00695)	(0.00914)	(0.00709)
Year fixed effects	YES	YES	YES	YES	YES	YES
Province-year interactions		YES		YES		YES
N	164881	164881	164881	164881	164881	164881

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Unemployment equals 1 if the job status is unemployed; otherwise, Unemployment equals 0. KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. In columns (3) and (4), we define workers who have an educational degree above high school as highly skilled workers and the others are considered low-skilled workers. In columns (5) and (6), we raise the cutoff to be a bachelor's degree. Standard errors in parentheses are clustered at the city level.

TABLE 7—EFFECTS ON UNEMPLOYMENT BY WORKFORCE GENDERS USING INDIVIDUAL-LEVEL DATA

	(1) Unemployment Probit	(2) Unemployment Probit
Male×KCAPC×Post	0.00995	0.00671
	(0.00930)	(0.00644)
Female×KCAPC×Post	0.0218**	0.0182**
	(0.0109)	(0.00806)
Year fixed effects	YES	YES
Province-year interactions		YES
N	164881	164881

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Unemployment equals 1 if the job status is unemployed; otherwise, Unemployment equals 0. KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Standard errors in parentheses are clustered at the city level.

Table 8—Heterogeneous employment effects by ownership

	(1) ln(SO2) FE	(2) ln(SO2 intensity) FE	(3) ln(Output) FE	(4) ln(SO2 generation) FE	(5) ln(Facility) FE	(6) ln(Labor) FE
State×KCAPC×Post	-0.304*	-0.304*	-0.001	-0.332**	-0.076***	-0.046**
	(0.155)	(0.155)	(0.028)	(0.156)	(0.029)	(0.020)
Private×KCAPC×Post	-0.350***	-0.346***	-0.004	-0.355***	0.008	-0.031**
	(0.129)	(0.128)	(0.020)	(0.127)	(0.022)	(0.015)
Foreign×KCAPC×Post	0.131	0.100	0.031	0.107	0.062	0.005
	(0.246)	(0.243)	(0.041)	(0.242)	(0.038)	(0.032)
State×Post	1.191	1.162	0.029	1.085	-0.134	-0.166*
	(0.745)	(0.758)	(0.134)	(0.764)	(0.149)	(0.095)
Private×Post	1.302*	1.107	0.196	1.031	-0.144	-0.066
	(0.745)	(0.756)	(0.134)	(0.764)	(0.150)	(0.095)
Foreign×Post	1.298*	1.058	0.240*	0.979	-0.127	0.073
	(0.752)	(0.766)	(0.133)	(0.775)	(0.150)	(0.094)
ln(Average wage)	-0.533	-0.566	0.033	-0.448	0.086	0.008
	(0.440)	(0.436)	(0.071)	(0.434)	(0.091)	(0.052)
ln(Industrial output)	0.190**	0.159*	0.031**	0.164*	0.024	0.020**
	(0.091)	(0.089)	(0.014)	(0.088)	(0.020)	(0.010)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions	YES	YES	YES	YES	YES	YES
N	97106	97106	97106	97106	97106	97106
R^2	0.567	0.583	0.931	0.583	0.762	0.940

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Firms are classified into three groups according to ownership. State equals 1 if a firm is state-owned; otherwise, State equals 0. Private equals 1 if a firm is private-owned; otherwise, Private equals 0. Foreign equals 1 if a firm is foreign-owned; otherwise, Foreign equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

Table 9—Effects on city-level outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(SO_2)$ FE	$\ln(SO_2$ intensity) FE	ln(Total Employment) FE	ln(Unemployment) FE	ln(Firm Number) FE	ln(Industrial Output) FE
KCAPC×Post	-0.259***	-0.296***	-0.046***	0.165***	-0.024	0.037
	(0.041)	(0.055)	(0.054)	(0.055)	(0.026)	(0.048)
Year fixed effects	YES	YES	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES	YES	YES
Province-year interactions	YES	YES	YES	YES	YES	YES
N	1240	1240	1220	1212	1240	1240
R^2	0.949	0.893	0.981	0.821	0.950	0.940

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a city is in the treatment group; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. For 1998 and 1999, some variables have missing values due to the incomplete statistical range of earlier years. Standard errors in parentheses are clustered at the city-year level.

Table 10—Falsification test on water pollution

	(1) ln(COD) FE	(2) ln(COD) FE	(3) ln(COD intensity) FE	(4) ln(COD intensity) FE
KCAPC×Post	-0.186	-0.034	-0.180	-0.030
	(0.128)	(0.131)	(0.131)	(0.131)
ln(Average wage)		0.072		0.048
		(0.493)		(0.490)
ln(Industrial output)		0.219**		0.186*
		(0.103)		(0.106)
Year fixed effects	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES
Province-year interactions		YES		YES
N	97106	97106	97106	97106
R^2	0.758	0.763	0.737	0.743

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

TABLE 11—HETEROGENEOUS AIR POLLUTION AND EMPLOYMENT EFFECTS BY PRE-PERIOD ENVIRONMENTAL PERFORMANCE

	(1)	(2)	(3)	(4)
	ln(SO_2)	ln(SO_2)	ln(Labor)	ln(Labor)
	FE	FE	FE	FE
Dirty×KCAPC×Post	-1.219***	-1.351***	-0.097***	-0.063***
	(0.138)	(0.147)	(0.018)	(0.017)
Clean×KCAPC×Post	-0.062	-0.056	-0.059***	-0.028**
	(0.104)	(0.118)	(0.016)	(0.014)
ln(Average wage)		-0.562		0.001
		(0.441)		(0.053)
ln(Industrial output)		0.193**		0.022**
		(0.090)		(0.010)
Year fixed effects	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES
Province-year interactions		YES		YES
N	97106	97106	97106	97106
R^2	0.563	0.568	0.938	0.940

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Firms in the treatment group are classified into two groups, dirty and clean, according to the level of pollution generated during the production process prior to the policy. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

TABLE 12—ROBUSTNESS CHECK ON WTO EFFECTS

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(SO_2) FE	ln(SO_2) FE	ln(SO_2 intensity) FE	ln(SO_2 intensity) FE	ln(Labor) FE	ln(Labor) FE
KCAPC×Post	-0.394***	-0.484***	-0.375***	-0.483***	-0.077***	-0.036***
	(0.098)	(0.115)	(0.101)	(0.115)	(0.015)	(0.014)
ln(Average wage)		0.212***		0.222***		-0.004
		(0.065)		(0.070)		(0.006)
ln(Industrial output)		0.305***		0.288***		0.018
		(0.094)		(0.093)		(0.012)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions		YES		YES		YES
N	91208	91208	91208	91208	91208	91208
R^2	0.566	0.571	0.581	0.586	0.939	0.941

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

Online Appendix

Supplementary material including figures and tables are presented in the following appendix.

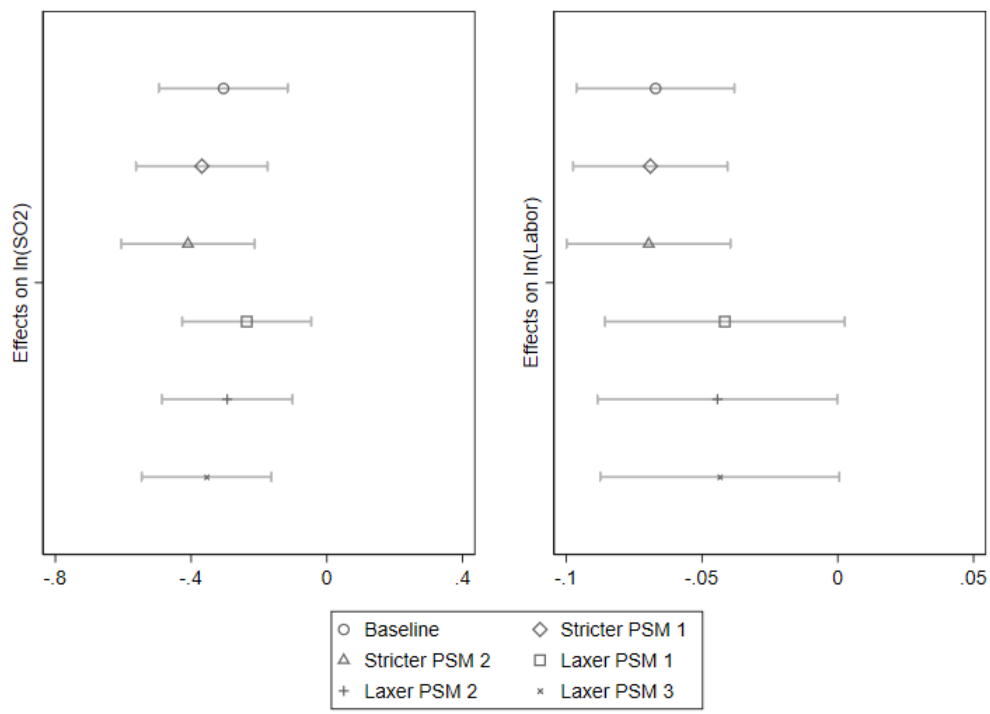

Figure A1. Robustness checks using alternative PSM strategies

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×Post interactions from the regression of Y on KCAPC×Post interactions, firm fixed effects, and industry -year interactions. All sample includes all the untreated cities in the control group. Baseline refers to the baseline PSM strategy. Stricter PSM 1 and 2 refer to models with more city characteristics. Laxer PSM 1,2, and 3 refer to stratgies that do not apply the common support restriction. Standard errors are clustered at the city-year level.

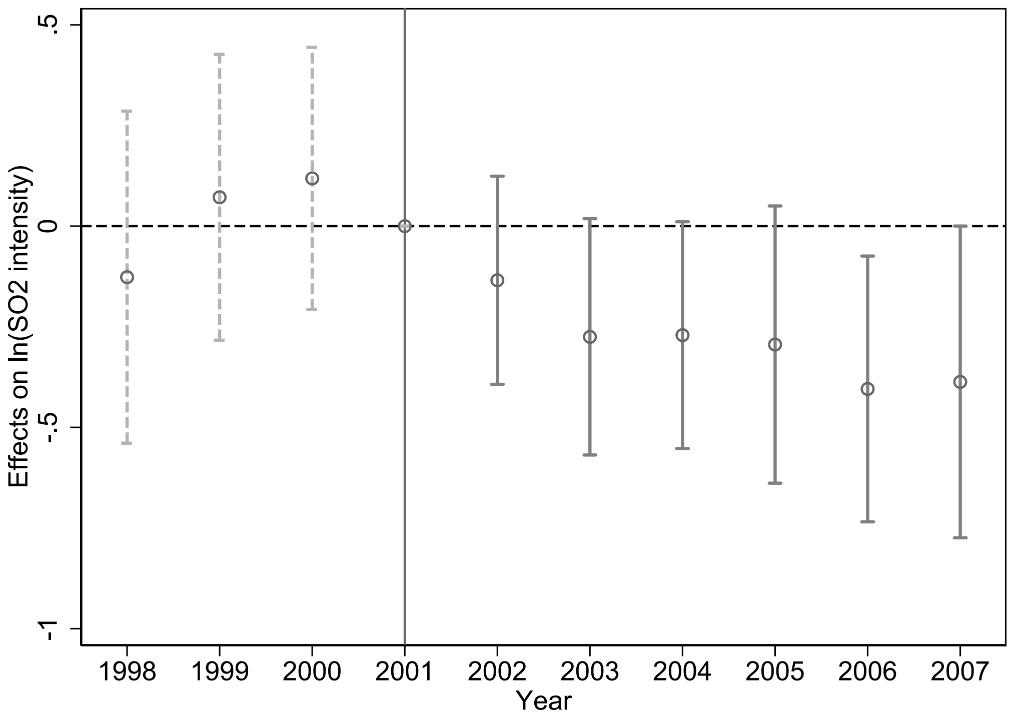

Figure A2. Treatment-year interaction coefficients for SO2 intensity

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of ln(SO2 intensity) on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-by-year level.

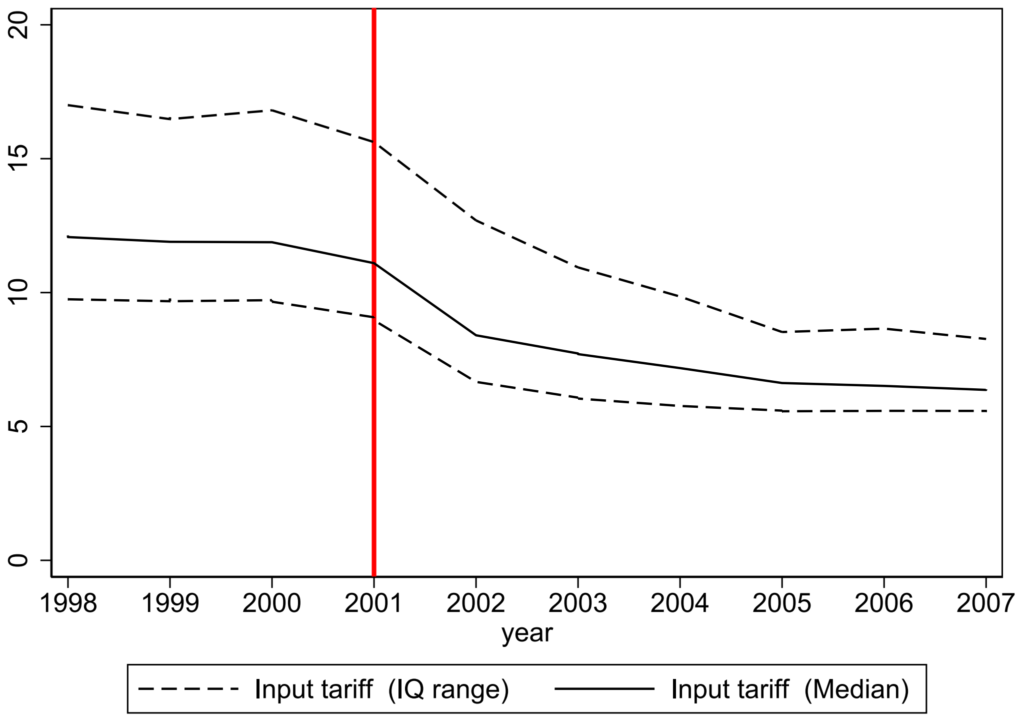

Figure A3. Evolution of Import Tariffs on Each Industry's Inputs

Notes: The solid lines show the median tariffs across industries, and dashed lines show the interquartile range.

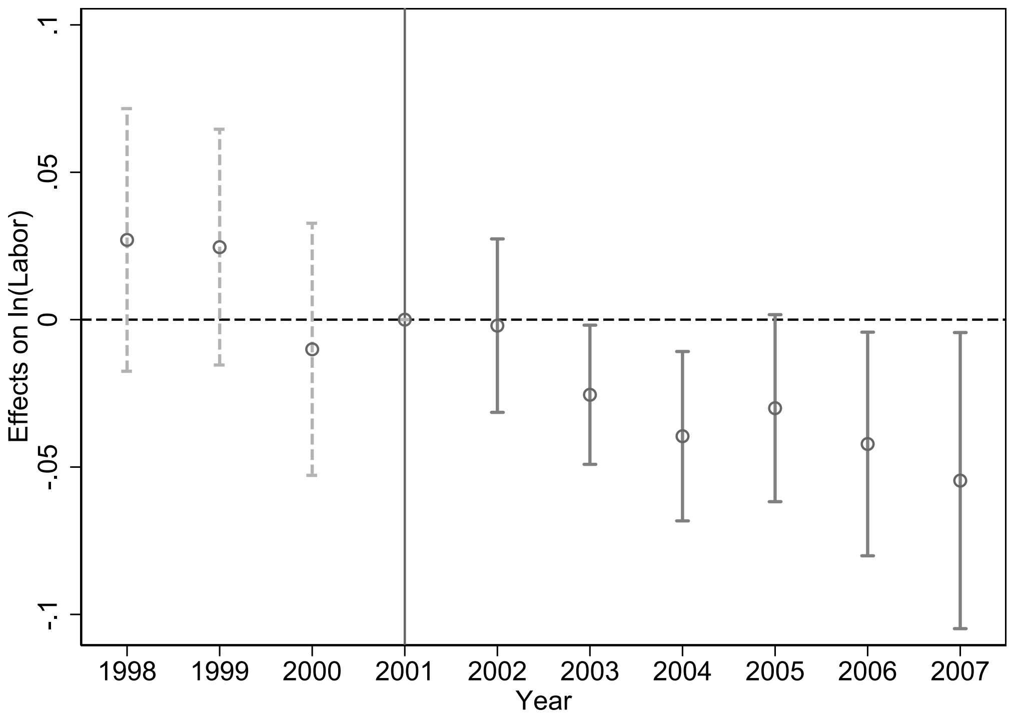

Figure A4. WTO-year interaction coefficients for labor demand

Notes: Figure presents coefficients and 95% confidence intervals on WTO×year interactions from the regression of ln(Labor) on WTO×year interactions, ln(Output), firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded WTO×year coefficient represents 2001. Standard errors are clustered at the industry-by-year level.

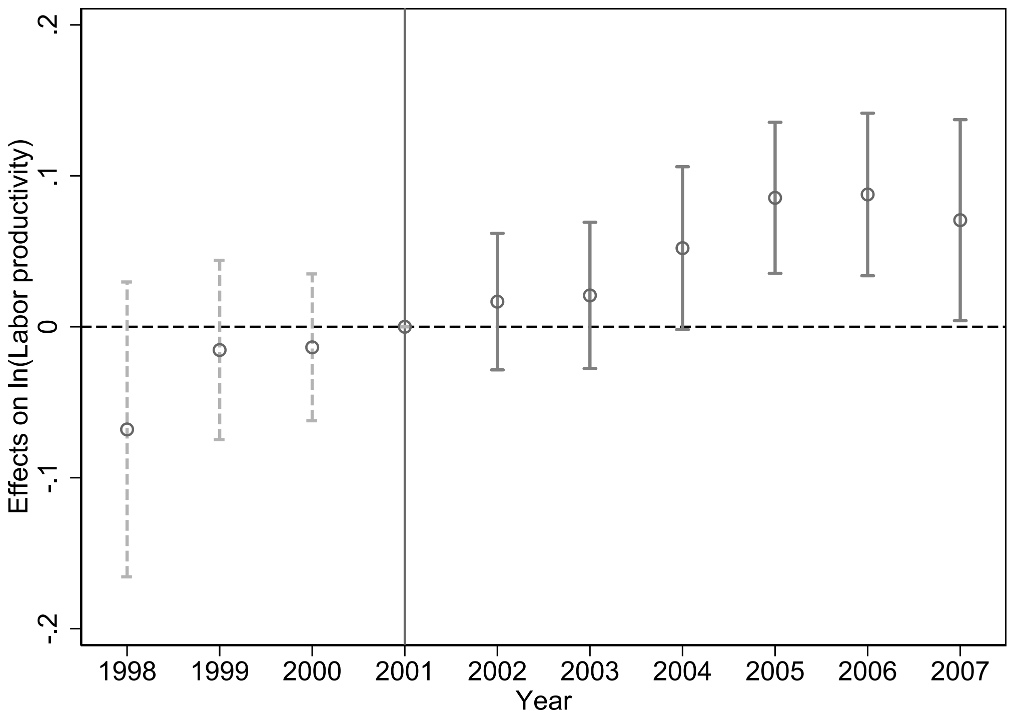

Figure A5. Treatment-year interaction coefficients for labor productivity

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of ln(Labor productivity) on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-by-year level.

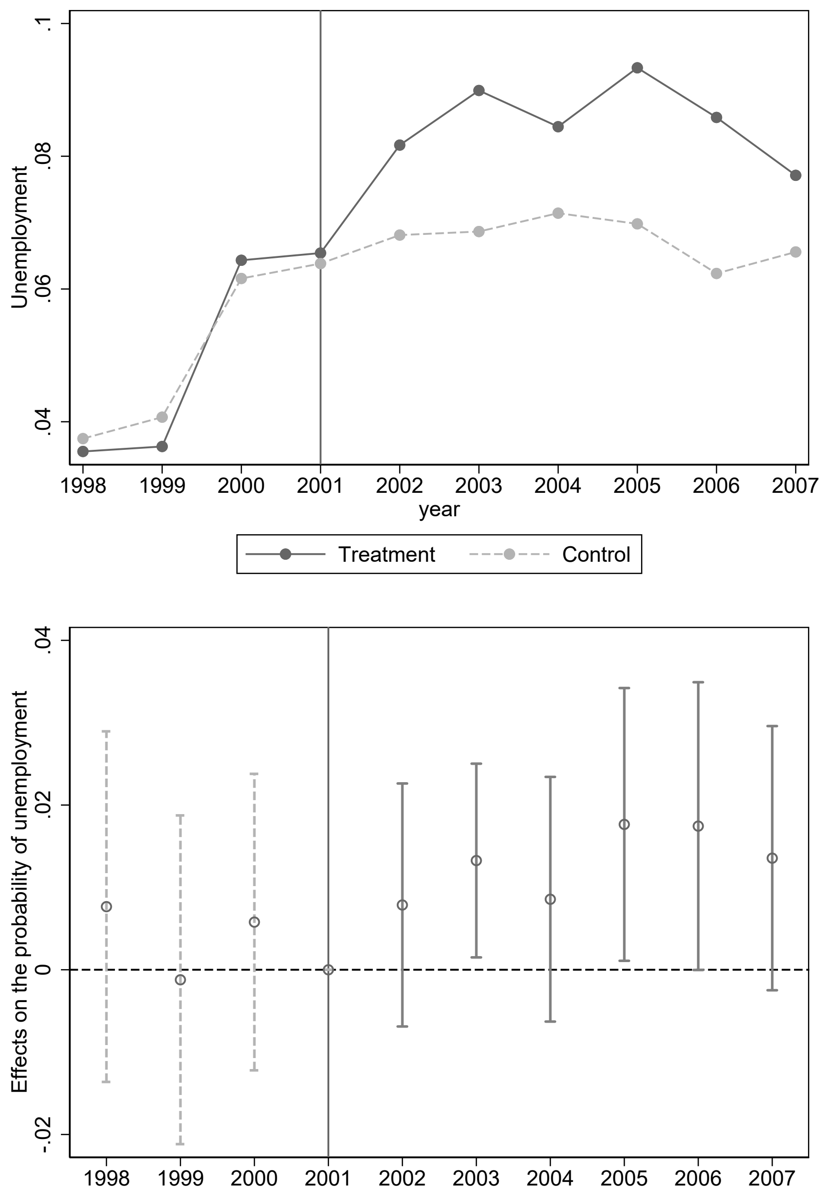

Figure A6. Individual-level results

Notes: Figure on the top shows the avearge value of the probability of unemployment in the two groups; Figure on the bottom shows coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of unemployment on KCAPC×year interactions and province-year fixed effects. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city level.

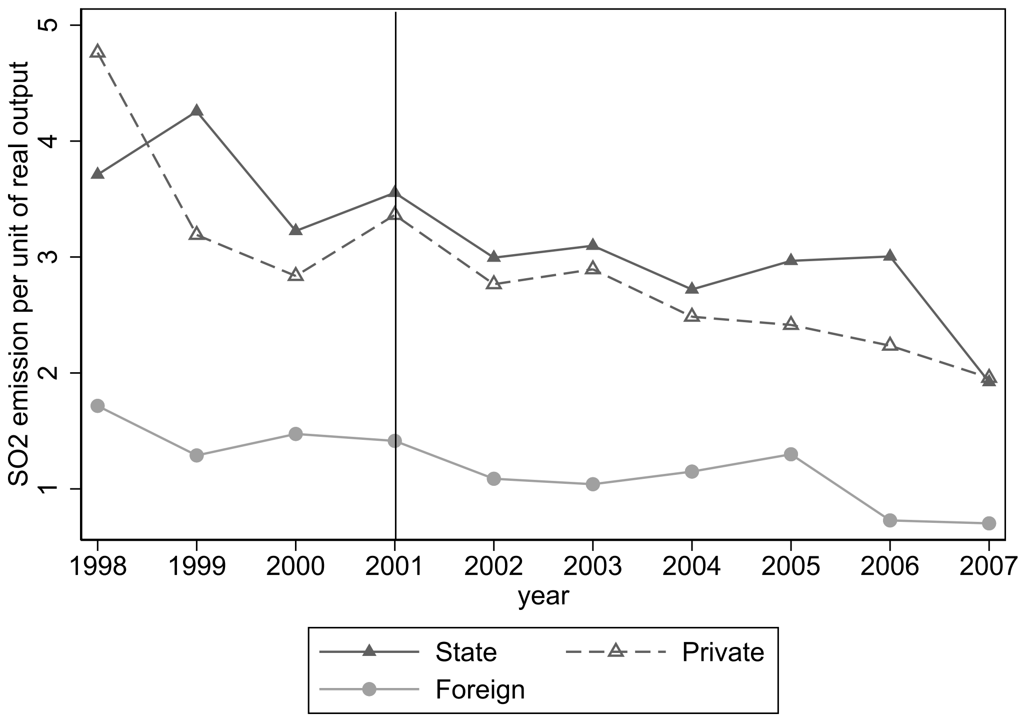

Figure A7. SO2 generation intensity by ownership

Notes: Figure represents environmental performance by ownership over year..

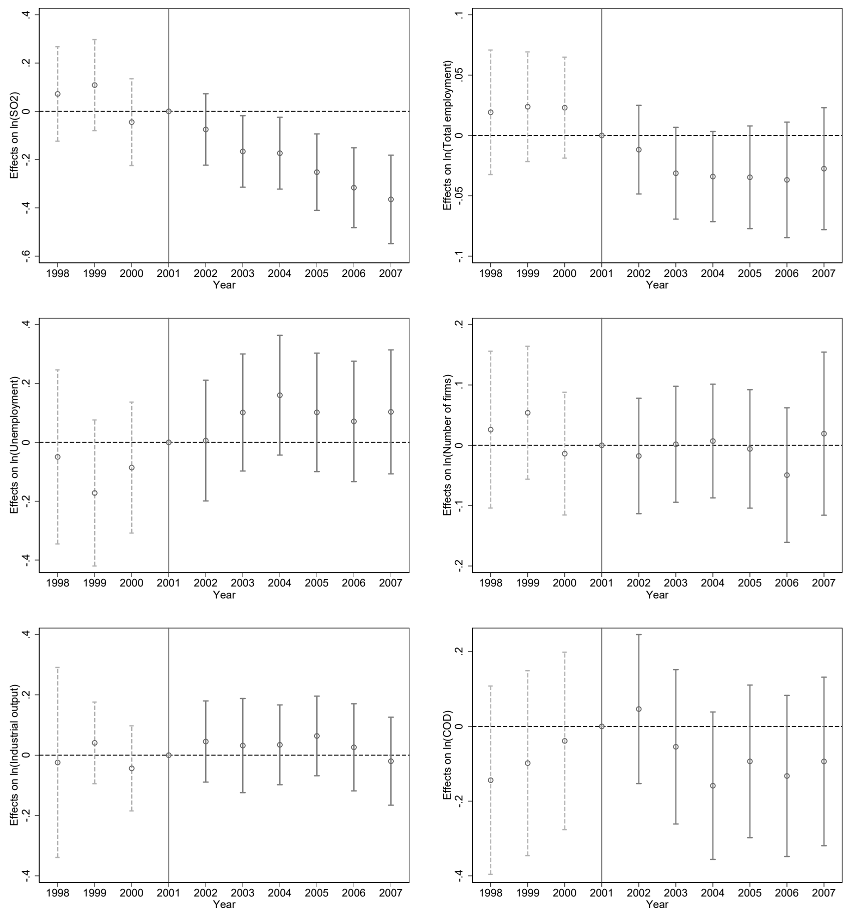

Figure A8. Treatment-year interaction coefficients for city-level outcomes

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of Y on KCAPC×year interactions, city fixed effects, and province-year interactions. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-year level.

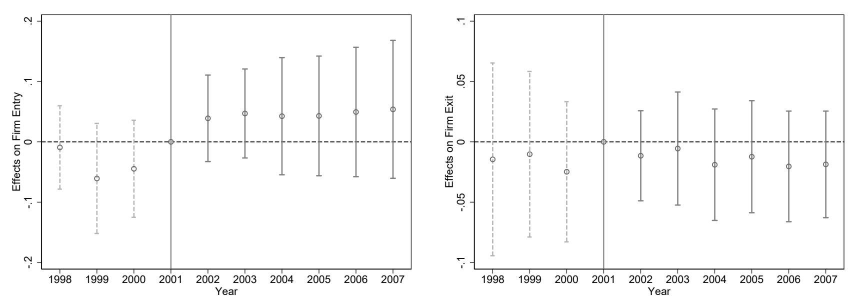

FIGURE A9. TREATMENT-YEAR INTERACTION COEFFICIENTS FOR FIRM ENTRY AND EXIT

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of Y on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-year level.

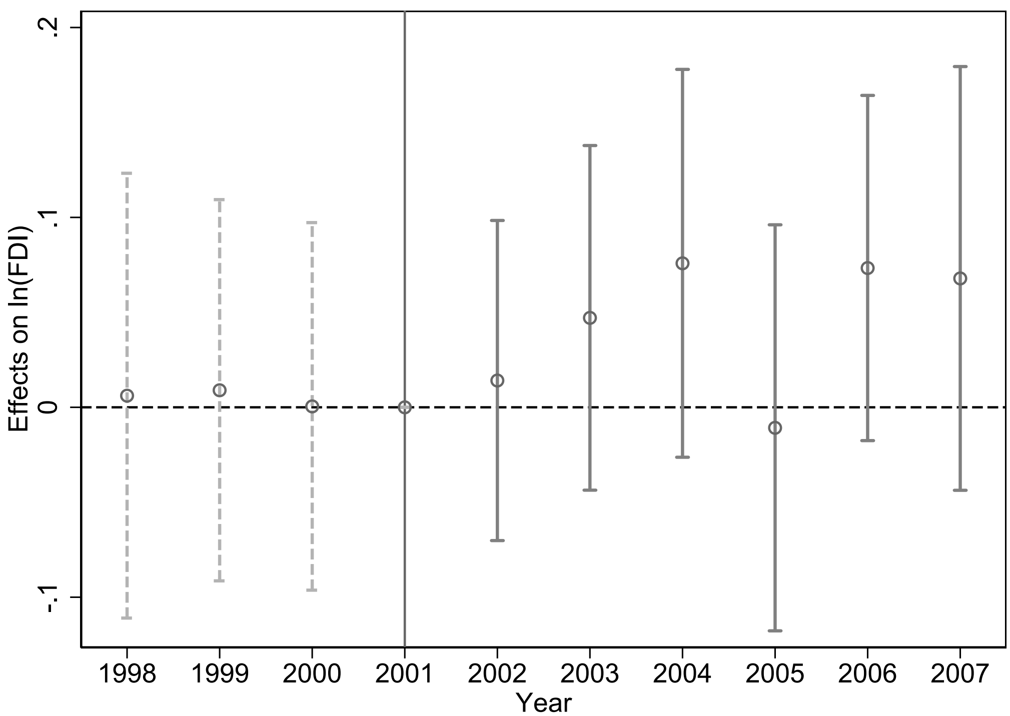

Figure A10. Treatment-year interaction coefficients for FDI

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of ln(FDI) on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-by-year level.

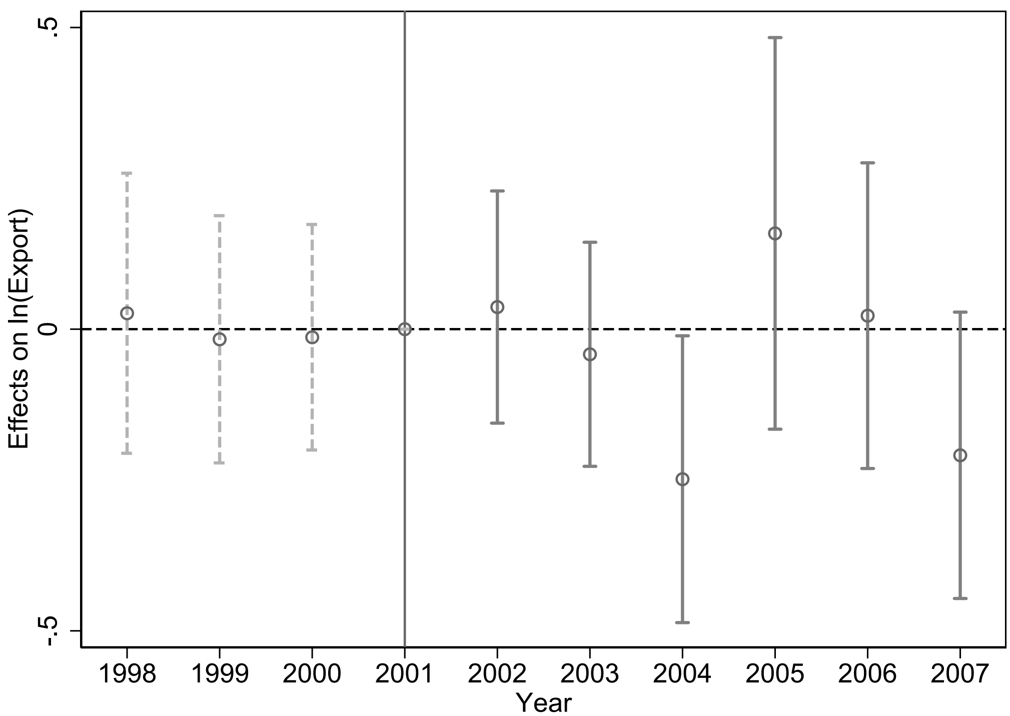

Figure A11. Treatment-year interaction coefficients for export

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of ln(Export) on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-by-year level.

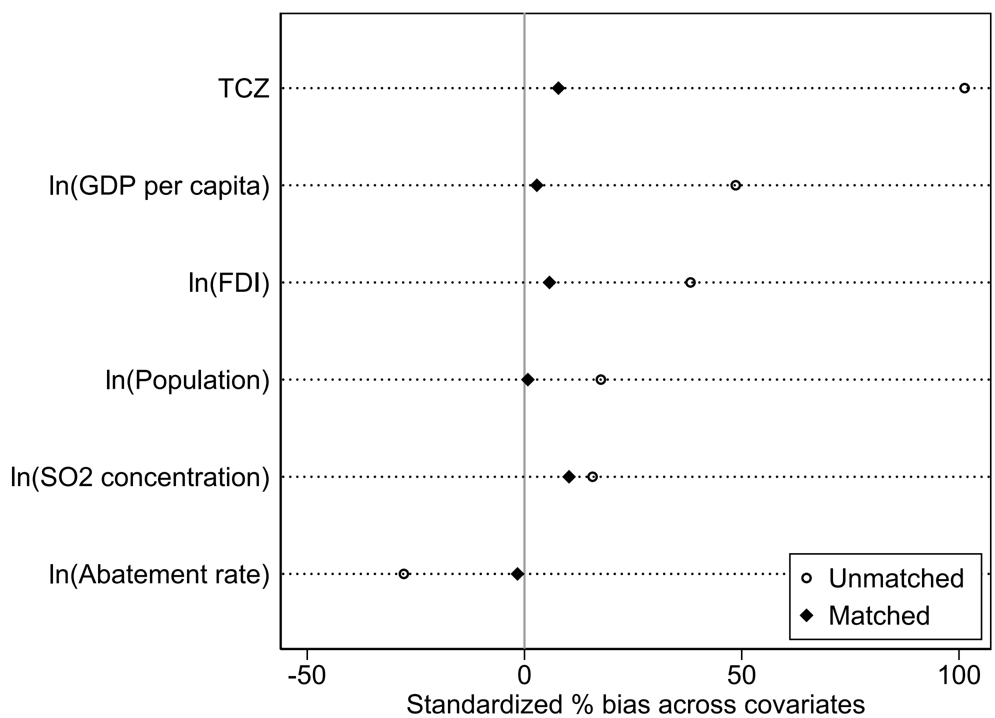

Figure A12. City characteristics bias before and after matching

Notes: City characteristics bias between the second batch of cities and untreated cities before and after matching.

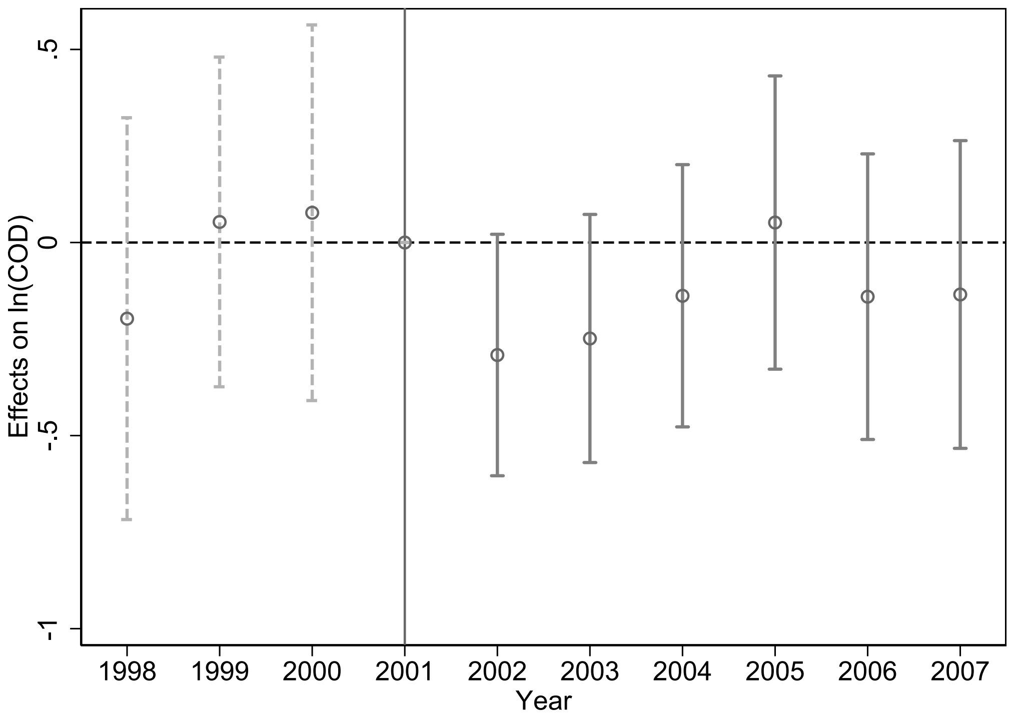

Figure A13. Treatment-year interaction coefficients for COD discharges

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of ln(COD) on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-year level.

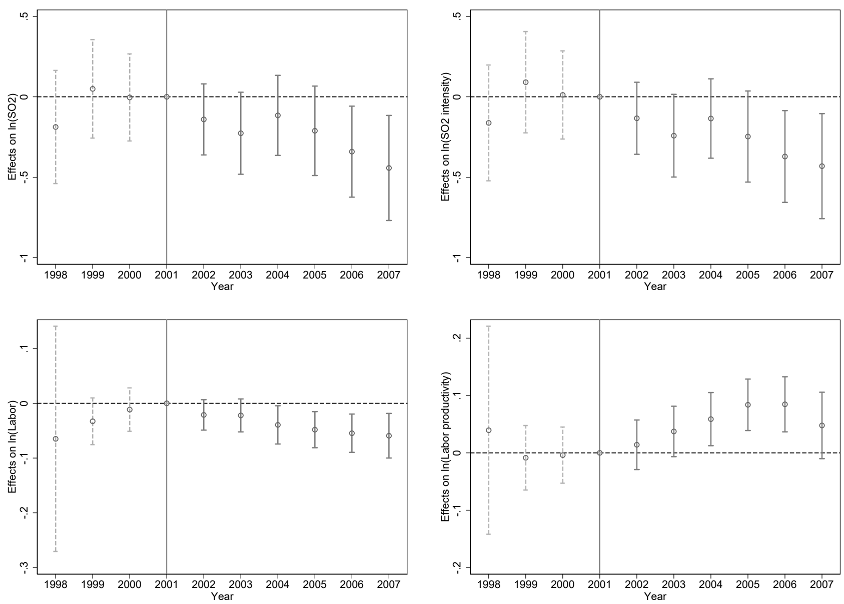

FIGURE A14. ROBUSTNESS CHECKS WITHOUT PSM

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of Y on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-year level.

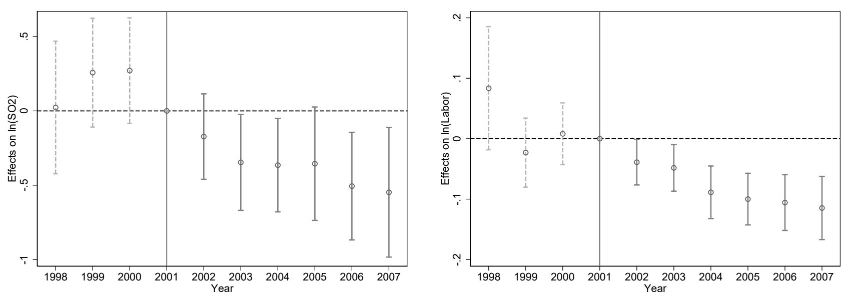

Figure A15. Robustness checks using firms in TCZ

Notes: Figure presents coefficients and 95% confidence intervals on KCAPC×year interactions from the regression of Y on KCAPC×year interactions, firm fixed effects, and industry-year fixed effects for manufacturing firms. The excluded KCAPC×year coefficient represents 2001. Standard errors are clustered at the city-year level.

Table A1—Firm characteristics for adopting technology upgrading

	High processing control	Low processing control	Difference	P value
Output	175972.0	257635.3	-81663.3	0.000
Capital	96080.5	164684.8	-68604.3	0.000
Labor	760.3	988.9	-228.4	0.000
Age	20.8	20.2	0.7	0.002
FDI	6113.0	2769.1	3343.8	0.004
Average wage	16.4	10.4	5.9	0.346
SO2 intensity	2.6	2.5	0.1	0.349

Notes: Firms in the treatment group are classified into two groups, high processing control and low processing control , according to the main pollution control strategies used after the policy is enacted.

Table A2—DID Results on FDI and Export at the Firm Level

	(1) ln(FDI) FE	(2) ln(FDI) FE	(3) ln(Export) FE	(4) ln(Export) FE
KCAPC×Post	0.038	-0.024	-0.034	0.028
	(0.032)	(0.032)	(0.070)	(0.065)
ln(Average wage)		0.087		-0.270
		(0.145)		(0.239)
ln(Industrial output)		-0.014		0.182***
		(0.032)		(0.055)
Year fixed effects	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES
Province-year interactions		YES		YES
N	97105	97105	97106	97106
R^2	0.804	0.805	0.867	0.871

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

TABLE A3—ROBUSTNESS CHECK ON WTO CONFOUNDER

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(SO_2) FE	ln(SO_2) FE	ln(SO_2 intensity) FE	ln(SO_2 intensity) FE	ln(Labor) FE	ln(Labor) FE
KCAPC×Post	-0.394***	-0.484***	-0.375***	-0.483***	-0.077***	-0.036***
	(0.098)	(0.115)	(0.101)	(0.115)	(0.015)	(0.014)
ln(Average wage)		0.212***		0.222***		-0.004
		(0.065)		(0.070)		(0.006)
ln(Industrial output)		0.305***		0.288***		0.018
		(0.094)		(0.093)		(0.012)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions		YES		YES		YES
N	91208	91208	91208	91208	91208	91208
R^2	0.566	0.571	0.581	0.586	0.939	0.941

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

Table A4—Effects on city-level water pollution

	(1)	(2)
	ln(COD) FE	ln(COD intensity) FE
KCAPC×Post	-0.011	-0.048
	(0.054)	(0.066)
Year fixed effects	YES	YES
City fixed effects	YES	YES
Province-year interactions	YES	YES
N	1240	1240
R^2	0.910	0.895

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a city is in the treatment group; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. For 1998 and 1999, COD emission has missing values due to the incomplete statistical range of earlier years. Standard errors in parentheses are clustered at the city-year level.

Table A5—Effects on air pollution and labor demand using unmatched data

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(SO2) FE	ln(SO2) FE	ln(SO2 intensity) FE	ln(SO2 intensity) FE	ln(Labor) FE	ln(Labor) FE
KCAPC×Post	-0.213***	-0.269***	-0.245***	-0.332***	-0.088***	-0.028***
	(0.076)	(0.069)	(0.076)	(0.068)	(0.015)	(0.011)
ln(Average wage)		0.038		0.076		0.002
		(0.073)		(0.060)		(0.054)
ln(Industrial output)		0.189**		-0.013		0.013
		(0.082)		(0.082)		(0.009)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions		YES		YES		YES
N	199873	199873	195882	195882	723785	723785
R^2	0.706	0.711	0.727	0.731	0.909	0.911

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

TABLE A6—EFFECTS ON AIR POLLUTION AND LABOR DEMAND USING FIRMS IN TCZ ONLY

	(1) ln(SO2) FE	(2) ln(SO2) FE	(3) ln(SO2 intensity) FE	(4) ln(SO2 intensity) FE	(5) ln(Labor) FE	(6) ln(Labor) FE
KCAPC×Post	-0.472***	-0.495***	-0.466***	-0.459***	-0.080***	-0.042***
	(0.105)	(0.125)	(0.108)	(0.125)	(0.016)	(0.015)
ln(Average wage)		-0.761		-0.860*		0.023
		(0.517)		(0.513)		(0.059)
ln(Industrial output)		0.253**		0.242**		0.023*
		(0.104)		(0.103)		(0.012)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions		YES		YES		YES
N	84338	84338	84338	84338	84338	84338
R^2	0.560	0.565	0.576	0.582	0.937	0.939

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.

TABLE A7—EFFECTS ON AIR POLLUTION AND LABOR DEMAND USING DATA FROM 1998 TO 2005

	(1) ln(SO2) FE	(2) ln(SO2) FE	(3) ln(SO2 intensity) FE	(4) ln(SO2 intensity) FE	(5) ln(Labor) FE	(6) ln(Labor) FE
KCAPC×Post	-0.249***	-0.213*	-0.244**	-0.205*	-0.055***	-0.035***
	(0.095)	(0.111)	(0.097)	(0.111)	(0.014)	(0.013)
ln(Average wage)		-0.293		-0.430		0.065
		(0.606)		(0.605)		(0.071)
ln(Industrial output)		0.175		0.145		0.019
		(0.119)		(0.118)		(0.013)
Year fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Industry-year interactions	YES	YES	YES	YES	YES	YES
Province-year interactions		YES		YES		YES
N	69234	69234	69234	69234	69234	69234
R^2	0.620	0.623	0.632	0.636	0.941	0.943

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: KCAPC equals 1 if a firm is located in the treated cities; otherwise, KCAPC equals 0. Post equals 1 for all years after 2001 (policy period); otherwise, Post equals 0. Industry is specified according to a 2-digit industry code. Standard errors in parentheses are clustered at the city-year level.