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China's Manufacturing Pollution, Environmental Regulation and Trade

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Abstract

Real manufacturing output increased rapidly in China from 1998 to 2012 while sulfur dioxide (SO2) pollution emissions grew at a much lower rate. To study the reasons for this, I focus on the contributions of environmental policy, trade liberalization, and other factors linked to China's development process. Using China's entry into the World Trade Organization and the 11th Five-Year Plan as policy shocks, the difference-in-differences analyses show that these policies effectively reduced firm-level pollution intensity. The change in pollution is primarily driven by within-sector firm heterogeneities rather than industry structural change toward less polluting sectors. Finally, the counterfactual analysis based on a quantitative model reveals that environmental regulations play a major role in reducing pollution and the implicit pollution tax faced by firms grew substantially over the period. In addition, tariff cuts due to trade liberalization reduce variable costs of trade and allow firms to abate pollution more.

Keywords: Pollution emission, Environmental regulation, International trade, China.
JEL classification: F18, F68, L60, Q56, Q58

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China's Manufacturing Pollution, Environmental Regulation and Trade *

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1 Introduction

The first decade of the 21st century witnessed rapid growth of real output in China. In Figure 1, the solid red line represents the aggregate real output of manufacturing industries at the national level, which grew near five times from 1998 to 2012. By comparison, the aggregate sulfur dioxide (SO_2) emission in green dashed line grew at a much lower pace and hardly doubled during the same period. As a result, the pollution intensity (SO_2 emission per unit of output) in the blue short-dashed line scaled by the left axis, dropped by around 60%.[1]

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[1] The emission intensity here refers to the revenue emission intensity rather than physical emission intensity, following the literature (see e.g. Rodrigue et al., 2022a). The production data do not include quantity information so I do not directly observe physical emission intensity. However, I can combine production data with trade data where there are export value and quantity, and impute export-related emissions, assuming that emission is proportional to production. The export quantity and value are plotted in Figure A.1a. The revenue versus physical emission intensities are shown in Figure A.1b. The magnitudes by the end of the period are not far from Figure 1.

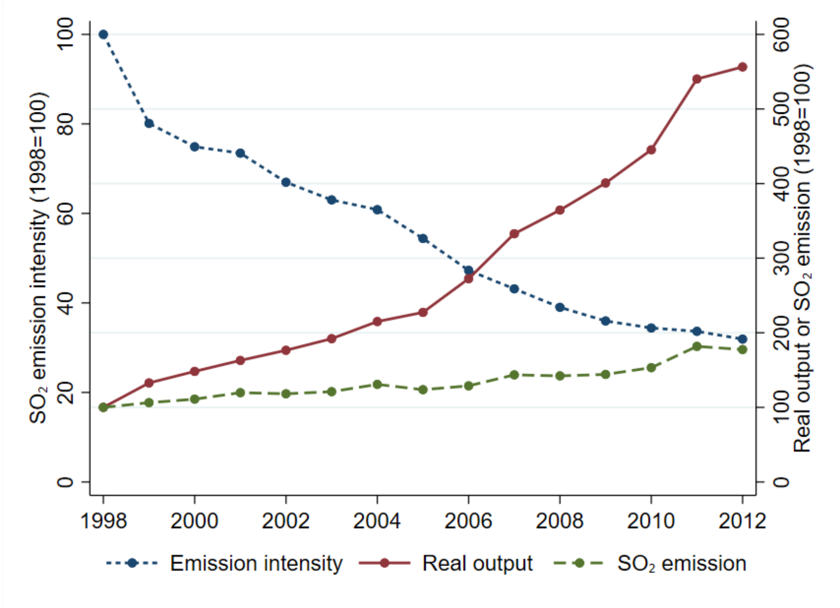


Figure 1. SO_2 emission and real output

Notes: The industrial output and 2-digit deflators come from China Statistical Yearbooks.[2] Firm-level emissions come from the Environmental Statistics Database. The trends of other pollutants show similar patterns and are summarized in Figure A.3.

This paper investigates the reasons behind the different patterns of output and pollution in Figure 1. There are several possible explanations. China's rapid output growth led to more pollution, and China's participation in world trade also contributed to this growth. However, the growth of the economy, accompanied by an increase in productivity, may reduce pollution intensity, so that firms can produce the same output with less input and pollution. Meanwhile, the industry structure changed, which may contribute to the pollution levels. During the same period, environmental regulations took place to tackle major air and water pollutants, which played a significant role in reducing pollution.

The main focus of this paper is the emissions of SO_2, a pollutant that has been studied frequently in the literature. SO_2 is one of the most important air pollutants and is common in cities. It is mainly produced by coal burning, which is used to produce more than 60% of electricity in China by 2020, according to the State Council. There are detrimental effects of SO_2 to the environment since it is the primary cause of acid rain, which harms plants, buildings and can lead to respiratory diseases. The more concentrated is the pollutant, the more harmful it is. Therefore, it is very much relevant that I study the pollution level and the pollution intensity of SO_2 in this paper. The SO_2 emission increased quickly in China after 2002, from 20 million tons per year to 25.9 million tons in 2006, according to the Ministry of Environmental Protection (MEP) of China. The amount was even higher than all OECD countries combined. Therefore, it was an urgent issue to curb the rapid growth in SO_2 emission in China. Another reason to study SO_2 is that the regulations set clear targets to reduce SO_2 and one can observe the effectiveness of the environmental policy. The data on SO_2 are also recorded with wider coverage of firms and more detailed than other pollutants. Extension to other pollutants in comparison to SO_2 is carried out in later sections.

Previous research in this field focused mainly on industry-level data and detailed firm-level

[2] I can alternatively use 4-digit industry deflators by extending the output deflators from Brandt et al. (2017) to 2010. The threshold of firm annual sales increased from 5 million RMB to 11 million RMB in 2011, making the sample not compatible with previous years, so I do not extend the deflators after 2010. Figure A.2 shows that the real output deflated at 4-digit industries closely follows the trend deflated at 2-digit industries.

data, especially on developing countries are relatively scarce (Jayachandran, 2022). This paper is among the first to use firm-level pollution data of China to explore the drivers of industrial pollution emissions. First, it provides evidence that large firms pollute more but firms that import and export more are less pollution-intensive. Firms with higher total factor productivity (TFP), which implies better technology, are associated with less pollution emissions. Moreover, using China's entry to the WTO and the environmental regulation during the 11$^{\text{th}}$ Five-Year Plan as policy shocks, with difference-in-differences (DiD) strategies, I show that trade liberalization and pollution policy are effective in reducing the emission intensity of firms across industries and provinces, respectively.

One reason for the change in pollution levels might be industry structural change. Clean industries may grow faster than dirty industries so that total pollution increased more slowly than output. To assess the role of industry structure, I decompose the total pollution level into scale, composition, and technique effects. The scale effect measures the change in pollution due to the growth of the economy, the composition effect reflects the change in pollution due to industry structure, and the technique effect is the residual effect due to industry-level pollution intensity. Among the three components, the scale effect drives up total pollution level but the technique effect significantly reduces it. The composition effect is very small, indicating that industry structural transformation contributes marginally to total pollution. Further firm-level decomposition reveals that the reduction in pollution intensity is mainly due to reallocation towards the less pollution-heavy firms within industries.

The decomposition exercises together with the regressions provide evidence on the channels that drive pollution emissions such as international trade, environmental regulation, and productivity. However, they are less informative about the overall contributions of primitive economic forces, neither do they shed light on the counterfactual effects of trade and environmental policies on pollution. To evaluate the overall effect of different channels under a general equilibrium framework, I use the quantitative model from Shapiro and Walker (2018) to study China's SO_2 pollution emissions. The model combines the classic international trade model (Melitz, 2003) with insights from environmental economics (Copeland and Taylor, 2003), and can account for various general equilibrium forces in counterfactual scenarios. It features heterogeneous firms that choose pollution abatement as a proportion of production costs, depending on environmental regulation, productivity and trade costs. One can derive a market-equivalent implicit pollution tax which is otherwise not directly observable from the data to capture the stringency of pollution policies. Not much has been done to structurally estimate the contribution of endogenous forces to pollution emission, especially in evaluating environmental policy in developing countries where the regulations are thought to be weaker. This paper contributes to the literature in this aspect through a quantitative model and matched data of pollution, production, and trade on Chinese firms.

The main results suggest that tighter environmental regulation would reduce around 50% of SO_2 pollution emissions according to the counterfactual analysis. The back-of-the-envelope estimate of the economic gain due to SO_2 emission reduction is 127.68 billion RMB in 2005, accounting for 0.68% of the annual GDP. The counterfactual wage would only decrease by 0.4%, which is relatively small. On the other hand, should there be no environmental regulation, the counterfactual pollution emissions of manufacturing industries would be 300% of the initial level by 2012, compared to the actual level of 162%. Although the competitiveness of Chinese firms in the international market would push up the pollution level through the scale effect, tariff cuts on Chinese exports due to trade liberalization imply a smaller portion of a firm's output must be paid in order to export, which leads to less pollution. The measured productivity only moderately decreases pollution level, which would be confounded with other forces as the technique effect in the conventional decomposition exercise. This indicates that more productive firms reduce more pollution because they have better export opportunities and larger domestic sales which allow them to better bear the abatement costs, rather than because of better technology alone.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 introduces the data used in the analysis and briefly explains the environmental policy in China before showing firm-level regression results in Section 4. I then do the decomposition exercises in Section 5 to explore the patterns of pollution emission within and across industries. Section 6 introduces the theoretical model, estimates the parameters and recovers historical values for counterfactual analysis in Section 7. Section 8 concludes the paper.

2 Literature

This paper is related to several strands of the literature. One topic closely related to pollution emissions is the role of international trade and technology. Many papers take free trade agreements as policy shocks and study their effects on pollution. The policies that attract most attentions are the North America Free Trade Agreement (NAFTA) and China's entry into the World Trade Organization (WTO). For example, Cherniwchan (2017) estimated the effects of NAFTA on emissions from manufacturing plants in the US and show that two-thirds of particulate matter (PM10) and sulfur dioxide (SO_2) emission reductions between 1994 and 1998 can be attributed to trade liberalization. Richter and Schiersch (2017) find a negative relation between export intensity and CO_2 emission intensity in Germany with a consistent production function framework. In another case, Gutiérrez and Teshima (2018) use plant-level data in Mexico and find that lower tariffs and import competition increase energy efficiency and thus reduce emissions. In India, foreign demand growth led to more carbon dioxide (CO_2) emissions but 40% was mitigated by reduced emission intensity (Barrows and Ollivier, 2021).

In the case of China, the WTO accession provides an ideal environment for difference-in-differences (DiD) analysis. Evidence shows that tariff cuts reduce firm-level SO_2 emission intensity through increased labor resources for environmental protection or higher abatement efforts (Cui et al., 2020; Pei et al., 2021). In addition, international trade allows firms to spread fixed costs of abatement investment across more units, increases firm productivity and thus reduces emission intensity, yet the overall effect on total emissions is not conclusive (Forslid et al., 2018; He and Huang, 2022; Rodrigue et al., 2022b; Chen et al., 2023). In this paper, I examine both total pollution and pollution intensity, and combine production, trade as well as pollution information at the firm-level. As pointed out by Cherniwchan and Taylor (2022), the long-run impact of trade on pollution remains an open question. Unlike Rodrigue et al. (2022b) who focus on the first few years of the WTO accession, I extend the analysis beyond the initial period until 2012, when the environmental regulations also started to affect pollution emissions, while combining detailed firm-level data in regressions and a quantitative model.

Another line of literature is focused on environmental regulations. The US enforced the Clean Air Act in the 1990s (Shapiro and Walker, 2018) and the Clean Water Act since 1972 (Keiser and Shapiro, 2018), which substantially abated air and water pollution nationwide. In China, the most frequently mentioned environmental regulation policies were introduced by the 11th Five-Year Plan, covering the period 2006-2010, including both air and water pollutants. Local regulations are effective when supervised by the central government, as shown in Kahn et al. (2015). However, the pollution regulation mandates may cause some firms to relocate or shift production to provinces where the regulations are less stringent (Wu et al., 2017; Chen et al., 2021). He et al. (2020) find evidence that the policy led to lower pollution levels upstream of a monitoring station, rather than downstream. Without misallocation, pollution would decline by 20% since more large, low-polluting firms survive (Qi et al., 2021). However, if environmental regulation policies loosen, the progress may be reversed (see Burgess et al., 2019 for Brazil). The evidence leads to the conclusion that environmental regulations are highly effective in most conditions and therefore are vital to the reduction of pollution emissions. However, it is important to take into account the general equilibrium effects in order to evaluate the environmental policies. In this paper, I study environmental regulations in China, in particular, the 11^{th} Five-Year Plan on SO_2 pollution reduction. With a structural model, I show that the policy is not only effective but quantitatively could reduce around half of total emission level.

There is a long history in the literature on the decomposition exercise to disentangle within and across industry forces that drive the level of pollution emissions (Copeland and Taylor, 1994; Grossman and Krueger, 1995; Antweiler et al., 2001; Levinson, 2009; Rodrigue et al., 2022a, etc.). Specifically, the total pollution emission level of an economy can be decomposed into scale, composition and technique effects at the sector-level. In addition, I decompose the pollution intensity at the firm-level, taking into consideration the entry and exit of firms (Melitz and Polanec, 2015). The evidence suggest that within-industry and across-firm production reallocation is a major force that affects pollution level, rather than industry structure change, consistent with the finding of Dong and Yu (2021). The result is different from the context of Germany, who is also a major country in international trade. For example, Rottner and von Graevenitz (2022) find that carbon emission from German manufacturing increased between 2005 and 2017 due to production scale, but there was a clean-up due to a shift towards a cleaner product composition from 2011 onwards.

Recently, there is a small strand of literature using quantitative models to tell apart the contribution of each potential channel to the total level of pollution emissions (Shapiro and Walker, 2018; Shapiro, 2020; Alvarez and Rossi-Hansberg, 2021) or to evaluate regulations quantitatively (Duflo et al., 2018; Blundell et al., 2020; Chen et al., 2021). Among them, Shapiro and Walker (2018) developed a two-country, multi-sector model featuring heterogeneous firms in a monopolistic competitive market based on workhorse models from international (Melitz, 2003) and environmental (Copeland and Taylor, 2003) literature. It is also the main quantitative reference of this paper, which applies the model to the Chinese context instead of the original US scenario. Their main finding is that the environmental regulation, i.e. the Clean Air Act, accounts for most of the emission reductions rather than productivity and trade between 1990 and 2008 in the US. Further exploration showed that import tariffs and non-tariff barriers are much lower on dirty than on clean industries due to greater protection of downstream industries which are relatively clean (Shapiro, 2020). In this paper, I use the quantitative model and study various endogenous factors including China's environmental regulation reform, as well as foreign and domestic market competitiveness. In addition, I extend the analysis and emphasize factors such as variable trade cost and productivity and explore their impacts on pollution emissions. Similar application of the model has been done on German carbon prices (Rottner et al., 2023), where the authors find the implicit carbon price on emission decreased from 2005 to 2019 in most manufacturing sectors.

Finally, there is a growing literature on the labor market outcomes due to pollution, with a focus on developing economies (Greenstone and Hanna, 2014; Arceo et al., 2016; Ebenstein et al., 2017; Barwick et al., 2018; Bombardini and Li, 2020). For instance, Bombardini and Li (2020) showed that the increase in pollution due to export expansion and output growth can raise infant mortality, but the increase in local incomes may instead reduce mortality. Air pollution level is also related to worker health and productivity (Chang et al., 2019), absenteeism and firm sales (Leroutier and Ollivier, 2023), earnings (Wan and Zhang, 2023), job reallocation (Li et al., 2023), and worker migration (Khanna et al., 2021). The analysis of the current paper is mainly on the level of pollution and pollution intensity, which can lead to the potential effects on health and labor market consequences, although they are not the main focus of this paper.

3 Data and policy background

3.1 Data

The firm-level data in the paper are sourced from the EPS (Economy Prediction System) China micro-economy database which has recently become available. Three sub-datasets at the firm-level are used. The first is the Environmental Statistics Database (ESD) provided by the Ministry of Environment Protection (MEP) of China. The second is the Annual Survey of Industrial Firms (ASIF) conducted by the National Bureau of Statistics (NBS). The third is the import and export data from the customs record. The advantage of the EPS data is that firms are matched by name, location and registration number so that I can combine production, pollution and trade information altogether at the firm-level. To take the common coverage among the datasets, I focus on the period 2000 to 2012. The time span of the study covers the fast development after China entered the WTO in 2001 and also the implementation of the 11th Five-Year Plan (2006-2010) when the government regulated pollution with specific caps for each province, specifically on sulfur dioxide (SO_2) for air pollution and chemical oxygen demand (COD) for water pollution. The majority of the firms are concentrated in the manufacturing sectors. All observations are at firm-level with 4-digit China Industry Classification (CIC) at each prefecture.

The reliability of the ESD data is a potential concern, since firms may misreport their emission levels. The ESD is by now the most comprehensive database available on firm-level pollution for China cross-verified by previous studies (Cui et al., 2020; Rodrigue et al., 2022b). The survey is conducted annually on firms that account for 85% of total emission in a prefecture. To reduce the incentive of misreporting, the Environmental Protection Law explicitly states that the survey cannot be used as a reference to punish or regulate polluting firms (He et al., 2020). In addition, the MEP carries out random monitoring checks and anonymous field inspections to verify the accuracy of the information reported. Rodrigue et al. (2022b) among others provide checks on the data by aggregating firm-level SO_2 across time and space, and compare with the annual reports to show that the dataset captures the majority of total emissions and is in line with the official statistics. They also crosscheck with the US satellite data and find no significant evidence of systematic reporting bias. The pollutants recorded include sulfur dioxide (SO_2), nitrogen oxides (NO_x) and smoke dust (close to particulate matter) for air pollution, chemical oxygen demand (COD), ammonia nitrogen (NH_3-N) and waste water for water pollution.

The ASIF data are frequently used in studies related to China's firm-level performance, which report the major production indicators in the financial statements. The data include all state-owned enterprises (SOEs) and private firms with annual sales above 5 million RMB.[3] With the information provided , I can estimate firm-level total factor productivity (TFP). Finally, the customs data record the import and export of firms with the quantity and value of each destination, and can be combined with the emission and production data to assess the effect of trade on pollution.

The geographic coverage of the datasets is plotted in Figure A.4. Though the number of firm-level observations shrinks progressively as more datasets are combined, the pattern remains consistent.[4] The eastern and coastal areas are more developed in general and have more firms included. Firms also concentrate around the four cities under direct central governance (Beijing, Shanghai, Tianjin, and Chongqing). In terms of industry distribution for SO_2, the manufacturing sector accounts for 53% of total emissions in the ESD dataset, followed by

[3]Since 2007, the ASIF data do not cover firms with annual sales below 5 million RMB. The threshold was further lifted to 20 million RMB in 2011. The equivalent US dollar value is 0.66 million in 2007, and 3 million in 2011, according to the average exchange rate (7.6 RMB per USD in 2007 and 6.5 RMB per USD in 2011) reported by the Central Bank of China.

[4]The total number of manufacturing firms in the pollution dataset between 2000 and 2012 is 245479, and shrinks to 130282 when merged with the ASIF dataset, which is further reduced to 38336 when again merged with the Customs dataset. Most firms appear in multiple years in the observations.

electricity, heat, gas and water production and supply, which cover 42% of total emissions in the sample period. Among manufacturing industries, the most pollution-heavy industries that account for more than 1% of total emissions of SO_2 are listed in Table B.1. The most "dirty" industries are metal smelting and processing.

At the aggregate level, I obtain the country-industry production and trade data from the World Input-Output Database (WIOD) for the period of 2000-2012 in the structural model estimations. Here I abstract from non-manufacturing industries and the industries are converted from ISIC Revision 4 to CIC 2017 at 2-digit level according to the concordance table by China's National Bureau of Statistics. Additional industry and province output and emission data come from China Statistical Yearbooks and China Environmental Statistical Yearbooks.

3.2 China's environmental policy

The main environmental policy during the sample period is China's 11$^{\text{th}}$ Five-Year Plan from 2006 to 2010. The policy plays an important role in controlling pollution emissions because there was a specific reduction target of 10% nationwide on pollutants such as sulfur dioxide (SO_2) and chemical oxygen demand (COD). The total target was in turn assigned to each province as a pollution quota. The evaluation of implementation was directly linked to local government performance and the promotion of local leaders. By 2010, most provinces achieved or even exceeded their targets (Shi and Xu, 2018). Local governments and firms have strong political incentives to comply with the environmental regulation policy and reduce the pollution emissions to the regional cap. Although during the 10$^{\text{th}}$ Five-Year Plan, there was also an overall pollution reduction target of 10%, not all provinces received a reduction quota, and the outcome was not directly linked to chances of political promotion. Therefore, the 10$^{\text{th}}$ Five-Year Plan was not as effective. By the end of the period, the total pollution emission of SO_2 even increased by 28% according to the China Environmental Statistical Yearbooks. After the 11$^{\text{th}}$ Five-Year Plan, there was the 12$^{\text{th}}$ Five-Year Plan, with further reduction goals. However, later rounds of Five-Year plans are beyond the period of observation with the current data and I leave the analysis for future updates. In addition to the 11$^{\text{th}}$ Five-Year Plan, there are other regional regulations in compliance with the 11$^{\text{th}}$ Five-Year Plan, such as the "three rivers and three lakes basins" region targeted by the central government to reduce chemical oxygen demand (COD) as an effort to control water quality (e.g. Wang et al., 2018) and the "Top 1000" program (later the "Top 10,000" program) that targeted the largest energy consuming firms in the most energy-intensive industries to improve energy efficiency (e.g. Karplus et al., 2020; Chen et al., 2021).

4 Firm-level regressions

In this section, I first run some reduced-form firm-level regressions to show patterns between pollution and a number of firms characteristics. Next, I run two sets of difference-in-differences (DiD) regressions to show the effects of the WTO accession and the 11$^{\text{th}}$ Five-Year Plan on pollution intensity.

4.1 Pollution and firm characteristics

The first set of regressions evaluates if importers and exporters pollute more using the following specifications:

$$\log SO_{2it} = \alpha_0 + \alpha_1 Exporter_{it} + \alpha_2 Importer_{it} + \alpha_3 \log\ sales_{it} + \mu_s + \mu_c + \mu_t + \epsilon_{it} \quad (1)$$

$$\log SO_2 int_{it} = \beta_0 + \beta_1 Exporter_{it} + \beta_2 Importer_{it} + \beta_3 \log\ sales_{it} + \mu_s + \mu_c + \mu_t + \epsilon_{it} \quad (2)$$

where logSO_{2it} is log SO_2 emission (kg) of firm i at year t, logSO_2int_{it} is log SO_2 emission (kg) per unit of output value (1,000 yuan). $Exporter_{it}$ and $Importer_{it}$ are exporter and importer dummies. log $sales_{it}$ represents log of sales at year t in 10,000 yuan and μ_t, μ_s, μ_c are year, 2-digit sector and city fixed effects. log $sales_{it}$, logSO_{2it} and logSO_2int_{it} are trimmed at the top and bottom 1% to rule out the influence of outliers. The summary statistics are shown in Table B.2.

The first two columns of Table 1 report the regression results of specification (1). Column (1) shows that importers and exporters tend to produce more pollution. Column (2) shows that once I control for firm size, firms that engaged in international trade actually pollute less intensively than their peers with the same production level. Column (3) follows specification (2) and confirms the pattern by showing that the pollution intensity of both exporters and importers are lower on average. This is also true when I control for size in column (4). These results are in line with the findings by Pei et al. (2021) and Rodrigue et al. (2022b), who show that exporters are less pollution intensive.

Table 1. SO_2 pollution and firm characteristics (all firms)

	(1) logSO_2	(2) logSO_2	(3) logSO_2int	(4) logSO_2int
Exporter	0.158***	-0.217***	-0.598***	-0.217***
	(0.008)	(0.007)	(0.008)	(0.007)
Importer	0.304***	-0.278***	-0.831***	-0.278***
	(0.010)	(0.009)	(0.010)	(0.009)
log *sales*		0.498***		-0.502***
		(0.001)		(0.001)
Observations	798,666	777,539	777,539	777,539
R-squared	0.194	0.376	0.414	0.545
Sector FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

Next, I focus on importers/exporters and see if the amount of international trade affects their pollution behavior. The specifications are the following:

$$\log SO_{2it} = \alpha_0 + \alpha_1 \log Export_{it} + \alpha_2 \log Import_{it} + \alpha_3 Labor_{it} + \mu_s + \mu_c + \mu_t + \epsilon_{it} \quad (3)$$

$$\log SO_2int_{it} = \beta_0 + \beta_1 \log Export_{it} + \beta_2 \log Import_{it} + \beta_3 Labor_{it} + \boldsymbol{\delta Control_{it}} + \mu_s + \mu_c + \mu_t + \epsilon_{it} \quad (4)$$

where logSO_{2it} and logSO_2int_{it} are SO_2 emission and emission intensity following the definitions in specifications (1) and (2). log$Export_{it}$ and log$Import_{it}$ are export and import value in logs, respectively. I use the number of employees $Labor_{it}$ in hundreds instead of sales as a proxy for firm size to reduce collinearity with import and export. The control variables $\boldsymbol{Control_{it}}$ include firm total factor productivity (TFP) following Levinsohn and Petrin (2003), with Ackerberg et al. (2015) correction.[5] FOE is foreign ownership status dummy. SO_2cap is the provincial SO_2 regulation cap in 10,000 tons by 2010. 2-digit sector, city and year fixed effects μ_s, μ_c and μ_t are controlled. log$Export_{it}$, log$Import_{it}$ and $Labor_{it}$ are trimmed at the top and bottom 1%. The summary statistics are shown in Table B.3.

The first two columns of Table 2 imply that the importers/exporters emit more pollution the more they trade. The next two columns (3) and (4) confirm the previous finding from Table

[5] Specifically, the TFP is measured by the log output minus a weighted sum of log labor, capital and materials: $TFP_{it} = y_{it} - \alpha_l l_{it} - \alpha_k k_{it} - \alpha_m m_{it}$. The output is deflated with 2-digit industry-specific producer price index, the capital is deflated with provincial fixed assets investment price index, and the materials are deflated with annual purchasing price index. All price indices are collected from China Statistical Yearbooks.

1 that taking the firm size into consideration, the pollution intensity of exporters and importers decreases with trade values. Column (5) shows that firms with higher TFP have significant lower pollution intensity. Column (6) controls for foreign ownership FOE. Compared to domestic-owned firms, foreign-owned firms pollute less intensively. Finally, the last column includes the pollution cap for each province by 2010 as an indicator of environmental policy stringency. The unit of observation is 10,000 tons. A higher cap means less strict enforcement. The positive significant coefficient indicates that a more stringent cap is correlated with a reduction in the pollution intensity of the firm.

Table 2. SO_2 pollution and firm characteristics (importers/exporters)

	(1) $\log SO_2$	(2) $\log SO_2$	(3) $\log SO_2int$	(4) $\log SO_2int$	(5) $\log SO_2int$	(6) $\log SO_2int$	(7) $\log SO_2int$
$\log Export$	0.130***	0.065***	-0.042***	-0.041***	-0.020***	-0.018**	-0.018**
	(0.005)	(0.007)	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)
$\log Import$	0.045***	0.016***	-0.138***	-0.124***	-0.099***	-0.095***	-0.094***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)
$Labor$		0.045***		-0.003***	0.004***	0.003**	0.003**
		(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
TFP					-0.739***	-0.737***	-0.738***
					(0.016)	(0.016)	(0.016)
FOE						-0.401***	-0.402***
						(0.047)	(0.047)
SO_2cap							0.015***
							(0.005)
Observations	51,191	26,411	41,696	25,786	18,385	18,385	18,385
R-squared	0.289	0.335	0.388	0.366	0.421	0.423	0.423
Sector FE	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

Using 4-digit industry fixed effects with 4-digit deflators from Brandt et al. (2017) to estimate TFP gives similar regression results in Table B.4 and Table B.5. Regressions including firm-level FE show similar patterns, see Table B.6 and Table B.7, where the estimated coefficients for foreign ownership are subsumed by the firm fixed effects and are therefore omitted.

Based on the basic patterns at the firm-level, I then explore the effects of two policies on China's SO_2 emission, namely the WTO accession and the 11$^{\text{th}}$ Five-Year Plan.

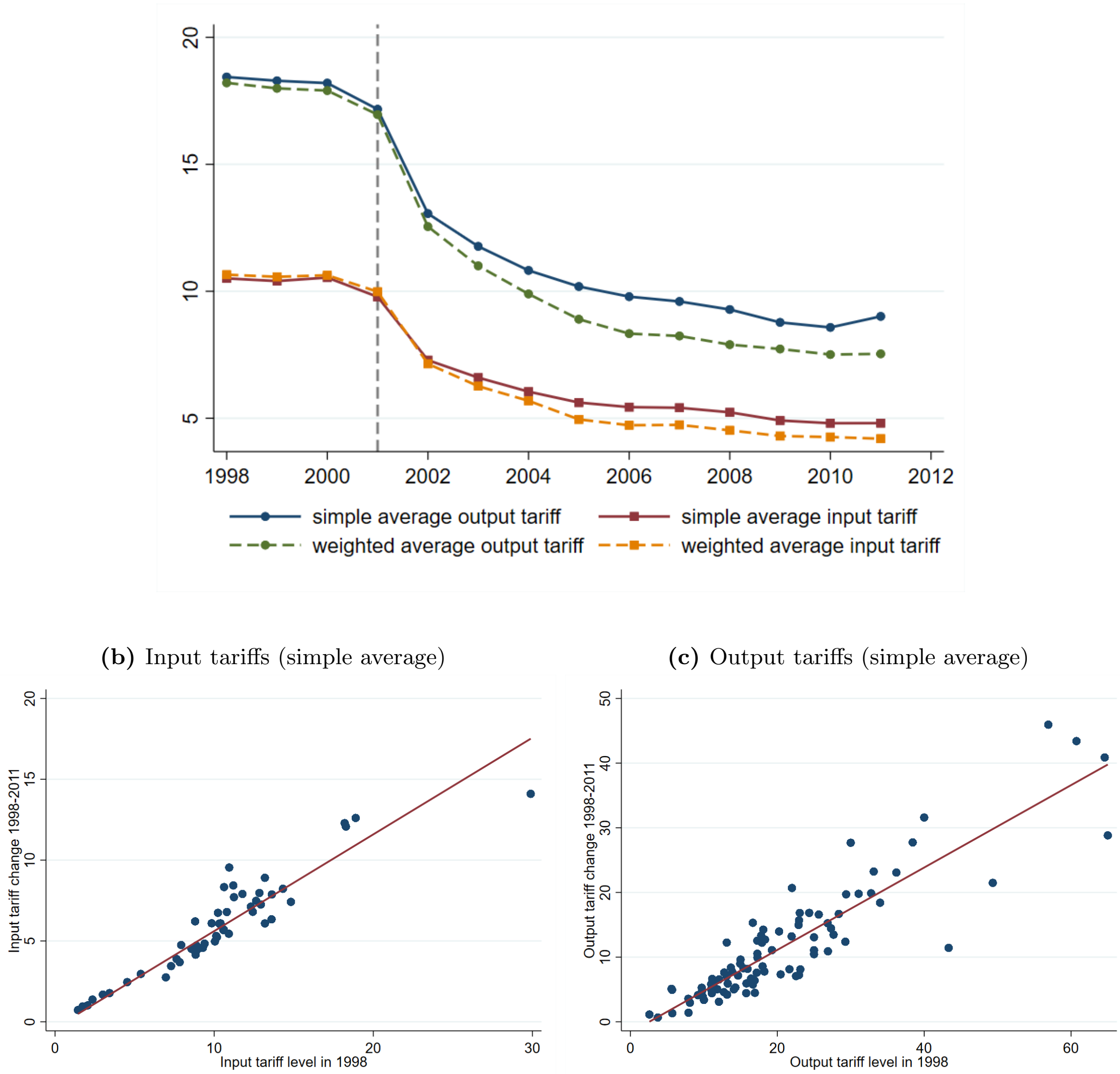
4.2 Trade liberalization

I use a generalized difference-in-differences (DiD) method (Pierce and Schott, 2016) to estimate the impact of WTO accession in 2001 on SO_2 pollution intensity. Following Brandt et al. (2017), I use import tariffs as the key measure of trade openness, because they provide the most accurate and detailed information on the trade reform. All the manufacturing industries experienced some bilateral tariff reduction, thus, there is not a control group that had no industrial tariff change. The research design leverages on the different degrees of trade reform across 429 manufacturing industries at the 4-digit level. The tariff levels are also continuous instead of a treatment dummy in the canonical DiD approach. Specifically, I estimate the following equation:

$$\log SO_2int_{it} = \beta_0 + \beta_1 \; tariff_s^{1998} \times WTO_t + \log \; sales_{it} + \eta_s + \delta_{ct} + \mu_i + \epsilon_{it} \qquad (5)$$

where $\log SO_2int_{it}$ denotes log of SO_2 pollution intensity (kg/1,000 yuan) of firm i at time t. WTO_t is a binary indicator of China's entry to the WTO, which is equal to 1 if the year is after

2001 and 0 otherwise. log $sales_{it}$ is log of firm sales in 1,000 yuan. η_s, δ_{ct}, and μ_i are 4-digit China Industry Classification (CIC) industry, city-year, and firm fixed effects. ϵ_{it} is the error term. The standard errors are clustered at the industry-year level.



(a) Average output and input tariffs

(b) Input tariffs (simple average)

(c) Output tariffs (simple average)

Figure 2. Tariff levels and tariff changes

I use $tariff_s^{1998}$ to denote the input/output tariff at the 4-digit CIC industry level in 1998, which is before the WTO accession at the beginning of the sample. Following Cui et al. (2020), I do not use tariffs in the current year because they may be endogenous to the pollution outcome. As pointed out by Lu and Yu (2015), the pre-accession tariff is a significant predictor of future import growth. Lagged tariffs also suffer from the problem. The import tariff rates at 4-digit ISIC level from 1998 to 2011 are retrieved from the World Bank's WITS dataset. The import tariff rates are not available in 2012. I keep both simple average and product line weighted average tariffs to obtain the output tariffs. Input tariffs are calculated using China's input-output (IO) table in 2002.[6] Specifically, input tariffs are weighted average of output tariffs,

[6]The input-output tables of China are available every five years. Using the input-output table of 1997 instead of 2002 gives very similar results. See Figure A.5 for the tariff levels and changes, Table B.13 for the baseline

where the weights are the industry input shares. The concordance table to convert 3-digit IO industries to 4-digit CIC industries is sourced from Brandt et al. (2017). Figure 2a shows the aggregate trend of output and input tariffs over time. The tariffs dropped significantly after China joined the WTO in 2001 and continued to decrease in the following years. The output tariffs are substantially higher than the input tariffs, as in Brandt et al. (2017). Figure 2b and 2c further shows that the simple average input and output tariff levels and tariff changes are positively related to each other. Thus, using the tariff level in 1998 reflects the impact of trade liberalization. Table B.8 presents the summary statistics of the key variables.

The estimation results of Equation (5) are presented in Table 3. WTO accession and tariff reduction decreases firm SO_2 pollution intensity. This is true for simple average or weighted average input tariffs in the first two columns, as well as for simple average and weighted average output tariffs in columns (3) and (4). Column (5) includes both simple average input and output tariffs, while column (6) includes both weighted average input and output tariffs. The effects remain consistent, though the coefficients of output tariffs become statistically insignificant. According to the baseline estimation, a 1% point lower input tariff in the initial period would decrease SO_2 emission intensity by 1.1% to 1.4% on average in the following years.

Table 3. Impact of trade liberalization on SO_2 pollution intensity

logSO_2int	(1)	(2)	(3)	(4)	(5)	(6)
$tariff^{1998}_{savg.input} \times WTO$	-0.014***				-0.014***	
	(0.002)				(0.002)	
$tariff^{1998}_{wavg.input} \times WTO$		-0.011***				-0.012***
		(0.002)				(0.002)
$tariff^{1998}_{savg.output} \times WTO$			-0.003***		-0.001	
			(0.001)		(0.001)	
$tariff^{1998}_{wavg.output} \times WTO$				-0.002***		-0.000
				(0.001)		(0.001)
log *sales*	-0.684***	-0.684***	-0.682***	-0.682***	-0.682***	-0.682***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	572,631	572,631	530,643	530,643	530,643	530,643
Adj. R-squared	0.845	0.845	0.847	0.847	0.847	0.847
Firm FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses, clustered at the industry-year level. "savg" and "wavg" represent simple average and weighted average tariffs respectively. * significant at 10%, ** significant at 5% , *** significant at 1%.

To get a better sense of the trade liberalization effect over time, I interact the tariff variable with each year in the sample, instead of one binary WTO variable and run the following regression:

$$\log SO_2int_{it} = \beta_0 + \sum^{t} \beta_t \; tariff^{1998}_s \times D_t + \log\, sales_{it} + \eta_s + \delta_{ct} + \mu_i + \epsilon_{it} \tag{6}$$

where D_t is the year dummy, and the beginning year of the sample period 1998 is omitted. The estimation results are plotted in Figure 3. Consistent with the regressions, the overall effects of input tariffs are larger than those of output tariffs. The effect of the input tariff was significant right after the WTO accession and grew larger over the following years till 2008. The effect of the output tariff was significant since 2004 and the magnitude became smaller since 2008. For both input and output tariffs, the effect on firm pollution intensity flattened out and even

regression results.

reversed in the last few years of the sample period, potentially because tariff rates stabilized and were sufficiently low to further influence pollution emissions.

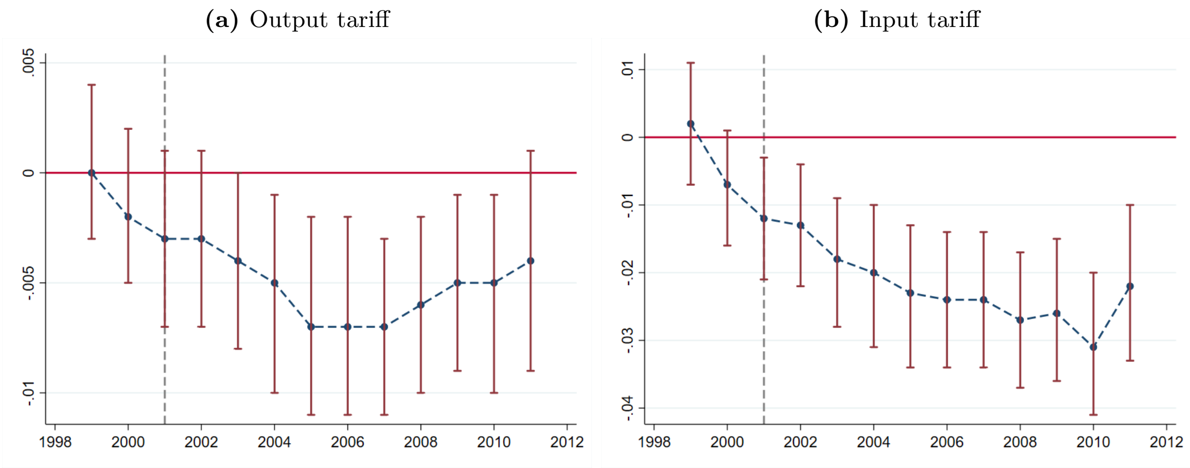


Figure 3. Impact of trade liberalization on SO_2 pollution intensity (simple average tariffs)

Notes: The graph plots the estimates of trade liberalization effects over time, along with the 95% confidence intervals. The vertical dashed line indicates the year of China's WTO accession.

To check the robustness of the baseline results, I use alternative tariffs to measure the extent of trade liberalization. In the spirit of Brandt et al. (2017), I use tariffs before the WTO accession in 1998 as instruments for the actual one-year lag tariffs to obtain predicted tariffs. I then calculate the change between the predicted tariffs and the tariffs at the beginning of the sample $\Delta\widehat{tariff}_{st}$. In this way, I could reduce endogeneity concerns such as reverse causality between tariffs and the outcome variable. The summary statistics of the alternative tariffs are presented in Table B.8. The regression results are presented in Table B.9. The first-stage regressions on instrument variables are presented in Table B.10. The initial period tariffs are strongly correlated with the current tariffs. The estimated coefficients are consistent with the baseline results, with larger magnitudes. A 1% point input tariff reduction would decrease SO_2 emission intensity by 1.7% to 2.1% on average in the following years. Using tariffs in 1998 as instruments of tariff changes directly with two-stage least-squares (2SLS) regressions gives close results in Table B.11 where the first stage is shown in Table B.12.

4.3 Environmental regulation

Next, I use different emission caps across provinces during the 11$^{\text{th}}$ Five-Year Plan to measure the effect of environmental regulation on firm SO_2 emission. One concern is that the trade reform and the environmental regulation may be correlated. Since the 11$^{\text{th}}$ Five-Year Plan started in 2006, which was five years after the WTO accession in 2001, it is unlikely that the environmental regulation affects the tariff reduction. In addition, as shown in Figure 2a, the tariff rates were sufficiently low after the first few years of the trade reform and already stabilized upon the beginning of the environmental regulation. However, the emission caps may be affected by the exposure to trade shocks across provinces. To check this concern, I construct the exposure to tariff shocks by province using 2-digit industry output shares from the yearbooks and run regressions on the emission caps. The results in Table B.15 show that the tariff shocks are not directly related to the emission caps by province.

Analogous to the DiD approach in the trade reform section, all the provinces received emission quotas, the difference lies in the stringency of the policy. Thus, there is not a control group that faced no environmental regulation. The research design leverages on the different degrees of treatment across provinces. The emission targets are also continuous instead of a treatment dummy in the canonical DiD approach. I estimate the following difference-in-differences (DiD) specification:

$$\log SO_2int_{it} = \beta_0 + \beta_1 \log Target_p \times FYP_t + \log\ sales_{it} + \delta_p + \eta_{st} + \mu_i + \epsilon_{it} \tag{7}$$

where $\log SO_2int_{it}$ is the log of emission intensity (kg/10,000 yuan) of firm i and year t. Since the emission quota was a negotiated outcome between the central government and each province, it may be related to the size of the province. Therefore, I use $\log Target_p$ which is the log SO_2 emission target in province p measured by the ratio of the province GDP (yuan) to SO_2 target level (kg) in 2010. FYP_t is an indicator variable of the 11^{th} Five-Year Plan which is equal to 1 if the year is after 2005, and 0 otherwise. A higher emission target indicates more strict regulation. The coefficient of interest β_1 reflects the effectiveness of the policy, a negative β_1 means firms in provinces with more strict regulation would emit less. $\log\ sales_{it}$ is log of firm sales in 1,000 yuan. δ_p, η_{st} and μ_i are province, industry-year and firm fixed effects. ϵ_{it} is the error term. The standard errors are clustered at the province-year level. The summary statistics are shown in Table B.14. The regression results are shown in Table 4. If the provincial $Target$ increases by 1 %, the firm-level pollution intensity would decrease by around 0.07% to 0.09%.

Again, I run the regression by period following the specification:

$$\log SO_2int_{it} = \beta_0 + \sum^{t} \beta_t \log Target_p \times D_t + \log\ sales_{it} + \delta_p + \eta_s + \mu_i + \epsilon_{it} \tag{8}$$

where D_t is the year dummy, and the beginning year of the sample period 1998 is omitted. Figure 4 shows that the impact of environmental regulation is not significant before the policy but becomes significant after the implementation of the 11^{th} Five-Year Plan, with a growing trend in magnitude.

Table 4. Impact of environmental regulation on SO_2 emission intensity

$\log SO_2int$	(1)	(2)	(3)	(4)
$\log Target \times FYP$	-0.089***	-0.091***	-0.074***	-0.079***
	(0.025)	(0.025)	(0.024)	(0.024)
$\log\ sales$	-0.676***	-0.676***	-0.673***	-0.673***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	588,157	588,157	588,157	587,870
Adj. R-squared	0.831	0.832	0.833	0.835
Firm FE	✓	✓	✓	✓
Year FE	✓	✓		
Province FE	✓	✓	✓	✓
2-digit Industry FE	✓			
4-digit Industry FE		✓		
2-digit Industry-Year FE			✓	
4-digit Industry-Year FE				✓

Notes: Standard errors in parentheses, clustered at the province-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

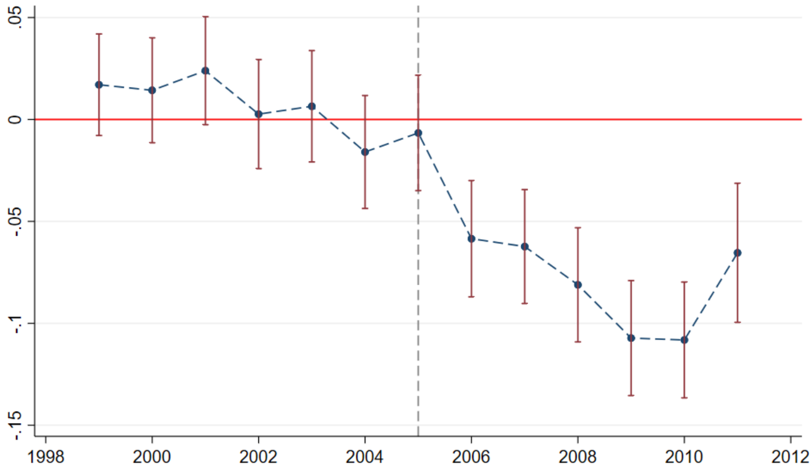


Figure 4. Impact of environmental regulation on SO_2 pollution intensity

Notes: The graph plots the estimates of environmental regulation effects over time, along with the 95% confidence intervals. The vertical dashed line indicates the start of China's 11th Five-Year Plan.

A concern with the DiD regressions is that the pollution targets may be correlated with some time-varying provincial characteristics that bias the results. Therefore, following Shi and Xu (2018) who studied the regional SO_2 regulation during the 10th Five-Year Plan, I carry out a triple difference (DDD) strategy and include variance in industry pollution emissions. The assumption is that firms in dirtier industries would respond to the emission cap more since the policy was implemented. The specification is the following:

$$\log SO_2int_{it} = \beta_0 + \beta_1 \log Target_p \times FYP_t \times \log SO_{2s} + \log\ sales_{it} + \gamma_{pt} + \delta_{ps} + \eta_{st} + \mu_i + \epsilon_{it} \quad (9)$$

where $\log SO_2int_{it}$ is the log of emission intensity (kg/10,000 yuan) of firm i and year t. $\log Target_p$ is the log SO_2 emission target in province p measured by the ratio of the province GDP (yuan) to SO_2 target level (kg) in 2010. FYP_t is an indicator variable of the 11th Five-Year Plan which is equal to 1 if the year is 2006 and afterwards, and 0 otherwise. $\log SO_{2s}$ is the log average SO_2 emission of each 2-digit industry between 2000 and 2005. γ_{pt}, δ_{ps}, η_{st} and μ_i are province-year, province-industry, industry-year and firm fixed effects. ϵ_{it} is the error term. The standard errors are clustered at the province-industry level. The regression results are shown in Table 5. More stringent pollution regulation during the 11th Five-Year Plan decreases firm pollution intensity, especially in industries with high SO_2 pollution emissions.

Since the WTO accession and the 11th Five-Year Plan have overlapping time periods, I combine them in the same regression to check if they affect each other. The details are in Appendix C and the results are consistent with the separate effects of the two policies.

One caveat of the DiD analysis is that the policy effects on pollution intensity come from relative changes across industries or across regions, while the industry structure may change over the years, and firm production may shift within a conglomerate (Chen et al., 2021). Therefore, it is necessary to check the contribution of industry structural change to total pollution in the following section using decomposition exercises. In addition, Section 6 introduces a multi-sector general equilibrium model to take into account the potential inter-regional shift of production and derive aggregate pollution outcomes due to the policies.

Table 5. Impact of environmental regulation on SO_2 pollution intensity (triple differences)

logSO_2int	(1)	(2)	(3)	(4)
log$Target \times FYP \times$ logSO_2	-0.026**	-0.006**	-0.028***	-0.006***
	(0.013)	(0.002)	(0.008)	(0.002)
log *sales*	-0.509***	-0.678***	-0.506***	-0.678***
	(0.008)	(0.009)	(0.007)	(0.008)
Observations	555,166	506,839	545,575	500,151
Adj. R-squared	0.541	0.838	0.711	0.845
Province-Year FE	✓			
Province-Industry FE	✓		✓	
Industry-Year FE	✓	✓	✓	✓
City-Year FE		✓		
City-Industry FE		✓		✓
Firm FE			✓	✓

Notes: Standard errors in parentheses, clustered at the province-industry level. * significant at 10%, ** significant at 5% , *** significant at 1%.

5 Decomposition

This section conducts the decomposition exercise of total pollution first at the industry-level following the notation of Levinson (2009). I then decompose pollution intensity at the firm-level in the spirit of Melitz and Polanec (2015), taking into consideration the entry and exit of firms.

5.1 Industry-level decomposition

The total manufacturing pollution Z can be written as:

$$Z = \sum_s z_s = \sum_s x_s e_s = X \sum_s \kappa_s e_s \tag{10}$$

where z_s is the pollution from each sector s, which equals the output x_s times the emission intensity e_s. $e_s = z_s/x_s$ is the pollution per unit of output. If each sector's share of total output is denoted as $\kappa_s = x_s/X$, Z equals the final term of equation (10). Put in vector forms:

$$Z = X\boldsymbol{\kappa}'\boldsymbol{e} \tag{11}$$

Totally differentiating equation (11) yields:

$$dZ = \underbrace{\boldsymbol{\kappa}'\boldsymbol{e}dX}_{\text{scale}} + \underbrace{X\boldsymbol{e}'d\boldsymbol{\kappa}}_{\text{composition}} + \underbrace{X\boldsymbol{\kappa}'d\boldsymbol{e}}_{\text{technique}} \tag{12}$$

The three terms on the right-hand-side of equation (12) represent the scale, composition and technique effects respectively. The scale effect reflects the change in total pollution due to the size of the manufacturing sectors, holding the sector composition and pollution intensity fixed. The composition effect accounts for the change in industry mix, keeping the total size of manufacturing sectors and pollution intensity constant. The technique effect captures the change in pollution intensity and represents the technical frontier of production, assuming the scale and composition are fixed. I then calculate these components according to equation (12), while the output is deflated with 2-digit industry-year specific indices from China Statistical

Yearbooks.[7,8] Both firm-level pollution and output are trimmed at 1% tails to remove outliers. The results are shown in Figure 5. The blue dashed line depicts what the total pollution level would look like relative to the year 1998 if the industry composition and technique remained the same and only the scale effect is at work. The red dashed line plots the hypothetical trend of pollution keeping the technique constant and let the scale and composition of industries change. The green solid line shows the actual change in total pollution by combining the scale, composition and technique effects. The scale effect increases pollution over the period. Adding the composition effect slightly reduces total pollution, but the trend closely follows that of scale effect alone, as in Cole and Zhang (2019) and Rodrigue et al. (2022a), whereas the technique effect greatly reduces pollution.[9]

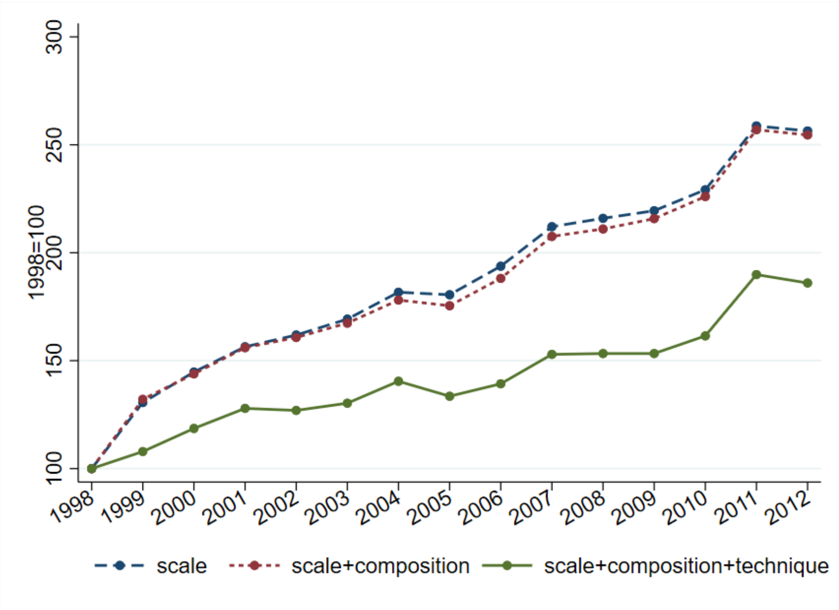


Figure 5. Industry-level SO_2 emission decomposition

The main difference between the components of Chinese and US pollution, as quantified by Shapiro and Walker (2018) is that the magnitude of China's pollution level relative to the baseline period is much higher than in the US. The sum of the three effects nearly doubled during 15 years in China while in the US the net pollution level decreased more than half over 20 years. The scale and composition effects are also different between China and the US, with China more than doubled and the US less than 40% growth.

One concern of the conventional industry-level decomposition in the literature is that heterogeneities in firm markups are not considered. To mitigate the bias of markups, I follow Rodrigue et al. (2022a) and use cost shares instead of revenue shares to aggregate emission intensities to

[7] The exact decomposition can be written as $\Delta Z_t = \Delta Z_t \sum_i \kappa_{it} e_{it} + Z_{t-1} \sum_i \Delta\kappa_{it} e_{it} + Z_{t-1} \sum_i \kappa_{i,t-1} \Delta e_{it}$. Another way is to write the scale and composition effects as $\Delta Z_t \sum_i \kappa_{it} e_{it}$ and $Z_t \sum_i \Delta\kappa_{it} e_{it}$, while the technique effect is the residual from ΔZ_t. Both the two methods of decomposition give similar results.

[8] The manufacturing industries begin with industry code 13-43, which are aggregated into 28 industries due to changes between different versions of classification.

[9] Cole and Zhang (2019) use yearbook statistics instead of firm-level aggregate data, while Rodrigue et al. (2022a) use pollution data matched with manufacturing survey, which reduces the number of firms by half. Fortunately, firm output information is readily available in the pollution data from EPS which allows me to use all firms to capture a full picture of manufacturing pollution in the decomposition. Decomposition at 4-digit industries with 4-digit deflators from Brandt et al. (2017) instead of decomposition at 2-digit industries gives similar results, see Figure A.6a. The composition effect is only positive when the revenues are not deflated and the decomposition is at 2-digit industries, see Figure A.6b. In either case, the magnitudes are similar.

the industry-level. To do this, I need to merge the pollution data with the production data, which reduces the pollution sample size by half. I use operating costs to compute cost shares and compare the decomposition with revenue shares. The results are summarized in Figure A.7. The dip around 2009 is because the production was reduced during the global financial crisis, which is reflected in the merged data. The decomposition using cost shares instead of revenue shares show slightly higher scale effect as well as the combination of scale and composition effects, but the overall trends remain close.[10]

5.2 Firm-level decomposition

Next, I decompose pollution intensity at the firm-level following the method of Melitz and Polanec (2015), taking into consideration the entry and exit of firms. The change in average emission intensity ι over time (from $t = 1$ to 2) can be decomposed into three groups of firms, namely, continuing (C), entering (E) and exiting (X) firms:

$$\begin{aligned} \iota_1 &= s_{C1}\iota_{C1} + s_{X1}\iota_{X1} \quad = \iota_{C1} + s_{X1}(\iota_{X1} - \iota_{C1}) = \bar{\iota}_{C1} + \text{cov}_{C1} + s_{X1}(\iota_{X1} - \iota_{C1}) \\ \iota_2 &= s_{C2}\iota_{C2} + s_{E2}\iota_{E2} \quad = \iota_{C2} + s_{E2}(\iota_{E2} - \iota_{C2}) = \bar{\iota}_{C2} + \text{cov}_{C2} + s_{E2}(\iota_{E2} - \iota_{C2}) \end{aligned} \tag{13}$$

The pollution intensity expressed in change $\Delta\iota$ is:

$$\begin{aligned} \Delta\iota &= (\iota_{C2} - \iota_{C1}) + s_{E2}(\iota_{E2} - \iota_{C2}) + s_{X1}(\iota_{C1} - \iota_{X1}) \\ &= \underbrace{\underbrace{\Delta\bar{\iota}_C}_{\text{within-firm}} + \underbrace{\Delta\text{cov}_C}_{\text{across-firm}}}_{\text{continuing firms}} + \underbrace{s_{E2}(\iota_{E2} - \iota_{C2})}_{\text{entering firms}} + \underbrace{s_{X1}(\iota_{C1} - \iota_{X1})}_{\text{exiting firms}} \end{aligned} \tag{14}$$

where $s_{Gt} = \sum_{i \in G} s_{it}$ represents the aggregate market share in revenue of firms in group G ($G \in \{C, E, X\}$) and $\iota_{Gt} = \sum_{i \in G}(s_{it}/s_{Gt})\iota_{it}$ is the group's weighted average emission intensity. Among continuing firms, the first term $\bar{\iota}_C = \frac{1}{n}\sum_{i=1}^{n} \iota_i$ is the unweighted mean firm emission intensity. The second term $\text{cov}_C = \sum_i (s_i - \bar{s})(\iota_i - \bar{\iota})$ is the covariance between revenue share and emission intensity, where $\bar{s} = 1/n$ is the mean market share within the subset of continuing firms. I take year 1998 as the initial period $t = 1$ and all the changes are relative to this baseline year.

Table B.16 reports the decomposition results in changes. The changes in firm pollution intensity are mainly because of within and across firm composition effects over the years (73% to 95%), while firm entry and exit account for much less. The decomposition outcome in pollution intensity levels is summarized in Table B.17. I then plot the decomposition results in Figure 6a. The green solid line represents the real pollution intensity levels when all firms are taken into account. The within-firm average scale effect is the upper dashed blue line, which drives up the emission intensity of Chinese manufacturing firms, though the within-firm effect declined over time. The dotted-dash red line includes both within and across firm effects, i.e., the pollution intensity levels of continuing firms. The result implies that cross-firm differences reduce the pollution intensity dramatically, which captures reallocation of market shares towards less pollution-intensive firms. The within-firm and across-firm effects combined is very close to the trend of all firms, which indicates that firm entry and exit contribute relatively less to the overall emission intensity. Figure 6b shows the effects of firm entry and exit in more details. I also conduct the firm-level decomposition by sector and then calculate sector averages of each component. The results are plotted in Figure A.8 and qualitatively similar.

[10] An alternative way is to follow Rodrigue et al. (2022a) and use intermediate inputs plus wage bills to represent costs. However, the data after 2007 are not available.

(a) Within and across continuing firms

(b) Entry and exit

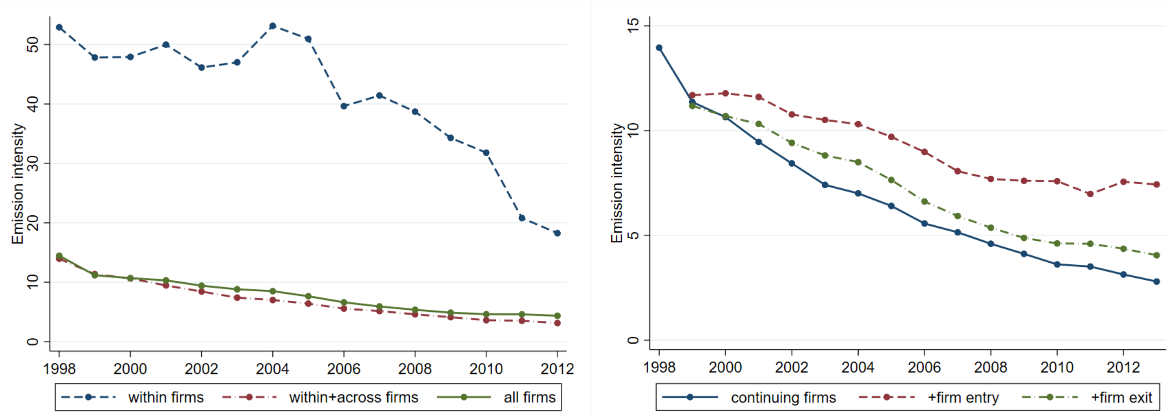


Figure 6. Firm-level SO_2 emission intensity decomposition

Another way to decompose emission intensity at the firm-level is proposed by Martin (2012). The details are in Appendix D. The decomposition results are consistent with the decompositions above in the sense that within-firm effect increases pollution intensity, and across-firm effect reduces pollution intensity, while across-industry effect of pollution emissions is relatively small.

The evidence from the regressions and decompositions show the following stylized facts: (i) Large firms pollute more but firms that import and export more are on average less pollution intensive. (ii) Firms in provinces with more stringent environmental regulations pollute less intensively. (iii) Higher TFP and foreign ownership help firms reduce pollution emission. (iv) Most pollution reduction is due to within-sector, across firm changes, rather than the composition of manufacturing industry structure. The next question is what are the mechanisms and magnitudes of trade, productivity and environmental regulation on pollution under general equilibrium? To answer it, I need a structural model with heterogeneous firms and variation across sectors over time in the following section.

6 A structural model of pollution emissions

I use a general equilibrium model from Shapiro and Walker (2018) to analyze pollution emission levels under various counterfactual conditions. I first introduce the setup of the model, and then estimate key parameters and recover historical values for counterfactuals. The model features firms that differ in productivity, and choose different pollution abatement costs. Labor is the only production factor and it is supplied inelastically. In addition to fixed and variable trade costs, firms also pay a pollution tax depending on their emissions. The model is static and hence it doesn't feature firm dynamics. The model takes bilateral export tariff costs to measure variable trade costs, so input tariffs are not part of the model, neither is foreign ownership. One can derive analytical solutions from the model to guide the counterfactual analysis.

6.1 Setup

6.1.1 Preferences

The representative consumer in destination country d has the following utility function:

$$U_d = \prod_s \left(\left[\sum_o \int_{\omega \in \Omega_{o,s}} q_{od,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right]^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\beta_{d,s}} \tag{15}$$

where utility across product varieties ω within a sector s is CES and Cobb-Douglas across sectors. $\Omega_{o,s}$ is the measure of goods from origin country o and each variety of good is denoted by ω. The parameter $\beta_{d,s}$ is country d's expenditure share on sector s which satisfies $\sum_s \beta_{d,s} = 1$. $q_{od,s}(\omega)$ is the quantity of goods and σ_s represents the elasticity of substitution across varieties in each sector.

Solving the representative agent's utility-maximization problem gives the demand for each variety $q_{od,s}$:

$$q_{od,s}(\omega) = \frac{(p_{od,s}(\omega))^{-\sigma_s}}{(P_{d,s})^{1-\sigma_s}} E_{d,s} \tag{16}$$

where the price index is:

$$P_{d,s} = \left[\sum_o \int_{\omega \in \Omega_{o,s}} p_{od,s}(\omega)^{1-\sigma_s} d\omega \right]^{\frac{1}{1-\sigma_s}} \tag{17}$$

and $E_{d,s} = \sum_o \int_{\omega \in \Omega_{o,s}} p_{od,s}(\omega) q_{od,s}(\omega) d\omega$ is national expenditure on sector s.

6.1.2 Firms and market structure

Firms in sector s pay a sunk entry cost $f^e_{o,s}$ to draw productivity φ from a given distribution and, conditional on operating, face fixed production costs $f_{od,s}$, which are specific to destination market d. Due to increasing returns to scale, each firm is the only producer of any variety and operates under monopolistic competition. In particular, a firm with productivity φ chooses its prices $p_{od,s}$ and emission abatement a to maximize the following profit function:

$$\pi_{o,s}(\varphi) = \sum_d \pi_{od,s}(\varphi) - w_o f^e_{o,s} \tag{18}$$

$$\pi_{od,s}(\varphi) = p_{od,s}(\varphi) q_{od,s}(\varphi) - w_o l_{od,s}(\varphi) \tau_{od,s} - t_{o,s} z_{od,s}(\varphi) \tau_{od,s} - w_d f_{od,s}$$

where $p_{od,s}(\varphi)$ is the price, w_o is the wage of labor $l_{od,s}(\varphi)$, $t_{o,s}$ represents pollution tax on pollution $z_{od,s}(\varphi)$ and $\tau_{od,s} \geq 1$ is the iceberg trade cost.

Assume productivity distribution is Pareto with cumulative distribution:

$$G(\varphi; b_{o,s}) = 1 - \left(\frac{\varphi}{b_{o,s}} \right)^{-\theta_s} \tag{19}$$

where $b_{o,s}$ is the location parameter which reflects the country-sector productivity, and θ_s is the shape parameter that describes the dispersion of productivity in sector s.

6.1.3 Production and pollution

Firms sell the number of units:

$$q_{od,s}(\varphi) = (1 - a_{od,s}(\varphi)) \varphi l_{od,s}(\varphi) \tag{20}$$

where $a_{od,s}$ is the abatement investment. A fraction $a_{od,s}$ of input is used to abate pollution and the remaining $1 - a_{od,s}$ is used to produce output.

Firms produce pollution emission:

$$z_{od,s}(\varphi) = (1 - a_{od,s}(\varphi))^{\frac{1}{\alpha_s}} \varphi l_{od,s}(\varphi) \tag{21}$$

where α_s is the pollution elasticity by sector. This equation shows that pollution is decreasing in abatement and increasing in output which is adopted by Copeland and Taylor (2003).

Combing equations (20) and (21), I can write output as a Cobb-Douglas function of pollution emissions and productive factors:

$$q_{od,s} = (z_{od,s})^{\alpha_s} (\varphi l_{od,s})^{1-\alpha_s} \tag{22}$$

where α_s is the Cobb-Douglas share of pollution emissions.

6.1.4 Intermediate results

Firms: Firms choose prices $p_{od,s}$ and abatement cost $a_{od,s}$ to maximize profits. The first-order condition for $a_{od,s}$ gives:

$$1 - a_{od,s} = \left(\frac{w_o}{\varphi t_{o,s}} \frac{\alpha_s}{1-\alpha_s} \right)^{\alpha_s} \tag{23}$$

The first-order condition for $p_{od,s}$ gives:

$$p_{od,s}(\varphi) = \frac{\sigma_s}{\sigma_s - 1} \frac{c_{o,s}\tau_{od,s}}{\varphi^{1-\alpha_s}} \tag{24}$$

where

$$c_{o,s} = \frac{(t_{o,s})^{\alpha_s}(w_o)^{1-\alpha_s}}{(\alpha_s)^{\alpha_s}(1-\alpha_s)^{1-\alpha_s}}$$

Thus the firm profits can be expressed as:

$$\pi_{od,s}(\varphi) = \frac{r_{od,s}(\varphi)}{\sigma_s} - w_d f_{od,s} \tag{25}$$

where $r_{od,s}(\varphi) = p_{od,s}(\varphi) q_{od,s}(\varphi)$ is firm revenue.

Cutoff productivity: Let $\varphi^*_{od,s}$ denote the cutoff productivity which makes a firm earn zero profits from selling in market d. Therefore, $\pi_{od,s}(\varphi^*_{od,s}) = 0$. Combining demand (16) and profit (25) implies:

$$w_d f_{od,s} = \frac{1}{\sigma_s} \frac{p_{od,s}(\varphi^*_{od,s})^{1-\sigma_s}}{P_{d,s}^{(1-\sigma_s)}} E_{d,s}$$

Substituting price (24) and then solving for $\varphi^*_{od,s}$ gives:

$$\varphi^*_{od,s} = \left[\frac{\sigma_s}{\sigma_s - 1} \frac{c_{o,s}\tau_{od,s}}{P_{d,s}} \left(\frac{\sigma_s w_d f_{od,s}}{E_{d,s}} \right)^{\frac{1}{\sigma_s - 1}} \right]^{\frac{1}{1-\alpha_s}} \tag{26}$$

Free entry: The equilibrium fixed entry cost should equal the expected profit from drawing a productivity:

$$w_o f^e_{o,s} = (1 - G(\varphi^*_{oo,s}))\, \mathbb{E}(\pi | \varphi > \varphi^*_{oo,s})$$

In addition, the conditional density of the Pareto distribution is :

$$g(\varphi | \varphi > \varphi^*_{od,s}) = g(\varphi)/(1 - G(\varphi^*_{od,s})) = \theta_s \frac{(\varphi^*_{od,s})^{\theta_s}}{\varphi^{\theta_s + 1}} \tag{27}$$

Substituting price (24), profit (25), the cutoff productivity (26) and the Pareto conditional density (27) yields that the zero profit productivity $\varphi^*_{oo,s}$ from producing domestically satisfies:

$$f^e_{o,s} \frac{\theta_s - (\sigma_s - 1)(1-\alpha_s)}{(\sigma_s - 1)(1-\alpha_s)} = \sum_d \frac{(b_{o,s})^{\theta_s}}{(\varphi^*_{oo,s})^{\theta_s}} \frac{w_d}{w_o} f_{od,s}$$

These results will be used later to derive conclusions in comparative statics.

6.1.5 Competitive equilibrium

There are two conditions for a competitive equilibrium. The first condition is on labor market clearing, where labor supply L_o must equal labor demand in each country:

$$L_o = L_o^e + L_o^p + L_o^t + L_o^m + L_o^{nx} \tag{28}$$

where labor demand includes sunk cost to draw a productivity L_o^e, pollution abatement cost L_o^p, paying pollution taxes L_o^t, market entry cost L_o^m and net export cost L_o^{nx}.

The second condition is that the expected profit must equal the fixed cost of drawing a productivity:

$$\frac{1-\alpha_s}{\theta_s}\frac{\sigma_s - 1}{\sigma_s}R_{o,s} = w_o f_{o,s}^e M_{o,s}^e \tag{29}$$

where $M_{o,s}^e$ measures attempted entrants, which is the mass of entrepreneurs drawing a productivity. $R_{o,s}$ is national revenue from sector s.

6.1.6 Comparative statics

Before carrying out the quantitative analysis, it is useful to explore the effects of pollution taxes, productivity and trade liberalization analytically to better understand the implications of the model. The proof is detailed in Appendix E.

PROPOSITION 1:

At the firm-level, pollution intensity is locally decreasing in productivity.

Analytically,

$$\frac{\partial i_{o,s}(\varphi)}{\partial \varphi} = (\alpha_s - 1)\frac{i_{o,s}(\varphi)}{\varphi} < 0$$

where $i_{o,s}(\varphi) = \sum_j z_{oj,s}(\varphi)/\sum_j q_{oj,s}(\varphi)$ is the pollution intensity of a firm with productivity φ.

The reason is that firms with higher productivity invest more in pollution abatement to maximize profit, as shown in the first-order condition (23).

PROPOSITION 2:

At the sector level, pollution intensity is locally decreasing in pollution taxes, in productivity and in trade liberalization.

Analytically,

$$\frac{\partial I_{o,s}}{\partial t_{o,s}} = \frac{I_{o,s}}{t_{o,s}}(\alpha_s \lambda_{oo,s} - 1) < 0, \quad \frac{\partial I_{o,s}}{\partial b_{o,s}} = -(1-\alpha_s)\frac{I_{o,s}}{b_{o,s}}\lambda_{oo,s} < 0, \quad \frac{\partial I_{o,s}}{\partial \tau_{do,s}} = \frac{I_{o,s}}{\tau_{do,s}}\lambda_{do,s} > 0.$$

where $I_{o,s} = Z_{o,s}P_{o,s}/R_{o,s}$ is the pollution intensity of a sector, and $\lambda_{od,s}$ is country d's expenditure share in sector s purchased from country o.

The intuition is that pollution tax makes firms invest more on pollution abatement as shown in (23). Productivity increases the output, thereby decreasing pollution intensity. Lower trade cost allows a sector to emit less pollution in order to obtain the same output. The reallocation effect of trade also shifts market share towards more productive firms that have lower pollution intensity.

To gauge the magnitude of contribution through each channel to the total pollution emissions level, I then move on to the quantitative counterfactual analysis.

6.1.7 Method of counterfactual analysis

To analyze counterfactuals, I use the hat algebra following Dekle et al. (2008) and rewrite each variable as a proportional change from a baseline year. The benefit of this method is that unchanged variables that are difficult to measure will be canceled out and do not appear in changes so that there is no need to worry about their exact values. Formally, let x denote a variable from the model, x' denotes the variable under a counterfactual scenario, the proportional change in the variable due to the counterfactual is $\hat{x} = x'/x$. China is considered the home country while the rest of world is considered as foreign. The equilibrium conditions (28) and (29) expressed in changes are as follows[11]:

$$1 = \psi_o \left(\frac{\sum_s \hat{M}^e_{o,s} R_{o,s} \frac{(\sigma_s - 1)(\theta_s - \alpha_s + 1)}{\sigma_s \theta_s} + \eta'_o}{\sum_s R_{o,s} \frac{(\sigma_s - 1)(\theta_s - \alpha_s + 1)}{\sigma_s \theta_s} + \eta_o} \right) \tag{30}$$

$$\hat{w}_o = \sum_d \frac{\zeta_{od,s} \hat{w}_o^{-\theta_s} \hat{\Gamma}_{od,s}}{\sum_o \lambda_{od,s} \hat{M}^e_{o,s} \hat{w}_o^{-\theta_s} \hat{\Gamma}_{od,s}} \hat{\beta}_{d,s} \frac{R'_d - NX'_d}{R_d - NX_d} \tag{31}$$

where firm entry $\hat{M}^e_{o,s}$ and nominal wage $\hat{w}_o$ are endogenous variables to be solved. The other variables can be obtained from the data. $\hat{\beta}_{d,s}$ is the Cobb-Douglas expenditure share, $\hat{\Gamma}_{od,s}$ is a market competitiveness measure detailed in Section 6.3, which contains the implicit pollution tax $\hat{t}_{o,s}$. $R_{o,s}$ is national revenue from sector s, and $\lambda_{od,s}$ is the share of country d's expenditure in sector s going to country o. $\zeta_{od,s} = X_{od,s}/\sum_d X_{od,s}$ is export share, and NX represents net exports (exports minus imports). σ_s, θ_s and α_s are parameters to be estimated in Section 6.2. ψ_o and η_o are parameter combinations.

From the two conditions I can solve a set of non-linear equations for each year and obtain the wages $\hat{w}_o$ and firm entry decisions $\hat{M}^e_{o,s}$ that characterize each counterfactual. The system has $2s+1$ equations and $2s+1$ unknowns so it is just-identified.

Each sector's pollution emissions in country o between a baseline year and a counterfactual is:

$$\hat{Z}_{o,s} = \frac{\hat{M}^e_{o,s} \hat{w}_o}{\hat{t_{o,s}}} \tag{32}$$

where $\hat{M}^e_{o,s}$ and $\hat{w}_o$ are endogenous variables that depend on changes in foreign and domestic market competitiveness, expenditure shares and pollution tax $\{\hat{\Gamma}_{od,s}, \hat{\beta}_{d,s}, \hat{t}_{o,s}\}$.

6.2 Parameter estimates

There are three sets of parameters to estimate in order to run the model, namely, the pollution elasticity α_s, the elasticity of substitution σ_s and the Pareto shape parameter θ_s for each sector s.

6.2.1 Pollution elasticity

The pollution elasticity is estimated in Shapiro and Walker (2018) by regressing pollution intensity on abatement investment. They then instrument changes in abatement cost share with changes in local environmental regulation stringency. However, it is not feasible with the Chinese data due to lack of precise abatement cost information and prefecture-level regulation stringency is neither readily available nor comprehensive.[12] Therefore, I estimate equation (22) instead:

$$q_{od,s} = (z_{od,s})^{\alpha_s} (\varphi l_{od,s})^{1-\alpha_s}$$

where the pollution elasticity α_s is the Cobb-Douglas share for pollution emissions. The firm productivity φ is the total factor productivity (TFP) following Levinsohn and Petrin (2003),

[11] I refer readers to the appendix of Shapiro and Walker (2018) for more details on the derivations.

[12] Rodrigue et al. (2022b) instead measures emission output abatement rather than abatement cost, and their measure is also endogenous.

with Ackerberg et al. (2015) correction.[13] The deflators come from China Statistical Yearbooks. I then rewrite the equation into the following econometric specification:

$$\ln q_{it} = \alpha \ln z_{it} + (1-\alpha)\ln(\varphi l_{it}) + \nu_t + \nu_c + \nu_s + \epsilon_{it} \tag{33}$$

where the pollution elasticity α_s is the estimated average coefficient of pollution emission z_{it} for all manufacturing firms, q_{it} and l_{it} are output and labor employment of firm i respectively, and φ is TFP.[14] The year, city and 4-digit industry fixed effects are also controlled. Once the average α is obtained, the industry-specific pollution elasticities at the 2-digit level are calculated using the pollution per unit cost of each industry as weights (Shapiro and Walker, 2018), where the weights are listed in column (1) of Table 6. The estimated pollution elasticity for each 2-digit sector s are listed in column (2) of Table 6. The mean pollution elasticity is 0.019, compared to 0.011 in Shapiro and Walker (2018). The industry with the lowest pollution elasticity is "Manufacture of communication equipment, computers and other electronic equipment" (α=0.0007), while the industry with the highest pollution elasticity is "Manufacture of non-metallic mineral products" (α=0.0789). In Shapiro and Walker (2018), the industry with the lowest pollution elasticity is "Radio, television, communication" (α=0.0005), and the industry with the highest pollution elasticity is "Basic metals" (α=0.0557). These industries are closely comparable.

Alternatively, I can estimate the production function taking into consideration labor, capital, materials, energy input and pollution emission together to simultaneously obtain the pollution elasticity and productivity, the result is an estimated average pollution elasticity $\alpha = 0.021$, which is very close to the baseline estimation of 0.019. Using 4-digit industry deflators from Brandt et al. (2017) gives the estimated average pollution elasticity 0.017, and 0.020 with the joint estimate, which are also close to the baseline estimate. In addition to the baseline SO_2 pollution elasticity, I also estimated the pollution elasticities of other pollutants as reported in Table B.18, where the magnitude ranges from 0.009 to 0.035.

The overall estimate of pollution elasticity implies that firms pay around two percent of their annual costs on pollution abatement. Though detailed firm-level data are not available to check this, I can compare with some related statistics. According to China Environmental Statistical Yearbooks, the average pollution abatement investment as a percentage of GDP of each province is 1.6 percentage, which is of similar magnitude to the estimate. Though this may seem large, it is of the same order of magnitude compared to the US. For example, Shapiro and Walker (2018) show that according to the Pollution Abatement Costs and Expenditures (PACE) survey, pollution abatement costs of manufacturing industries account for about 0.5% of total manufacturing sales.

An alternative way to check the accuracy of the estimation of α_s is to retrieve the abatement cost $a_{od,s}$ by combining equations (20) and (21) to get $\frac{z_{od,s}}{q_{od,s}} = (1-a)^{(1-\alpha_s)/\alpha_s}$ and compare to the data. I use industrial waste gas abatement cost as a proxy for SO_2 abatement cost since SO_2 is a major component of waste gas. Figure A.9 compares the abatement cost in industrial waste gas summed by province according to China Environmental Statistical Yearbooks and the abatement cost implied by the model. The trends are very similar between data and model.

[13] Specifically, the TFP is measured by the log output minus a weighted sum of log labor, capital, materials and energy input: $TFP_{it} = y_{it} - \alpha_l l_{it} - \alpha_k k_{it} - \alpha_m m_{it} - \alpha_e e_{it}$. The output is deflated with 2-digit industry-specific producer price index, the capital is deflated with provincial fixed assets investment price index, the materials are deflated with annual purchasing price index, and the energy input is measured by industrial coal consumption. Coal is the major source of energy for manufacturing industries in China. Coal consumption takes up 71% of total manufacturing energy consumption in 2012 according to the EPS database. All price indices are collected from China Statistical Yearbooks.

[14] Physical output $q_{od,s}$ is proxied with revenue, deflated by 2-digit industry-specific output price deflators from China Statistical Yearbooks.

Table 6. Parameter estimates

CIC sector		Pollution per unit cost (g/yuan)	Pollution elasticity (α)	Input share	Elasticity of substitution (σ)	Pareto shape parameter (θ)
Code	Name	(1)	(2)	(3)	(4)	(5)
13	Processing of food	0.88	0.0114	0.89	10.01	14.06
14	Manufacture of food	0.99	0.0128	0.76	4.31	5.51
15	Manufacture of beverages	1.09	0.0141	0.63	2.77	2.73
16	Manufacture of tobacco	0.29	0.0038	0.45	1.81	1.41
17	Manufacture of textile	0.81	0.0104	0.85	7.02	10.87
18	Manufacture of textile wearing apparel, footware, and caps	0.32	0.0042	0.79	4.84	5.56
19	Manufacture of leather, fur, feather and related products	0.16	0.0021	0.87	8.04	12.12
20	Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products	1.47	0.0189	0.89	10.57	13.38
21	Manufacture of furniture	0.25	0.0032	0.77	4.38	9.37
22	Manufacture of paper and paper products	4.03	0.0520	0.83	8.13	10.17
23	Printing, reproduction of recording media	0.21	0.0027	0.78	4.54	5.56
24	Manufacture of articles for culture, education and sport activities	0.14	0.0018	0.85	6.57	13.19
25	Processing of petroleum, coking and nuclear fuel	0.90	0.0116	0.90	11.18	11.20
26	Manufacture of raw chemical materials and chemical products	2.40	0.0310	0.80	5.68	6.94
27	Manufacture of medicines	0.97	0.0125	0.57	2.37	2.35
28	Manufacture of chemical fibers	1.55	0.0200	0.83	6.57	7.00
29	Manufacture of rubber and plastics	0.92	0.0119	0.82	5.79	7.64
30	Manufacture of non-metallic mineral products	6.11	0.0789	0.76	5.82	8.28
31	Smelting and pressing of ferrous metals	2.54	0.0328	0.87	10.43	10.93
32	Smelting and pressing of non-ferrous metals	4.75	0.0614	0.82	7.73	7.94
33	Manufacture of metal products	0.27	0.0035	0.83	5.92	6.84
34	Manufacture of general purpose machinery	0.31	0.0039	0.78	4.51	4.83
35	Manufacture of special purpose machinery	0.56	0.0072	0.79	4.88	6.14
36	Manufacture of transport equipment	0.21	0.0027	0.81	5.32	4.81
38	Manufacture of electrical machinery and equipment	0.13	0.0016	0.78	4.57	4.83
39	Manufacture of communication equipment, computers and other electronic equipment	0.05	0.0007	0.82	5.58	5.64
40	Manufacture of measuring instruments and machinery for cultural activity and office work	0.14	0.0018	0.80	5.07	5.18
41	Manufacture of artwork and other manufacturing	0.49	0.0063	0.81	5.54	5.87
	Mean	1.18	0.019	0.79	6.07	7.51

One assumption of the model is that firms spend a fraction a if input on pollution abatement, while the remaining $1-a$ is used on production. The higher is the pollution abatement cost a, the more emission should be reduced. The EPS data provide information on the pollution generated by each firm, the emission reduction, and the final emission. Although this information is not directly on the cost of emission abatement, as suggested by Rodrigue et al. (2022b), one can measure the level of outcome on emission abatement using the difference between the emission generated and the emission reduction. Figure A.10 shows the correlation between the emission reduction share and abatement cost share by industry across time on the left, and the levels of emission reduction (ton kg) with abatement cost (billion yuan) on the right. In any case, the emission reduction and the abatement cost are positively correlated, which supports the implication of the model. The results remain robust with firm-level regressions in Table B.19.

6.2.2 The elasticity of substitution

Next, I calibrate the elasticity of substitution σ_s using the following equation:

$$w_o L^p_{o,s} = (1-\alpha_s)\frac{\sigma_s - 1}{\sigma_s} R_{o,s} \tag{34}$$

where w_o is the nominal wage of the origin country, $L^p_{o,s}$ is the labor used in production. The product of the two $w_o L^p_{o,s}$ represents firm costs. α_s is the pollution elasticity estimated above, and $R_{o,s}$ is sector revenue. The elasticity of substitution σ_s is estimated separately for each 2-digit industry as follows:

$$\sigma_s = (1-\alpha_s)/(1-\alpha_s - w_o L^p_{o,s}/R_{o,s}) \tag{35}$$

where $w_o L^p_{o,s}/R_{o,s}$ is the sector input share reported in column (3) of Table 6. The approach to estimate the elasticity of substitution is built on Hsieh and Ossa (2016) and Antràs et al. (2017) and the estimates are plausible as they are similar to previous findings.[15] I use the information provided by the Annual Survey of Industrial Firms (ASIF) to estimate this set of parameters and the results are listed in column (4) of Table 6. The sector with the largest elasticity of substitution is Processing of petroleum, coking, and nuclear fuel (11.18), which has more homogeneous products and the sector with the smallest elasticity of substitution is Manufacture of tobacco (1.81) followed by Manufacture of medicines (2.37), which have relatively more differentiated products. The industries are comparable to the estimates in Shapiro and Walker (2018).[16]

6.2.3 The Pareto shape parameter

Finally I estimate the Pareto shape parameter according to the Pareto tail cumulative distribution function $\Pr\{x > X_{i,s}\} = (b_{i,s}/X_{i,s})^{\theta_s/(\sigma_s-1)}$ for $X_{i,s} \geq b_{i,s}$. Taking logs gives:

$$\ln(Pr\{x > X_{i,s}\}) = \gamma_{0,s} + \gamma_{1,s}\ln(X_{i,s}) + \epsilon_{i,s} \tag{36}$$

where $X_{i,s}$ represents sales. I estimate the coefficient $\gamma_{1,s}$ and the Pareto shape parameter is in turn given by $\theta_s = \gamma_{1,s}(1-\sigma_s)$. Only firms above the 90th percentile of sales within each

[15] Antràs et al. (2017) estimate the elasticity of 3.85 for the US, while Hsieh and Ossa (2016) estimate the median elasticity of 6.1 for China. The cross-sector mean estimate of 6.07 falls within this range. Alternative estimates using China's trade data with the Soderbery (2015) method developed on Feenstra (1994) and Broda and Weinstein (2006) give the mean elasticity of 5.72, which is also close to the baseline estimates. I will later use the alternative elasticity of substitution σ independent of the pollution elasticity α to substitute the baseline parameters in the counterfactual section and show that the results are qualitatively robust.

[16] In Shapiro and Walker (2018) the elasticity of substitution is highest for Coke refined petroleum, and nuclear fuels sector (8.18), while the elasticity of substitution is smallest for Medical, precision, and optical products sector (2.89), with a cross-sector mean of 4.76.

sector are used because the Pareto distribution best fits the right tail of the firm distribution. The results are in column (5) of Table 6. The estimates support the assumption of the model that $\theta_s > (\sigma_s - 1)(1 - \alpha_s)$.

6.3 Recovering historical values of key variables

There are three main components in the model that may generate counterfactual pollution emission outcomes if they were not taken at their actual historical values. The components are environmental regulation, expenditure shares, and market competitiveness of home and foreign. Next I recover the historical values of these variables to prepare for the counterfactual analysis.

6.3.1 The environmental regulation

The first set of historical values to recover is the environmental regulation measured by model-implied pollution tax, which is indicative on its own. It is useful to clarify that the pollution tax is an exogenous variable in the model. Since there is not a clear mapping between actual policies and this variable, I need to retrieve it from the behavior of other endogenous variables that react to the tax. One of the equations pinning down general equilibrium delivers an expression that can be easily quantified using the available data. The pollution tax is measured by the following equation:[17]

$$\hat{t}_{o,s} = \frac{\hat{M}^e_{o,s}\hat{w}_o}{\hat{Z}_{o,s}} \tag{37}$$

The implicit pollution tax is $\hat{t}_{o,s}$ and $\hat{Z}_{o,s}$ is the change in pollution of origin country o in sector s. $\hat{M}^e_{o,s}$ and $\hat{w}_o$ are changes in firm entry and factor prices, respectively. The pollution tax implied by the model is determined by the change in the mass of firm entry, factor price and pollution emission, which reflects the overall level of regulation on SO_2. Equation (37) contrasts the technique effect from the sector-level decomposition exercise, which is the change in pollution per unit of *real* output within sector $\hat{Z}_{o,s}/(\hat{R}_{o,s}/\hat{P}_{o,s})$. In other words, the decomposition exercise does not consider the price index, which may be influenced by trade, productivity, and environmental regulations. The recovered trend is shown in Figure 7.

The dirty industries are those with pollution elasticity above the sector mean and the clean industries are below the mean pollution elasticity.[18] The two groups of industries are weighted by baseline industry revenue. The figure retrieved from the model uses revenue data from the World Input-Output Tables (WIOT). I also plot the implied pollution tax for other pollutants in Figure A.11 and it seems that the implicit pollution taxes for the other pollutants are also relatively high and the magnitude does not necessarily increase with mean pollution elasticity α.

There is not a direct pollution tax for firms since local governments may implement policies at different times and with various reduction details. One can think of the pollution tax as a measure of shadow price of pollution. According to the State Council, SO_2 pollution charges were to be doubled within three years since 2007, from 0.63 yuan per kg to 1.26 yuan per kg. Figure 7 reflects the change in pollution tax with similar magnitudes, especially for dirty industries, which is reassuring that the model-implied measure of pollution tax is not far from the goal of the policy.

Alternatively, I can divide implicit pollution tax into high regulation provinces and low regulation provinces. The province regulation level is measured by change in SO_2 emission

[17] Equation (23) of Shapiro and Walker (2018), where the derivation can be found in their appendix.

[18] The dirty industries include Manufacture of paper and paper products, Processing of petroleum, coking and nuclear fuel, Manufacture of raw chemical materials and chemical products, Manufacture of chemical fibers, Manufacture of non-metallic mineral products, Smelting and pressing of ferrous metals, and Smelting and pressing of non-ferrous metals. The rest are relatively clean industries.

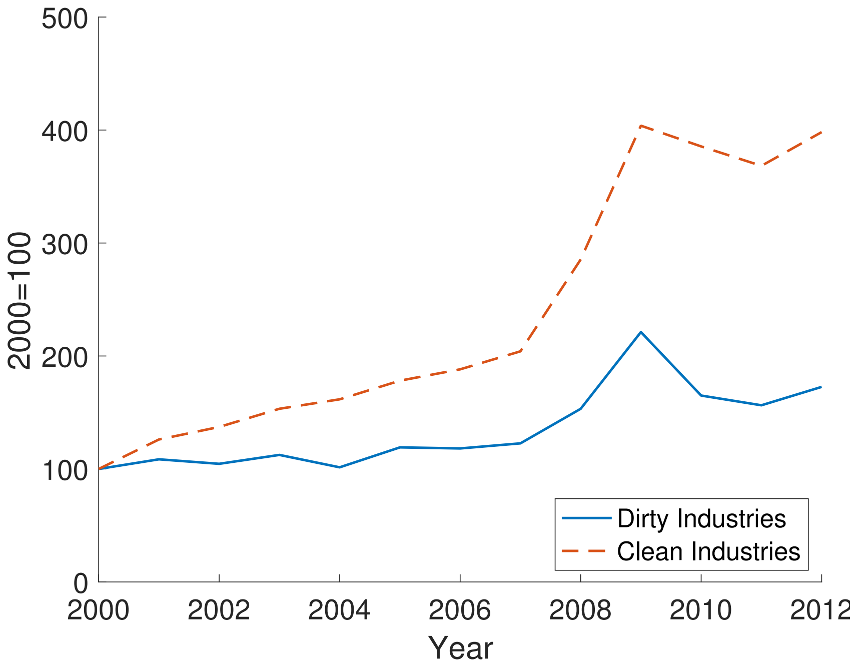


Figure 7. Implicit pollution tax of SO_2 (model-implied)

Note: Dirty industries have pollution elasticity α_s above average, while clean industries are below average, weighted by baseline output of each industry.

divided by change in output before and after the 11$^{\text{th}}$ Five-Year Plan between 2005 and 2010. Provinces with high regulation are below the average value and provinces with low regulation are above average.[19] The province pollution tax is obtained by using the implicit pollution tax by industry from the model and take industry output share in the initial year as weights. The results are plotted in Figure A.12. High regulation provinces face higher level of implicit pollution tax compared to low regulation provinces and the gap slowly widened over the sample period.

6.3.2 Expenditure share

The second set of historical values to recover is expenditure share. The equation to derive expenditure shares is as follows:

$$\hat{\beta}^*_{d,s} = \frac{\sum_o X'_{od,s} / \sum_{o,s} X'_{od,s}}{\sum_o X_{od,s} / \sum_{o,s} X_{od,s}} \tag{38}$$

which is the sectoral expenditure share of a country's expenditure on sector s in a counterfactual, divided by the baseline year value. Here I use data from the WIOT and convert the ISIC Revision 4 sectors to CIC 2017 2-digit industries. Whenever there are multiple sectors with the CIC 2017 codes linked to the same ISIC Revision 4 sector, I assign equal weights to the number of sectors linked. The retrieved values are shown in Figure 8. The definition of dirty and clean industries are the same as above, where dirty industries have above average pollution elasticities and clean industries below average. The two groups are aggregated using unweighted mean. The rest of the world apart from China is aggregated into Foreign as one destination. In both panels, the change in dirty industries are higher in general than clean industries. There are drops in expenditure shares of dirty industries after the 2008 financial crisis and increases in expenditure shares of clean industries.

[19]Provinces with low regulation include Hebei, Shanxi, Liaoning, Shandong, Henan, Guangxi, Chongqing, Sichuan, Guizhou, Shaanxi, and Ningxia. The rest are with relatively high regulation.

6.3.3 Market competitiveness

The third group of historical values to recover are foreign and Chinese market competitiveness. Here, Chinese "competitiveness" refers to the ability of Chinese firms to sell to the international market a wide range of varieties at relatively lower prices, and vice versa for foreign competitiveness. Mainly, competitiveness combines productivity, environmental regulation and trade costs for both foreign and domestic countries. Here foreign competitiveness is taken as a single variable because it does not provide further explanations to domestic pollution, and I also lack the data on each single component of foreign competitiveness. The expressions are:

$$\hat{\Gamma}_{od,s} = (1/\hat{b}_{o,s})^{-\theta_s}(\hat{\tau}_{od,s})^{-\theta_s/(1-\alpha_s)}(\hat{f}_{od,s})^{1-\theta_s/(\sigma_s-1)(1-\alpha_s)}(\hat{t}_{o,s})^{-\alpha_s\theta_s/(1-\alpha_s)} \tag{39}$$

$$= \frac{\hat{\lambda}_{od,s}}{\hat{M}^e_{o,s}\hat{w}_o^{-\theta_s}}, \ o \neq \text{China} \tag{40}$$

$$\hat{\Gamma}_{od,s} = (1/\hat{b}_{o,s})^{-\theta_s}(\hat{\tau}_{od,s})^{-\theta_s/(1-\alpha_s)}(\hat{f}_{od,s})^{1-\theta_s/(\sigma_s-1)(1-\alpha_s)} \tag{41}$$

$$= \hat{t}_{o,s}^{\frac{\alpha_s\theta_s}{1-\alpha_s}} \frac{\hat{\lambda}_{od,s}}{\hat{M}^e_{o,s}\hat{w}_o^{-\theta_s}}, \ o = \text{China} \tag{42}$$

where the endogenous variables are nominal wage $\hat{w}_o$, and firm entry $\hat{M}^e_{o,s}$. $\hat{\lambda}_{od,s}$ is the share of country d's expenditure on sector s that is purchased from country o.

The historical values of the Foreign and Chinese wages, firm entry and market competitiveness in changes are shown in Figure 8. The wage data are retrieved from the model. The nominal wages for countries outside of China dropped gradually after 2000 to reach a level of 80% its initial value. In contrast, the nominal wages for China increased to over 300% of their level in 2000.

To compare the foreign wages in the cases of China and the US, Shapiro and Walker (2018) report that the US nominal wage in 2008 from the model is around 70% of the 2000 level, while the wage in the rest of world grew by less than 20%. In the case of China, the US account for a large weight of the foreign wages, which corresponds to the model-implied mild decline in foreign wages. The rapid wage increase of China contributes to the wage growth of the rest of world in the US case.

To verify the Chinese wage changes solved from the model, I compare the results to wage data from other sources. One source of the Chinese wages is the average wage bill from financial accounts of industrial firms in the EPS database, weighted by the annual firm employment. Figure A.13 shows that by the end of 2012, the average wage was over 250% of the 2000 level. The caveat is that the data from 2008 to 2010 are missing, and many firms did not report their payroll information. Another source of the Chinese wage data is the Urban Household Survey (UHS) conducted by the National Bureau of Statistics (NBS), where the manufacturing workers in urban areas were asked about their earnings. Figure A.13 plots the trend, which shows that manufacturing wages increased to over 450% of the 2000 level. The alternative sources of Chinese industrial wages are not perfect substitutes of the retrieved values from the model, however, they offer a reasonable range where the endogenous values lie in between.

The firm entry effects reflect the changes in expenditure shares. Both China and Foreign witnessed a slight drop at the beginning of the 21st century and then grew rapidly until 2008 when the global financial crisis hit and firm entry dropped sharply before recovering. However, clean industries in China seem to be less affected by the crisis since they experienced a much milder shock.

The equivalent of firm mass in the data can be the relative number of firms by industry across time. Figure **??** plots the correlation between the two measures and shows that they are positively correlated. One caveat is that the firms from the EPS data are relatively large firms above certain threshold and are not the universe of firms. So the map to firm mass from the model may not be exact. However, they are positively correlated, which reflects that the model captures the variances across industry and time.

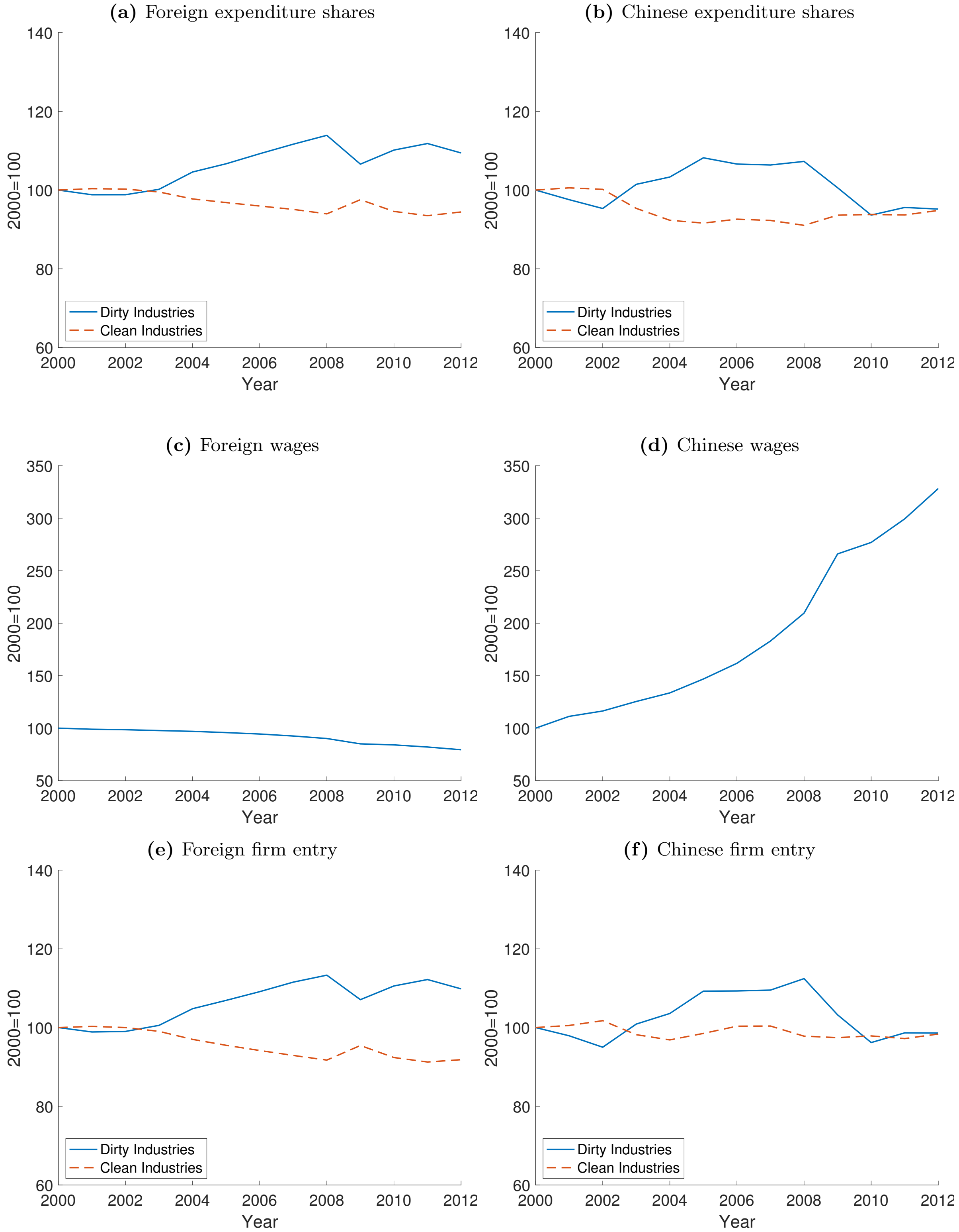


Figure 8. Historic values

Note: Dirty industries have pollution elasticity α_s above average, while clean industries are below average, unweighted mean.

7 Counterfactuals

In this section, I run counterfactual analysis on what the pollution emission would look like if I take the trade, pollution emissions and production from the initial year 2000 and add the historical values of foreign and domestic competitiveness, environmental regulation and expenditure shares $\{\hat{\Gamma}^{*}_{od,s}, \hat{t}^{*}_{o,s}, \hat{\beta}^{*}_{o,s}\}$ one at a time, keeping the other components at their 2000 values. The purpose of the exercise is to disentangle the contribution of each channel to the total level of SO_2 pollution emissions in a general equilibrium framework.

The baseline counterfactual results are plotted in Figure 9. The blue solid line represents the actual data when all variables follow their historical values. The red dashed lines represent the contribution of Foreign competitiveness, Chinese competitiveness, Chinese regulation and Chinese expenditure share respectively, keeping the other variables at their initial levels in year 2000. The figure shows that Chinese competitiveness would greatly increase total SO_2 pollution emission level, while Chinese regulation would drive down emissions by more than 50%. In contrast, foreign competitiveness and Chinese expenditure share do not seem to affect the pollution levels by much.

7.1 Baseline results

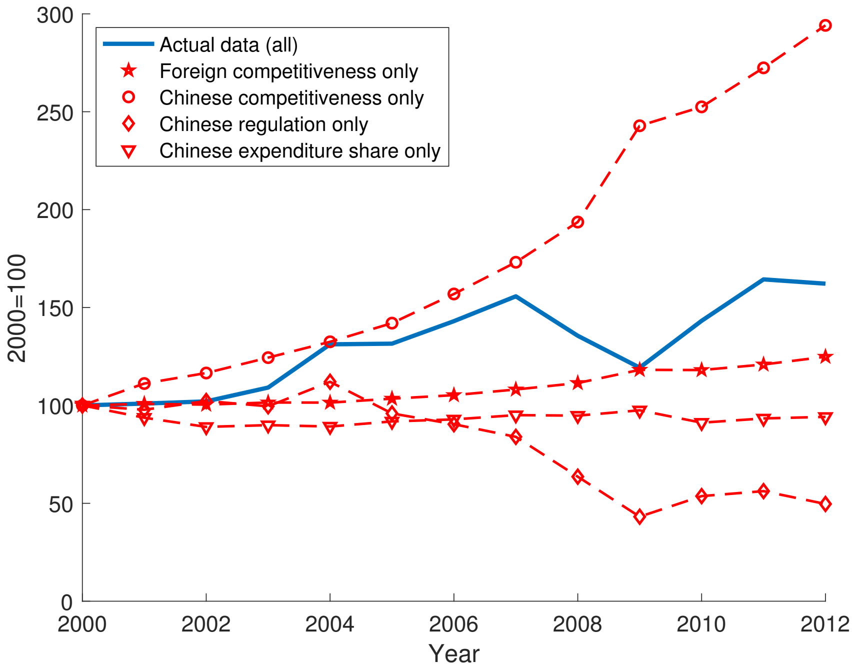


Figure 9. Counterfactual Chinese manufacturing pollution emissions

In addition to the baseline counterfactual results, I extend the exercises of Shapiro and Walker (2018) and further decompose the Chinese competitiveness according to equation (41) into sector productivity measured by the Pareto location parameter $\hat{b}_{o,s}$, and export tariff $\hat{\tau}_{od,s}$ which is the variable cost of trade. The remaining part of the Chinese competitiveness is the fixed entry cost $\hat{f}_{o,s}$, which is the residual and hard to measure directly. Therefore, I do not look at the counterfactual with respect to fixed entry cost. In this way, one can further disentangle the role of the sub-components of Chinese competitiveness in pollution level. This would also link the model to the regression analysis and allow me to check the pollution response to policy interventions.

The Pareto location parameter $b_{o,s}$ can be obtained along with the estimation of the Pareto shape parameter θ_s.[20] I use effective applied (AHS) simple average export tariff data for China from the World Bank's WITS dataset at 4-digit ISIC Revision 3 level and convert to CIC 2-digit level to account for tariff $\tau_{od,s}$. The retrieved historical values of the additional set of variables are shown in the Figure A.15.[21] I can then look at counterfactual pollution emissions if only each of these sub-series follows the historical values. The additional counterfactual results are plotted in Figure 10. The blue dashed lines show that the tariff changes would reduce the total SO_2 pollution emission level by the most among other channels after 2004, later surpassed by Chinese regulation after 2008. While the sector productivity would reduce pollution level, however, the magnitudes are moderate.

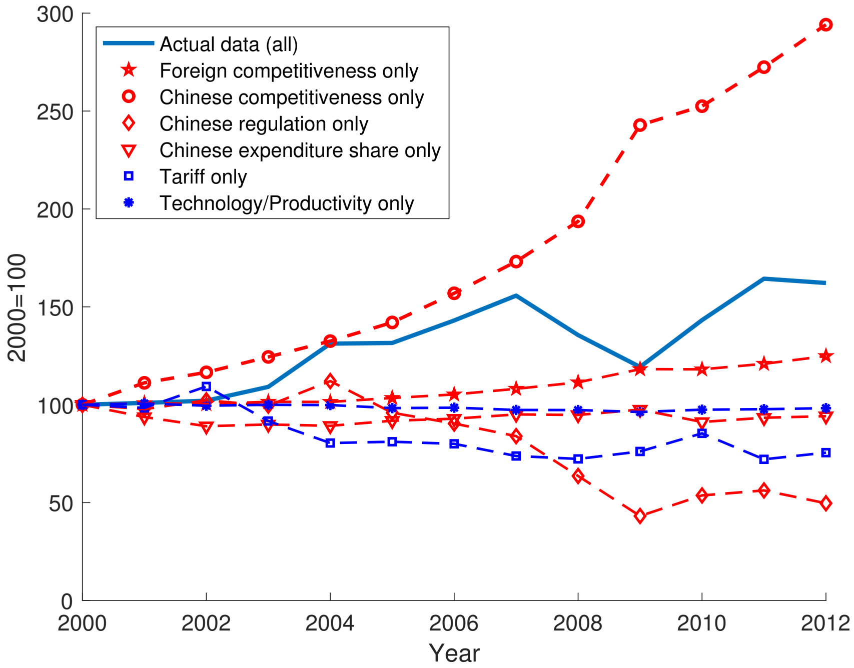


Figure 10. Additional counterfactuals (decomposed Chinese expenditure share)

In the benchmark counterfactual results, I aggregate firm-level pollution merged with production information used for parameter estimates, so there is a dip in actual total pollution level in 2009. Alternatively, I can aggregate firm-level pollution without matching the production information and apply the estimated parameters to all firms with emission records. Another approach is to use yearbook pollution data, which includes the total amount of emission in each 2-digit CIC industry. The results are reported in Figure A.17a and Figure A.17b, respectively. The counterfactual pollution levels are qualitatively similar, though the effect of tariff is more pronounced than in the benchmark.

7.2 Other counterfactuals

This section explores other counterfactual results including the effect of a single channel, the wage effects and pollution intensity outcomes.

[20]Effectively, the Pareto location parameter $b_{o,s}$ is the lower bound of the productivity distribution. Alternatively, I could substitute $b_{o,s}$ with sector average total factor productivity weighted by firm sales. The counterfactual results in Figure A.16 show a bigger effect in reducing total pollution emissions level.

[21]The retrieved historical values of firm productivity from the production function estimation are very similar to sector productivity from Pareto distribution in terms of both trend and magnitude.

7.2.1 Effect of a single channel

The counterfactual effects of a single channel (e.g. flat pollution tax or no environmental policy), computed by keeping one variable at the initial value, while the other variables follow their historical values are shown in Figure A.18. If the Chinese regulation is constant, the total pollution level by 2012 would be 300% of the initial level in year 2000, which is much higher than the actual pollution level at 162%. If the level of trade liberalization is kept at the original level, SO_2 pollution would have increased to over 200%. In contrast, if Chinese market competitiveness stayed constant, pollution would be lower by 50%. If foreign market competitiveness stayed constant, pollution would also be slightly lower than the actual level. The effects of productivity and expenditure shares are relatively less important.

7.2.2 Wage effects

One can solve for the nominal wages relative to the levels in year 2000 under each counterfactual scenario from the set of equations under the equilibrium conditions (30) and (31). The counterfactual effects on home and foreign wages are depicted in Figure A.19. The blue solid lines represent the historical wages retrieved from the actual data. Among all the channels, Chinese competitiveness is the main driver of home and foreign wages, while the other channels have marginal effects on wages.

7.2.3 Pollution intensity

In terms of pollution intensity, Figure A.20 shows that it dropped over the period to less than 50% of the initial value, corresponding to the pattern in the introduction. All the factors examined decrease pollution intensity proportional to their effects on pollution level. In line with the comparative statics propositions, productivity, pollution tax and trade liberalization help reduce pollution intensity, and each channel alone would decrease pollution intensity to the level of around 30%, 15% and 20% of the base year respectively by the end of 2012.

7.3 Magnitudes of model and data

In this section, I take the data and the estimates from the regressions as external validity of the model predictions. Specifically, I look at the "elasticity" of pollution intensity to trade liberalization and environmental regulation, which are the main forces to reduce pollution in the model.

7.3.1 Trade liberalization

Recall that in Table B.9 with the instrument variable specification, a 1% point reduction in input tariff would reduce firm SO_2 intensity by 1.7% to 2.1% on average. I then regress the industry-specific counterfactual pollution intensity from the model on average industry tariff, the result is that 1% tariff cut would reduce pollution intensity by 1.4% to 1.9% (Table B.20), which is close to the estimate from the regressions.

7.3.2 Environmental regulation

Table 4 shows that if the province SO_2 pollution regulation stringency (yuan/kg) increases by 1%, firm pollution intensity would decrease by 0.07% to 0.09%. Taking the implied pollution tax to approximate the pollution regulation, I then regress the industry-specific counterfactual pollution intensity on the average pollution tax from the model. Table B.20 shows that 1% increase in the pollution tax would reduce the pollution intensity by roughly 0.13% to 0.16%, which is larger than the estimate from the DiD regressions.

One caveat is that the DiD analysis examines the policy difference across provinces during the 11$^{\text{th}}$ Five-Year Plan, while there might be other local policies. Also, the response of pollution intensity to regulation identified in the regressions is across provinces, but the model exploits variance across industries, which may be different from regional differences.

7.3.3 Economic cost of environmental regulation

According to the report by the Ministry of Environment Protection (MEP), the economic cost of SO_2 emission was 20,000 yuan per ton in 2005.[22] The baseline counterfactual pollution level of Chinese environmental regulation is approximately 50% of the initial level in 2000, while the actual pollution level by 2012 is 162% of the initial level, which means that the net effect of environmental regulation is 112% of SO_2 emission reduction in manufacturing industries. The manufacturing SO_2 emission in 2000 was 5.7 million tons according to the China Environmental Statistical Yearbook, which indicates that the environmental policy reduced 6.384 million tons of SO_2 emission (5.7 million tons $\times$112%), equal to 127.68 billion RMB in 2005 (6.384 million tons $\times$ 20,000RMB/ton), roughly 0.68% of annual GDP.[23] The equivalent in 2021 is 218.18 billion RMB, or 33.83 billion USD (at the exchange rate 1 USD=6.45 RMB).[24]

7.4 Sensitivity analysis

I conduct a series of sensitivity analysis on the main counterfactuals in this section. The first row of Table 7 presents the actual change in SO_2 pollution emissions between 2000 and 2012, setting the level in 2000 to 100. The value means China's manufacturing SO_2 pollution emissions were 162.180 percent of the 2000 level in 2012. The second row shows the main estimates where each column corresponds to a counterfactual in the baseline Figure 10. Again, Chinese environmental regulation alone would reduce total pollution level by approximately one half, followed by tariff cost reduction which would decrease 36% of pollution emissions, while technology/productivity and expenditure shares contribute only slightly to pollution reduction.

One concern about the current results is that the parameters are essentially based on the estimation of pollution elasticity α. To alleviate the potential bias in parameter estimation, I use an alternative approach to estimate the elasticity of substitution σ independently from trade data using the method from Soderbery (2015), which is an improvement based on Feenstra (1994) and Broda and Weinstein (2006). The counterfactual results are summarized in row 3 of Table 7. Compared to the main counterfactuals, this exercise provides very similar results, except that the change in tariff is slightly less effective in reducing SO_2 pollution level.

Rows 4 and 5 explore counterfactuals when the Pareto shape parameter θ of productivity distribution is estimated using alternative cutoffs at the right tail. The model is not sensitive to changes in parameter θ since counterfactuals change only marginally. Rows 6 and 7 explore sensitivity to changes in the estimated pollution elasticity α. The counterfactuals are a bit more volatile to changes in parameter α shown in the table, but remain qualitatively stable.

Regarding regulation, row 8 presents partial equilibrium where there is no change in factor prices or firm entry: $\hat{w}_o = \hat{M}^e_{o,s} = 1$. In this case, market competition and expenditure shares do not affect pollution emissions and only environmental regulation consistently decreases total pollution emissions by almost one half.

[22]The estimate by the European Commission for EU25 Member States is 5,600 EUR at a lower bound in 2005, which is equivalent to 53,200 RMB per ton of of SO_2 at the exchange rate of 1 EUR=9.5 RMB in 2005. However, the GDP per capita in EU25 Member States was significantly higher than China, and GDP per capita is positively related to the economic cost of pollution.

[23]The GDP of China in 2005 was 18.73 trillion RMB.

[24]The GDP deflator is 68 in 2005 and 116.2 in 2021 with base year 2015, according to the World Bank.

Table 7. Sensitivity analysis

	Foreign competitiveness	Chinese competitiveness	Chinese expenditure shares	Chinese environmental regulation	Tariff	Technology/ productivity
1. Actual change			162.180			
2. Main estimate	124.857	294.114	94.152	49.663	63.566	98.361
3. σ: Feenstra	124.289	292.573	94.124	49.768	73.522	96.444
4. θ: top 25 %	124.400	289.512	94.136	49.800	71.307	95.794
5. θ: top 50 %	124.250	289.732	94.120	49.916	72.071	93.669
6. α: $\times$ 0.5	124.443	285.016	94.139	50.323	71.442	97.976
7. α: $\times$ 2	125.592	343.825	94.181	44.728	75.549	99.519
8. Partial equilibrium	100.000	100.000	100.000	50.815	100.000	100.000

7.5 Counterfactual policies

In this section, I explore the counterfactual effects of alternative policies regarding pollution tax and tariff cost. Recall from Figure 7 that the pollution tax faced by dirty industries is smaller than clean industries. Suppose all industries face the same level of pollution tax so that they are treated equally by the policy. Figure A.21a displays the scenario when all industries receive the same level of environmental regulation so that they face uniform pollution tax. The counterfactual shows that Chinese environmental regulation would further decrease pollution in 2012 by 3% of the 2000 level. If the implicit pollution tax were twice of the actual level, SO_2 emissions would further decrease to 25% of the initial level. By contrast, if the implicit pollution tax were half of the baseline level, SO_2 would not effectively decrease at the end of the period because the regulation is too weak to be effective.

One can also examine the counterfactual pollution emissions due to alternative tariff rates. Figure A.21b shows that if tariff costs were reduced by half, SO_2 emissions would further decrease to 38% of the initial level. However, if the tariff costs were doubled, the emission level would instead increase by 30%. The results indicate that trade conflicts such as the US-China trade war would have inverse effects on pollution emissions. As tariff cost increases, firms are left with little room to abate pollution, and as a result, emission level will rise significantly.

7.6 Counterfactuals for other pollutants

Apart from SO_2, I reproduce the counterfactual analysis with regard to other pollutants following the same procedure in the model. The comparison between other pollutants to SO_2 may provide insights about the spillover of SO_2 regulations on other airborne pollutants. The analysis on water pollutants such as COD (chemical oxygen demand), which was also targeted by the environmental policy during the 11$^{\text{th}}$ Five-Year Plan can offer comparable assessment on the effect of policies. The counterfactual exercises are summarized in Figure A.22. Reassuringly, the counterfactual trends of COD are close to those of SO_2, showing that the environmental policies affect targeted pollutants in a similar way. Firms are more pollution efficient and emit less under the environmental policies. In terms of other air pollutants, environmental regulations would have reduced NO_x (nitrogen oxides) emissions by around 50%, while almost all of smoke dust emissions could be reduced. These results indicate that there is spillover of environmental policies on air pollutants that are not directly targeted. This could be achieved through pollution abatement investment and end-of-pipe filtering equipment. For water pollutants, the effectiveness of pollution policies is smaller in magnitude than air pollutants, probably because the pollutants are more likely to be carried down the rivers and into the water bodies across regions, which makes it harder to regulate locally. However, tariff reduction would become more useful to reduce emissions in later years.

8 Conclusion

The relationship between economic growth, international trade and pollution has been under debate for years. However, studies that comprehensively disentangle the primitive drivers of pollution level have been rare, especially in developing countries where more economic growth and potentially more pollution are expected. In this paper, I look into the problem by first combining China's firm-level data on financial statistics, trade and pollution information. I find that large firms pollute more but are less pollution intensive, so are firms that participate in international trade. Higher TFP and more stringent regulations are associated with lower pollution. Policies such as international trade liberalization and environmental regulation can reduce the emission intensity of firms. I then perform both industry-level and firm-level decompositions and find that within sector firm heterogeneities are important in explaining the changes in pollution levels.

To complement the evidence from the data, I follow the quantitative approach of Shapiro and Walker (2018) to structurally estimate the contributions of each possible channel. The model applies insights from environmental economics to the international trade literature and features heterogeneous firms that pay a pollution tax and decide on pollution abatement costs under monopolistic competition in open economies. The parameters can be estimated using firm-level data on pollution and production. The counterfactual exercises show that environmental regulation is very effective in reducing the total SO_2 emission level that the policy alone would reduce pollution by over one half, with model-implied pollution tax significantly increased. In contrast, China's market competitiveness would greatly push up total pollution and I further single out trade costs measured by tariffs and productivity improvement due to technology upgrading. The results show that tariff cuts from trade liberalization is the force second to environmental regulation to drive down pollution level. Meanwhile, productivity alone would reduce pollution only moderately. Finally, I explore some alternative environmental policies and tariff costs to derive the counterfactual emission outcomes.

The findings of this paper highlight the importance of environmental policies in reducing pollution emissions. Government regulations can be crucial to keep a low level of pollution while sustaining economic growth. This is not only true for industrialized countries (e.g. Shapiro and Walker, 2018) but also for developing economies (e.g. Burgess et al., 2019). The analysis could potentially be extended to pollutants other than what have been discussed in this paper such as green house gases (GHG) or carbon dioxide (CO_2) and alternative environmental policies where data are available. It would also be interesting to explore the relationship between environmental regulations, intermediate inputs and product markups in future work.

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Appendix

A Additional figures

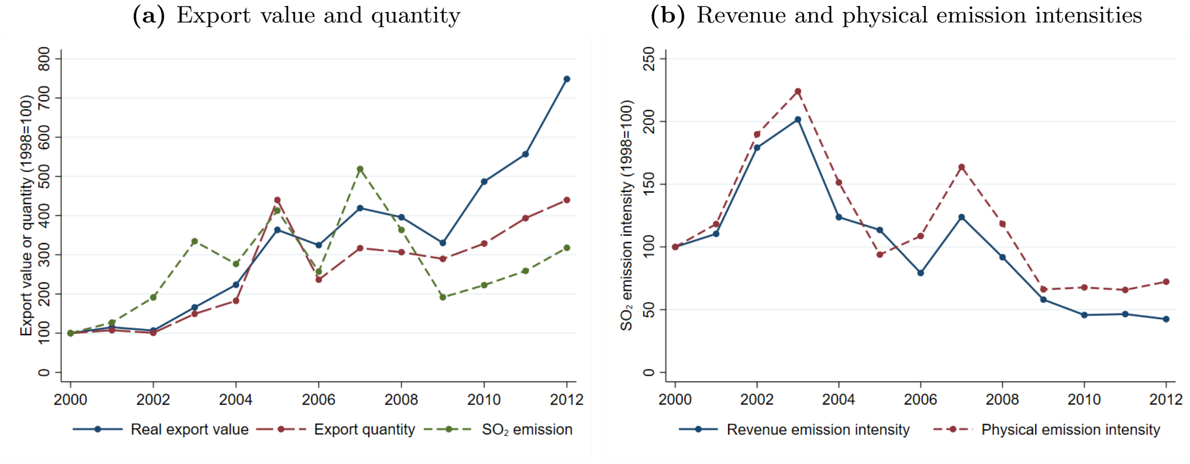


Figure A.1. Export emission intensities

Notes: The export data come from the customs, the pollution data come from the Ministry of Environment Protection (MEP).

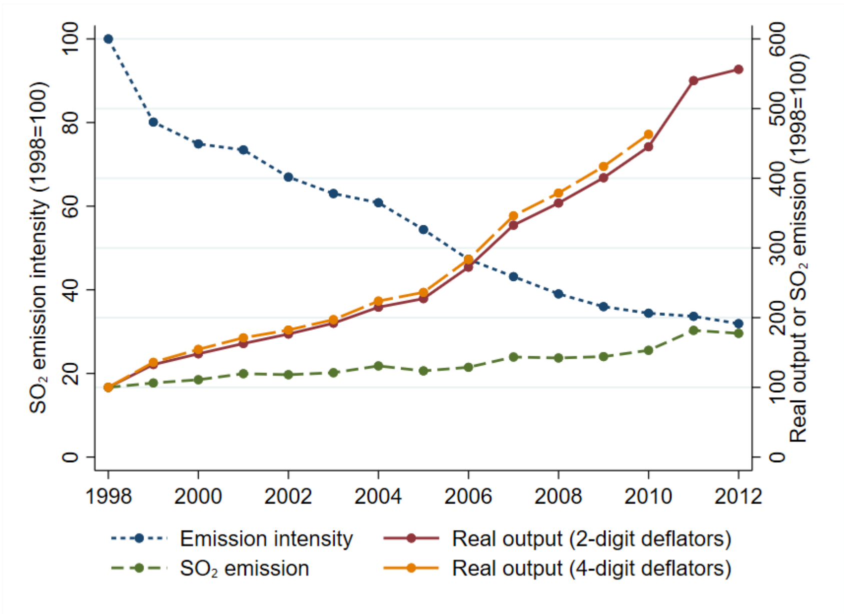


Figure A.2. SO_2 emissions and real output (different deflators)

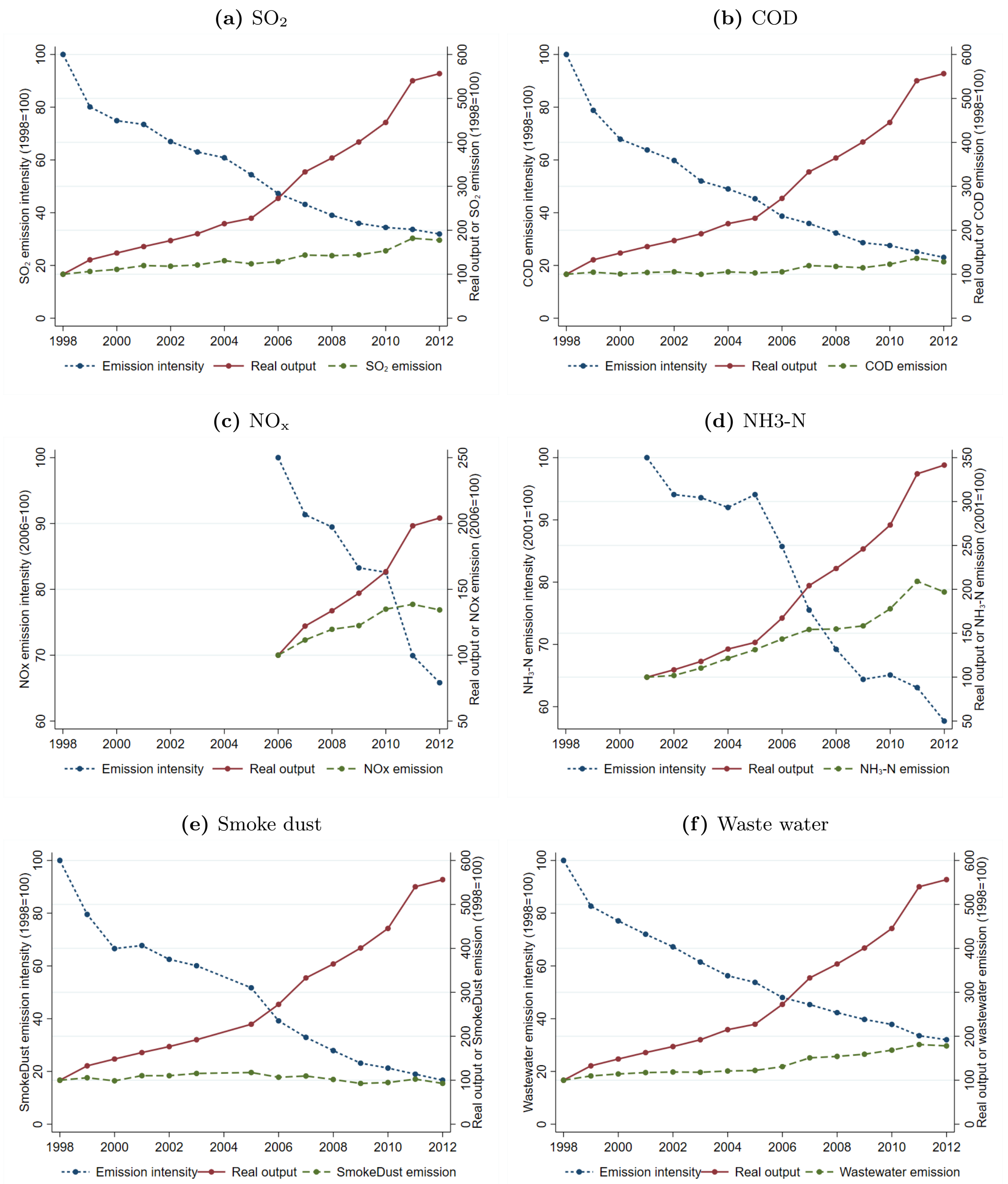
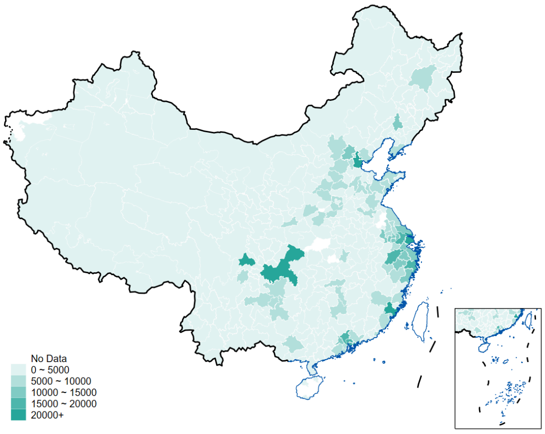
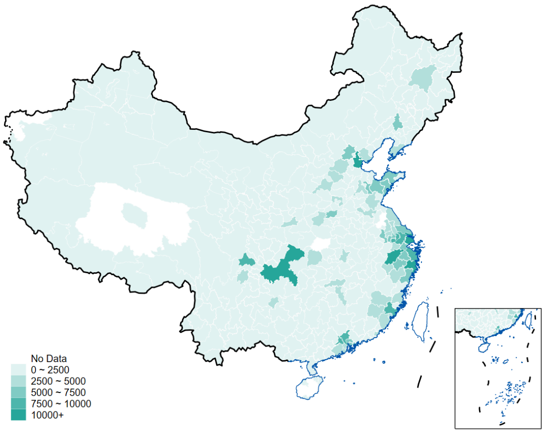


Figure A.3. Pollution emissions and real output- (other pollutants)

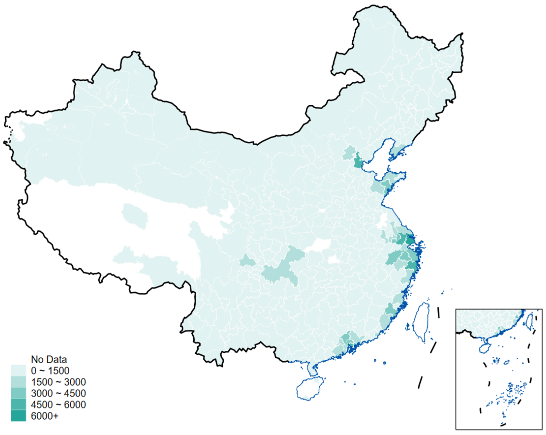
Notes: The pollutants include sulfur dioxide (SO_2), nitrogen oxides (NO_x) and smoke dust for air pollution, chemical oxygen demand (COD), ammonia nitrogen (NH_3-N) and waste water for water pollution. The data are not available for NO_x before 2006 and for NH_3-N before 2001.



(a) Pollution



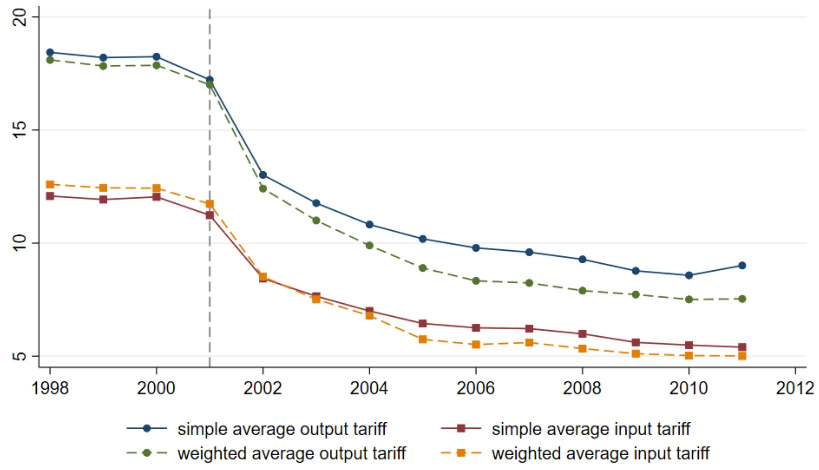
(b) Pollution+ASIF



(c) Pollution+ASIF+Customs

Figure A.4. Number of firm-level observations 2000-2012

(a) Average output and input tariffs



(b) Input tariffs (simple average)

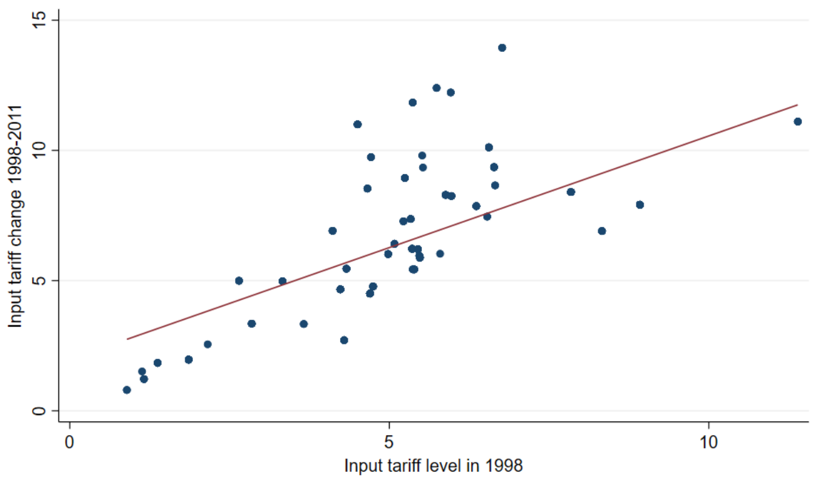
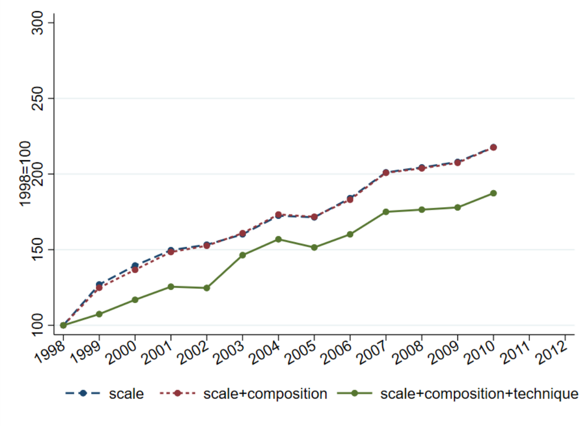


Figure A.5. Tariff levels and tariff changes (1997 input-output table)

(a) 4-digit deflator



(b) Revenue not deflated

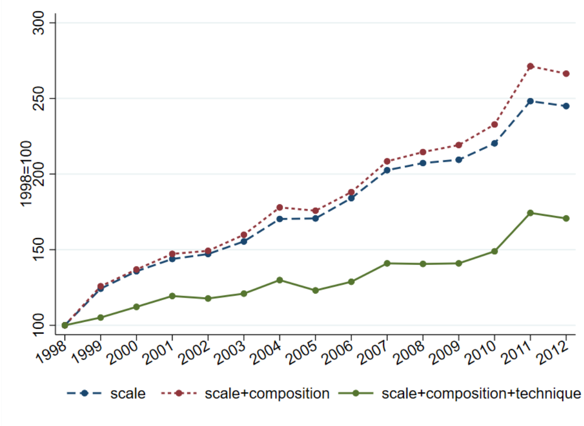
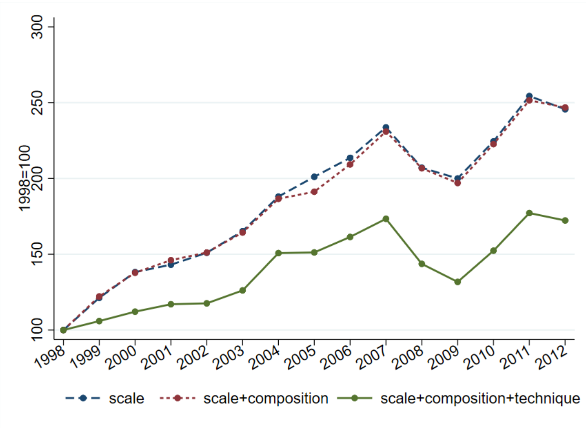


Figure A.6. Industry-level SO_2 emission decomposition (alternative deflators)

Note: The sample with 4-digit deflator covers 1998-2010 due to compatibility of deflators.

(a) Revenue shares



(b) Cost shares

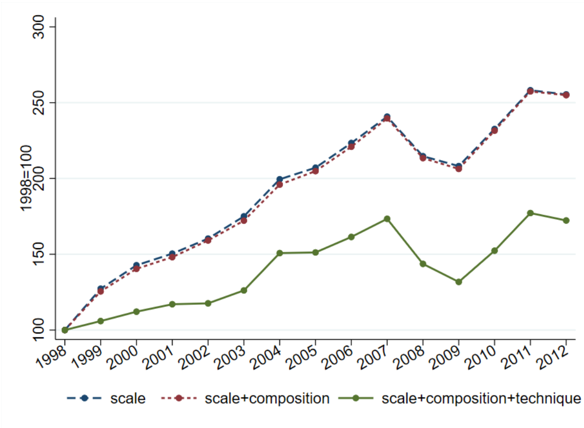


Figure A.7. Industry-level SO_2 emission decomposition (alternative shares)

Figure A.8. Firm-level SO_2 emission intensity decomposition (by industry)

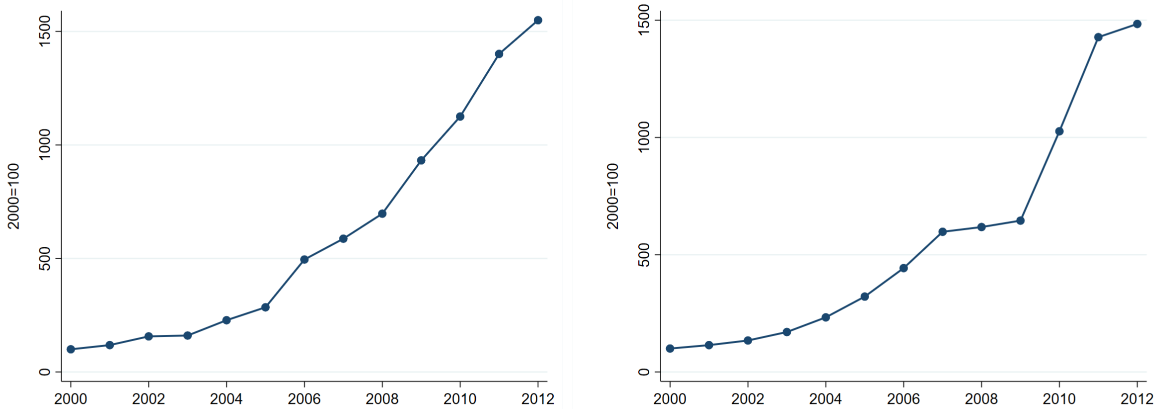


Figure A.9. Abatement cost data and model

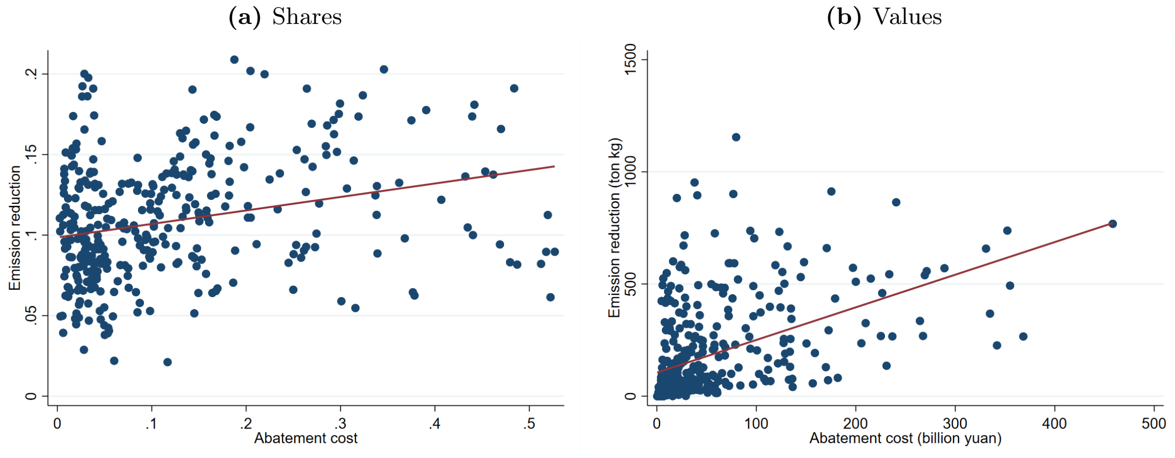


Figure A.10. Correlation between abatement cost and emission reduction

Note: Each point represents industry-year level abatement cost from the model on the horizontal axis and the emission reduction from the data on the vertical axis.

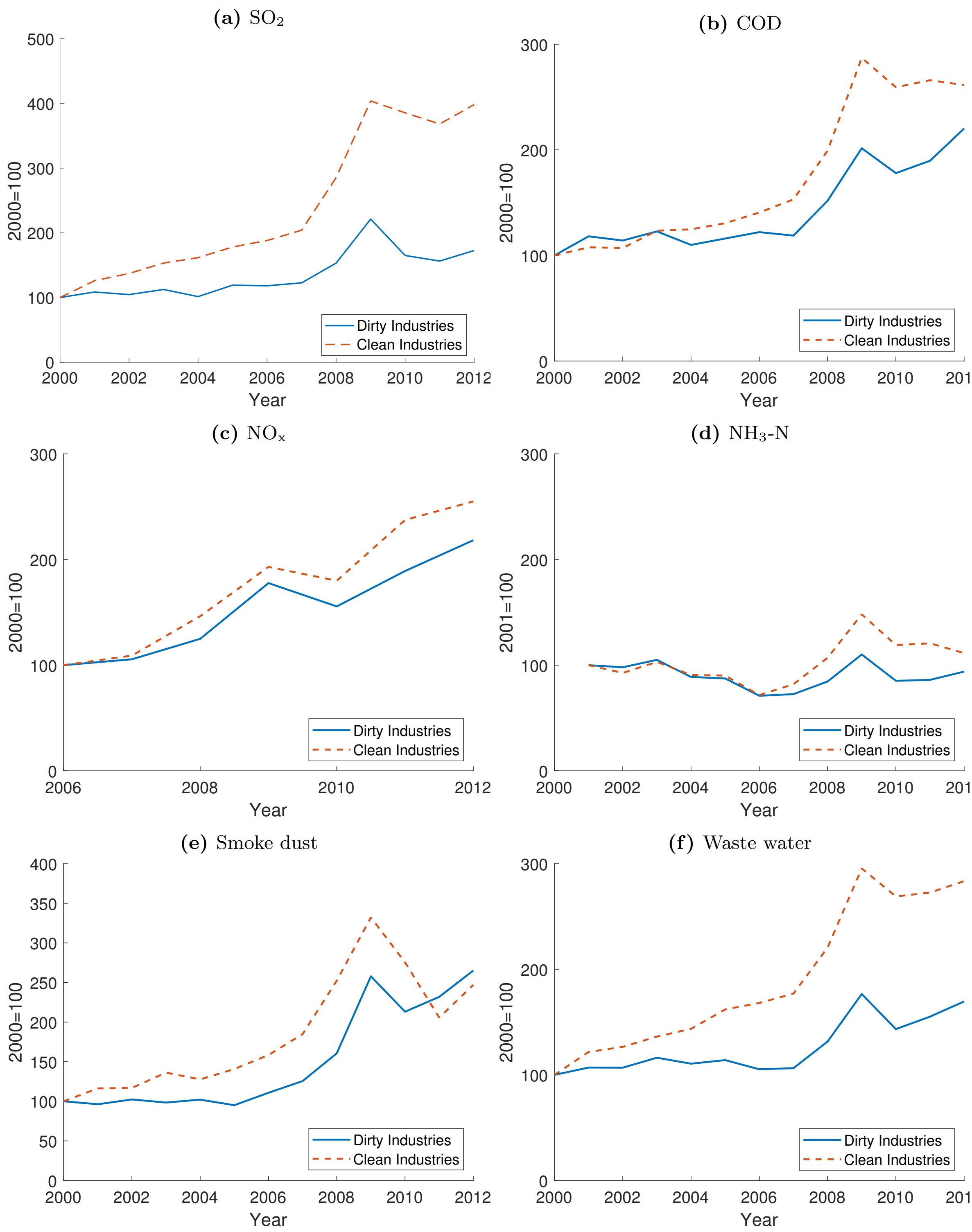


Figure A.11. Implicit pollution tax across pollutants

Note: The pollutants include sulfur dioxide (SO_2), nitrogen oxides (NO_x) and smoke dust for air pollution, chemical oxygen demand (COD), ammonia nitrogen (NH_3-N) and waste water for water pollution. Dirty industries have pollution elasticity α_s above average, while clean industries are below average, weighted by baseline output of each industry. The data are not available for NO_x before 2006 and for NH_3-N before 2001.

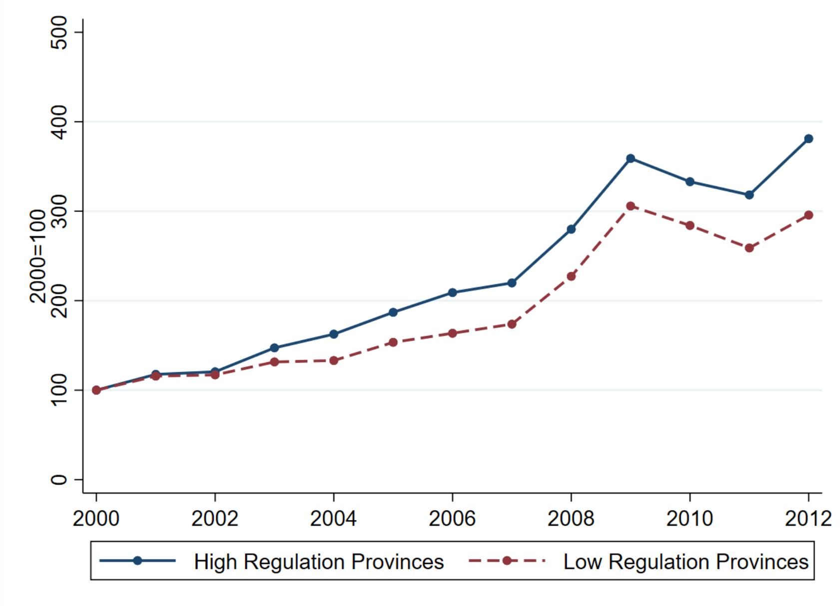


Figure A.12. Implicit pollution tax by province

Note: High regulation provinces have below average change in SO_2 cap over change in GDP between 2005 and 2010, while high regulation provinces are above average, weighted by initial year output of each province.

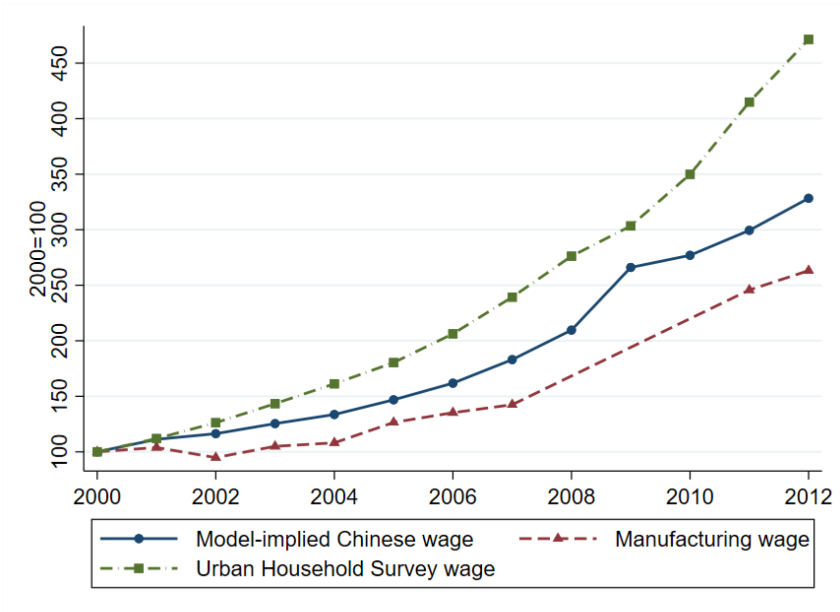


Figure A.13. Chinese wages

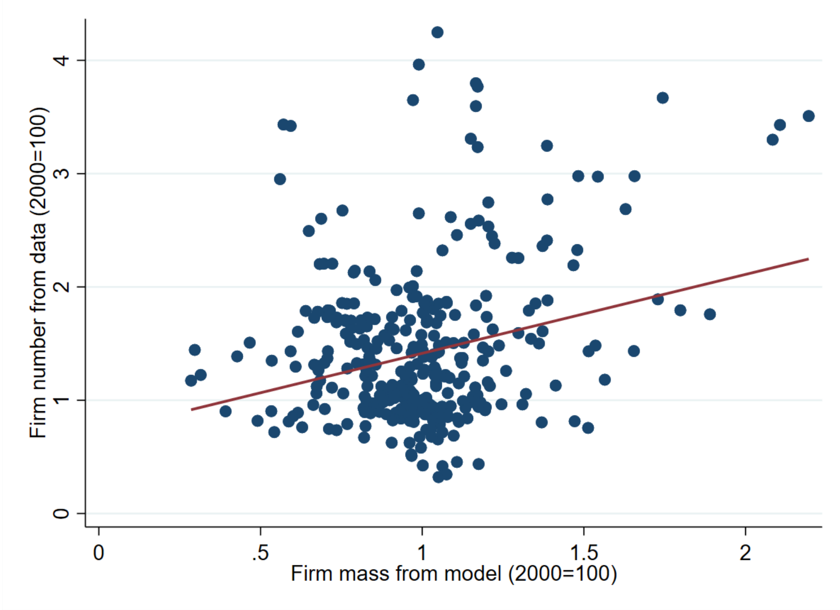
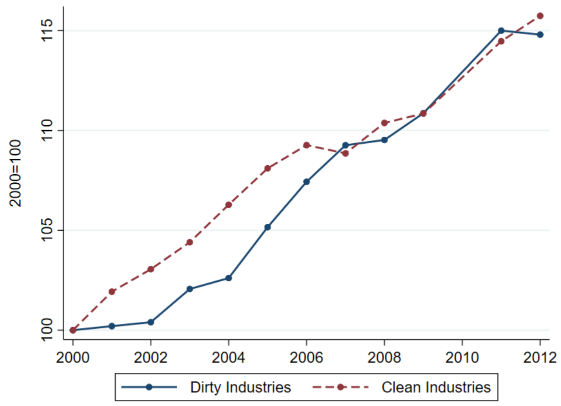


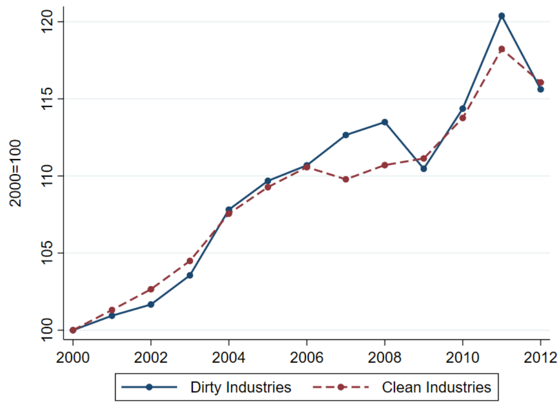
Figure A.14. Correlation between firm number and firm mass

Note: Each point represents industry-year level firm number.

(a) Log sector productivity



(b) Log firm productivity



(c) Export tariff

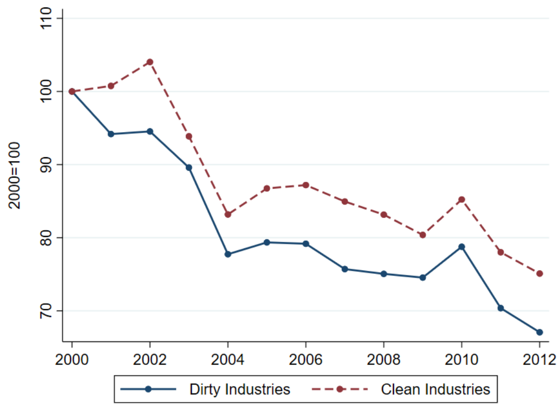


Figure A.15. Historic values of additional variables

Note: Dirty industries have pollution elasticity α_s above average, while clean industries are below average, unweighted mean.

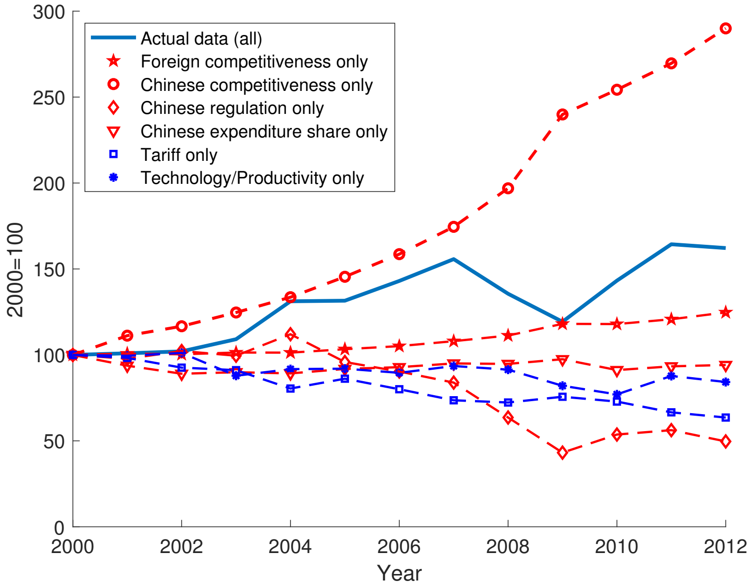


Figure A.16. Additional counterfactual with weighted average sector productivity

(a) All polluting firms

(b) Yearbook pollution

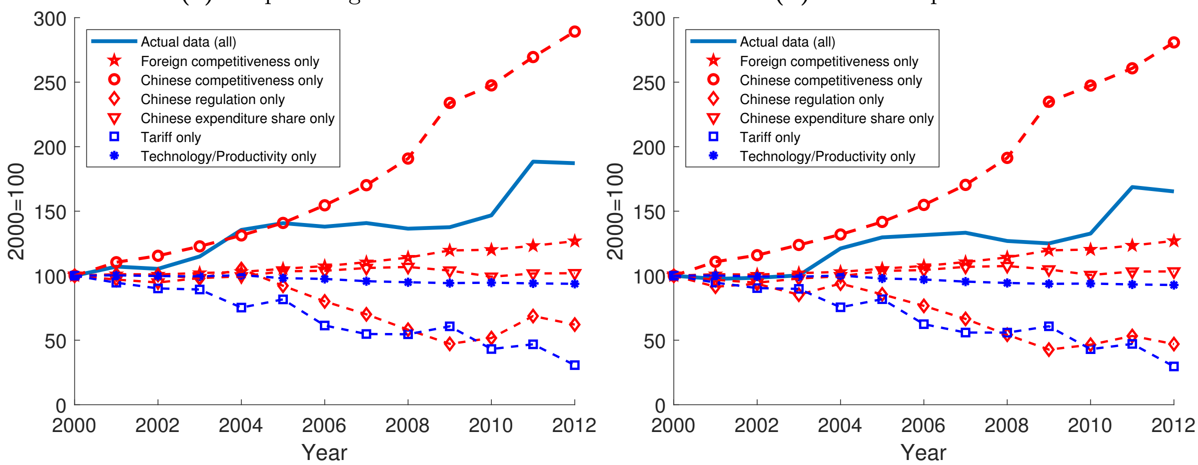


Figure A.17. Additional counterfactuals with alternative pollution data

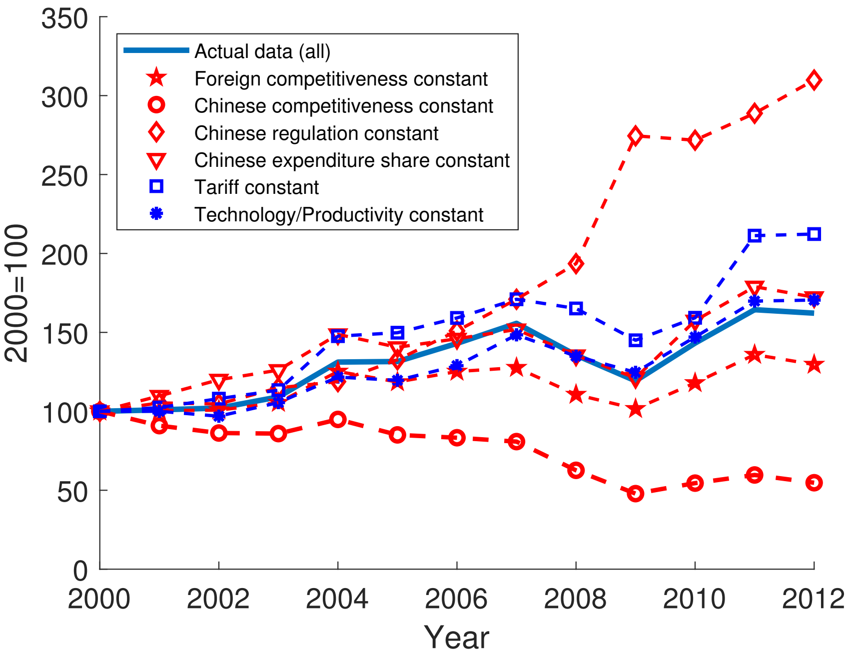


Figure A.18. Counterfactual Chinese manufacturing pollution emissions (single channel)

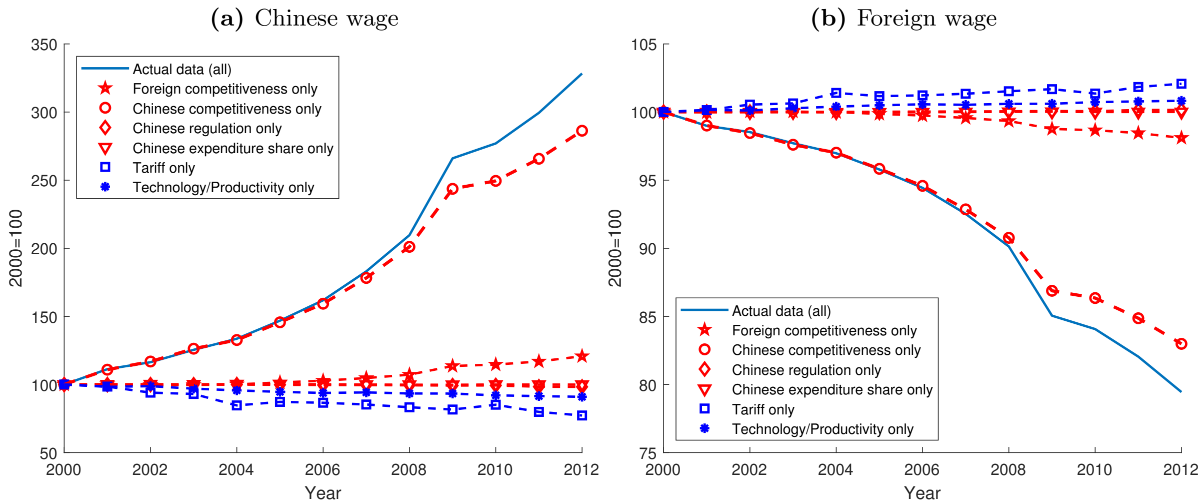


Figure A.19. Counterfactual effects on home and foreign wages

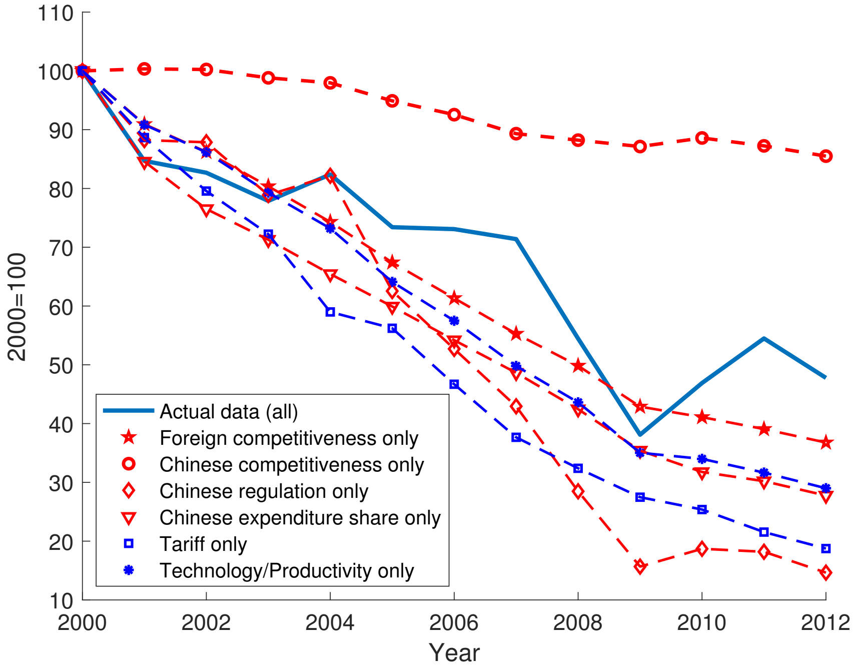


Figure A.20. Counterfactual Chinese manufacturing pollution intensities

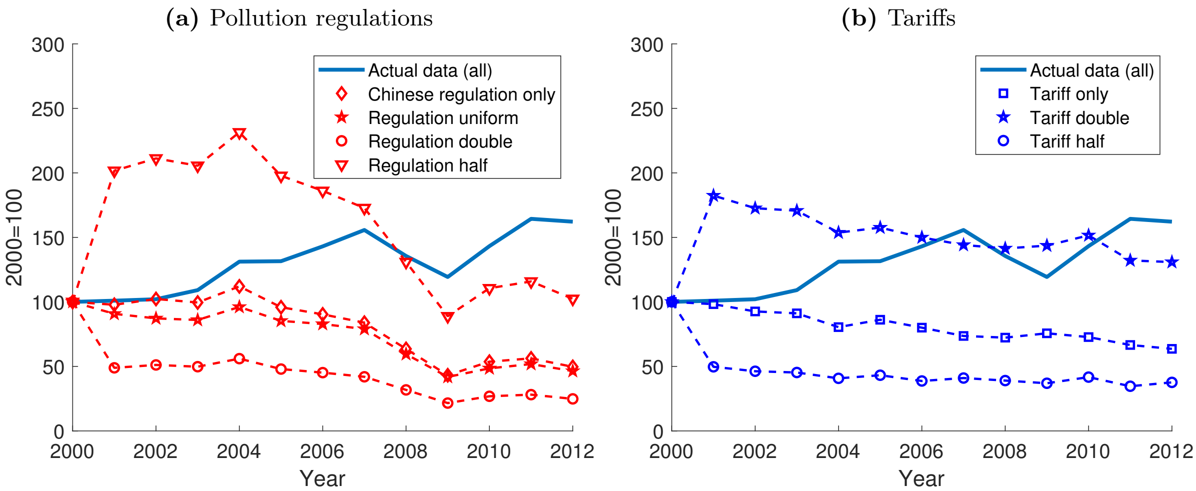


Figure A.21. Counterfactual SO_2 emissions of alternative policies

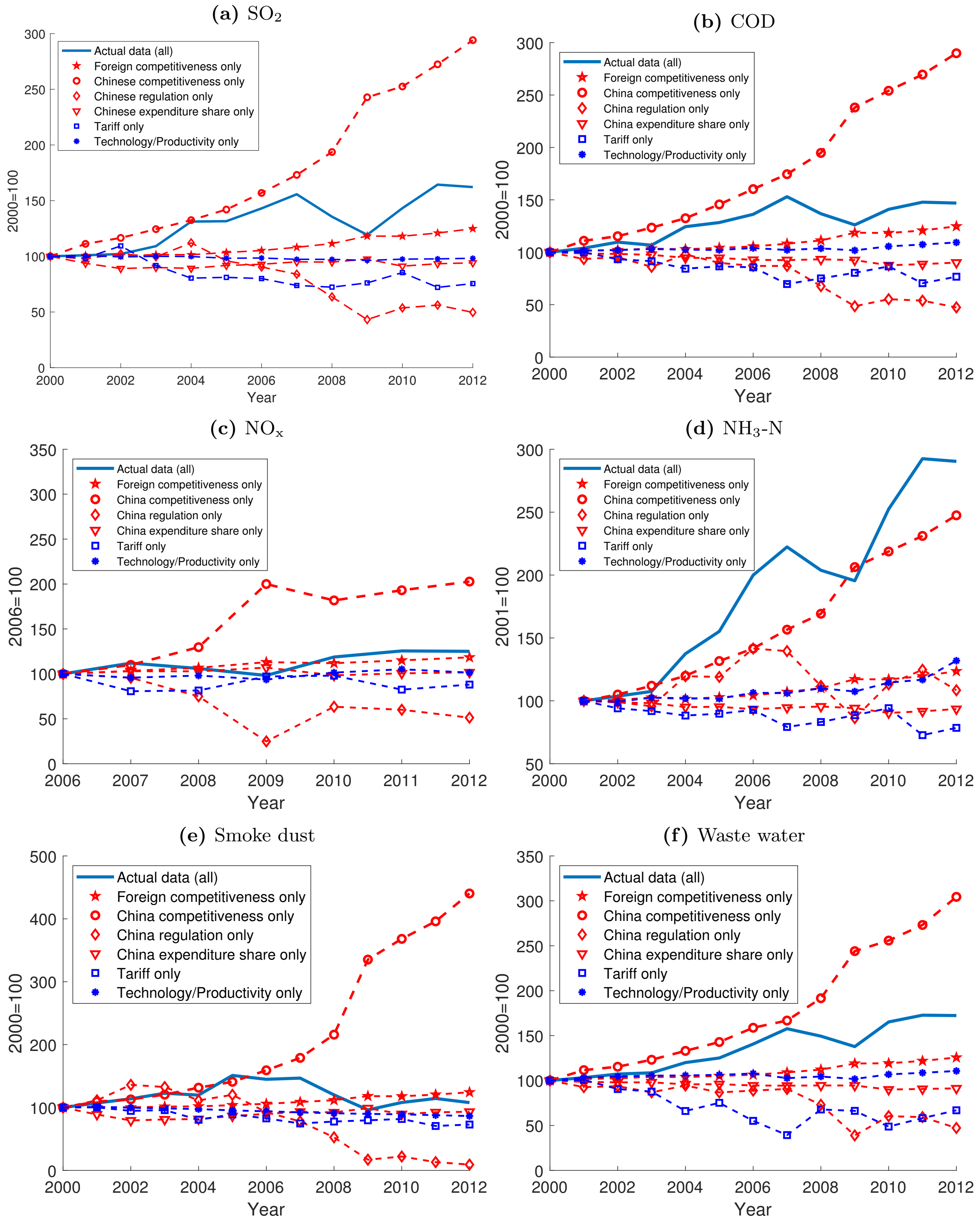


Figure A.22. Counterfactuals of other pollutants

Note: The pollutants include sulfur dioxide (SO_2), nitrogen oxides (NO_x) and smoke dust for air pollution, chemical oxygen demand (COD), ammonia nitrogen (NH_3-N) and waste water for water pollution. The data are not available for NO_x before 2006 and for NH_3-N before 2001.

B Additional tables

Table B.1. Top manufacturing industries of SO_2 emissions

Code	2-digit CIC name	Emission share
30	Non-metallic mineral products industry	22%
31	Ferrous metal smelting and rolling industry	20%
26	Chemical raw materials and chemical products manufacturing	15%
32	Non-ferrous metal smelting and calendering industry	11%
25	Petroleum processing, coking and nuclear fuel processing industries	8%
22	Paper and paper products industry	6%
15	Beverage manufacturing	4%
17	Textile industry	4%
13	Agricultural and food processing industry	2%

Notes: CIC stands for China industrial classification. Manufacturing industries that account for more than 1% of SO_2 emissions are listed. The data coverage is 2000-2012.

Table B.2. Summary statistics of all firms

Variable	Obs	Mean	Std. Dev.	Min	Max
$Exporter$	1,207,342	0.135	0.341	0	1
$Importer$	1,207,342	0.101	0.301	0	1
log $sales$	1,165,399	7.301	1.919	2.789	12.454
logSO_2	877,406	9.580	1.899	3.738	14.353
logSO_2int	854,355	2.360	2.223	-8.641	11.290

Notes: logSO is log SO_2 emission (kg), logSO_2int is log SO_2 emission(kg) per unit of output value (1,000 yuan). $Exporter$ and $Importer$ are exporter and importer dummies. log $sales$ represents log of sales in 10,000 yuan. log $sales$, logSO and logSO_2int are trimmed at the top and bottom 1% to rule out the influence of outliers.

Table B.3. Summary statistics of importers/exporters

Variable	Obs	Mean	Std. Dev.	Min	Max
logSO_2	116,747	9.421	2.224	2.485	15.011
logSO_2int	85,124	0.356	2.340	-10.523	9.734
log$Export$	168,672	14.545	2.223	7.746	19.612
log$Import$	125,785	13.606	2.883	5.375	19.891
$Labor$	84,449	8.762	22.830	0.310	80.190
TFP	64,049	0.252	0.960	-11.421	9.241
FOE	142,316	0.163	0.369	0	1
SO_2cap	178,747	83.377	44.386	0.200	160.200

Notes: logSO_2 is log SO_2 emission (kg), logSO_2int is log SO_2 emission(kg) per unit of output value (1,000 yuan). log$Export$ and log$Import$ are export and import value in logs. $Labor$ is the number of employment in hundreds. TFP is firm total factor productivity. FOE is foreign ownership status dummy. SO_2cap is the provincial SO_2 regulation cap in 10,000 tons by 2010. log$Export_{it}$, log$Import_{it}$ and $Labor_{it}$ are trimmed at the top and bottom 1% to rule out the influence of outliers.

Table B.4. SO_2 pollution and firm characteristics (all firms 4-digit industry)

	(1) $\log SO_2$	(2) $\log SO_2$	(3) $\log SO_2int$	(4) $\log SO_2int$
Exporter	0.249***	-0.090***	-0.447***	-0.090***
	(0.008)	(0.007)	(0.008)	(0.007)
Importer	0.309***	-0.226***	-0.741***	-0.226***
	(0.009)	(0.009)	(0.010)	(0.009)
log *sales*		0.501***		-0.499***
		(0.001)		(0.001)
Observations	798,660	677,667	677,667	677,667
R-squared	0.291	0.451	0.460	0.574
Sector FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: The sample covers 2000-2010 due to compatibility of deflators. Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.5. SO_2 pollution and firm characteristics (importers/exporters 4-digit industry)

	(1) $\log SO_2$	(2) $\log SO_2$	(3) $\log SO_2int$	(4) $\log SO_2int$	(5) $\log SO_2int$	(6) $\log SO_2int$	(7) $\log SO_2int$
$\log Export$	0.142***	0.078***	-0.042***	-0.047***	-0.015*	-0.013*	-0.013*
	(0.005)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
$\log Import$	0.031***	0.000	-0.130***	-0.120***	-0.096***	-0.092***	-0.091***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)
Labor		0.047***		0.000	0.006***	0.005***	0.005***
		(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
TFP					-0.773***	-0.773***	-0.773***
					(0.016)	(0.016)	(0.016)
FOE						-0.338***	-0.339***
						(0.045)	(0.045)
SO_2cap							0.013***
							(0.005)
Observations	51,141	26,331	41,645	25,706	18,357	18,357	18,357
R-squared	0.389	0.447	0.465	0.454	0.522	0.524	0.524
Sector FE	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: The sample covers 2000-2010 due to compatibility of deflators. Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.6. SO_2 pollution and firm characteristics (all firms with firm FE)

	(1) logSO_2	(2) logSO_2	(3) logSO_2int	(4) logSO_2int
Exporter	0.016**	-0.018***	-0.092***	-0.018***
	(0.007)	(0.007)	(0.007)	(0.007)
Importer	0.049***	0.018**	-0.042***	0.018**
	(0.007)	(0.007)	(0.008)	(0.007)
log *sales*		0.323***		-0.677***
		(0.002)		(0.002)
Observations	829,220	806,958	806,958	806,958
R-squared	0.810	0.820	0.838	0.872
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.7. SO_2 pollution and firm characteristics (importers/exporters with firm FE)

	(1) logSO_2	(2) logSO_2	(3) logSO_2int	(4) logSO_2int	(5) logSO_2int	(6) logSO_2int
log$Export$	0.045***	0.036***	-0.054***	-0.055***	-0.045***	-0.045***
	(0.005)	(0.008)	(0.007)	(0.010)	(0.011)	(0.011)
log$Import$	0.011***	0.004	-0.033***	-0.036***	-0.050***	-0.050***
	(0.004)	(0.006)	(0.005)	(0.007)	(0.008)	(0.008)
Labor		0.010***		-0.003	-0.006**	-0.006**
		(0.002)		(0.002)	(0.003)	(0.003)
TFP					-0.732***	-0.732***
					(0.018)	(0.018)
SO_2cap						-0.007
						(0.011)
Observations	50,836	22,357	37,066	21,768	14,531	14,531
R-squared	0.856	0.846	0.834	0.825	0.841	0.841
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.8. Summary statistics of trade liberalization

Variable	Obs	Mean	Std. dev.	Min	Max
$\log SO_2 int$	641,278	2.355	2.175	-8.641	11.290
WTO	891,669	0.761	0.427	0	1
$tariff^{1998}_{savg.output}$	791,849	18.989	11.221	2.590	65.000
$tariff^{1998}_{wavg.output}$	791,849	19.527	14.132	3.700	107.060
$tariff^{1998}_{savg.input}$	866,255	9.408	3.796	1.443	29.893
$tariff^{1998}_{wavg.input}$	866,255	9.734	4.298	1.468	29.419
$\Delta\widehat{tariff}_{\text{savg.output}}$	1,126,273	6.192	2.350	1.289	18.131
$\Delta\widehat{tariff}_{\text{wavg.output}}$	1,126,273	6.525	3.218	0.709	22.643
$\Delta\widehat{tariff}_{\text{savg.input}}$	1,126,273	3.719	1.076	0.922	10.176
$\Delta\widehat{tariff}_{\text{wavg.input}}$	1,126,273	4.361	1.255	1.249	10.541
log *sales*	861,545	7.300	1.888	2.789	12.448

Notes: $\log SO_2 int$ is log SO_2 emission (kg) per unit of output value (1,000 yuan). log $sales_{it}$ is log of firm sales in 1,000 yuan. WTO is a binary indicator of China's entry to the WTO, which is equal to 1 if the year is after 2001 and 0 otherwise. "savg" and "wavg" represent simple average and weighted average tariffs respectively.

Table B.9. Impact of trade liberalization on SO_2 pollution intensity (tariff changes)

$\log SO_2 int$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widehat{tariff}_{savg.input} \times WTO$	-0.021***				-0.020***	
	(0.004)				(0.004)	
$\Delta\widehat{tariff}_{wavg.input} \times WTO$		-0.017***				-0.018***
		(0.003)				(0.003)
$\Delta\widehat{tariff}_{savg.output} \times WTO$			-0.005***		-0.002	
			(0.002)		(0.002)	
$\Delta\widehat{tariff}_{wavg.output} \times WTO$				-0.003***		-0.001
				(0.001)		(0.001)
log *sales*	-0.684***	-0.684***	-0.682***	-0.682***	-0.682***	-0.682***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	572,631	572,631	530,643	530,643	530,643	530,643
Adj. R-squared	0.845	0.845	0.847	0.847	0.847	0.847
Firm FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses, clustered at the industry-year level. "savg" and "wavg" represent simple average and weighted average tariffs respectively. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.10. First-stage regressions of tariffs

	(1) $tariff_{savg.input}$	(2) $tariff_{wavg.input}$	(3) $tariff_{savg.output}$	(4) $tariff_{wavg.output}$
$tariff^{1998}_{savg.input}$	0.649***			
	(0.001)			
$tariff^{1998}_{wavg.input}$		0.637***		
		(0.001)		
$tariff^{1998}_{savg.output}$			0.641***	
			(0.002)	
$tariff^{1998}_{wavg.output}$				0.643***
				(0.002)
log *sales*	-0.011***	-0.004***	0.040***	0.075***
	(0.001)	(0.002)	(0.006)	(0.008)
Observations	770,843	770,843	699,579	699,579
Adj. R-squared	0.954	0.944	0.901	0.872
Firm FE	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓

Notes: Standard errors in parentheses. "savg" and "wavg" represent simple average and weighted average tariffs respectively. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.11. Impact of trade liberalization on SO_2 pollution intensity (2SLS)

logSO_2int	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widehat{tariff}_{savg.input} \times WTO$	-0.027***				-0.025***	
	(0.003)				(0.003)	
$\Delta\widehat{tariff}_{wavg.input} \times WTO$		-0.022***				-0.022***
		(0.002)				(0.003)
$\Delta\widehat{tariff}_{savg.output} \times WTO$			-0.006***		-0.003***	
			(0.001)		(0.001)	
$\Delta\widehat{tariff}_{wavg.output} \times WTO$				-0.004***		-0.001
				(0.001)		(0.001)
log *sales*	-0.682***	-0.683***	-0.681***	-0.681***	-0.680***	-0.680***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	560,858	560,858	518,866	518,866	518,866	518,866
Firm FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses, clustered at the industry-year level. "savg" and "wavg" represent simple average and weighted average tariffs respectively. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.12. First-stage regressions of tariffs (2SLS)

	(1) $\Delta tariff_{savg.input}$ $\times WTO$	(2) $\Delta tariff_{wavg.input}$ $\times WTO$	(3) $\Delta tariff_{savg.output}$ $\times WTO$	(4) $\Delta tariff_{wavg.output}$ $\times WTO$
$tariff^{1998}_{savg.input}$	0.488***			
$\times WTO$	(0.001)			
$tariff^{1998}_{wavg.input}$		0.498***		
$\times WTO$		(0.001)		
$tariff^{1998}_{savg.output}$			0.557***	
$\times WTO$			(0.002)	
$tariff^{1998}_{wavg.output}$				0.631***
$\times WTO$				(0.002)
K-P F-stat.	180,956	216,542	106,849	88,279

Notes: Standard errors in parentheses. The subscripts "savg" and "wavg" represent simple average and weighted average tariffs respectively. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.13. Impact of trade liberalization on SO_2 pollution intensity (1997 input-output table)

logSO_2int	(1)	(2)	(3)	(4)	(5)	(6)
$tariff^{1998}_{savg.input} \times WTO$	-0.012***				-0.015***	
	(0.002)				(0.002)	
$tariff^{1998}_{wavg.input} \times WTO$		-0.008***				-0.010***
		(0.002)				(0.002)
$tariff^{1998}_{savg.output} \times WTO$			-0.003***		-0.000	
			(0.001)		(0.001)	
$tariff^{1998}_{wavg.output} \times WTO$				-0.002***		-0.000
				(0.001)		(0.001)
log *sales*	-0.683***	-0.683***	-0.681***	-0.681***	-0.680***	-0.681***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	572,631	572,631	530,643	530,643	530,643	530,643
Adj. R-squared	0.845	0.845	0.847	0.847	0.847	0.847
Firm FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses, clustered at the industry-year level. "savg" and "wavg" represent simple average and weighted average tariffs respectively. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.14. Summary statistics of environmental regulation

Variable	Obs	Mean	Std. dev.	Min	Max
logSO_2int	641,278	2.355	2.175	-8.641	11.290
FYP	891,669	0.503	0.500	0	1
log$Target$	891,669	12.308	0.620	10.594	14.747
log *sales*	861,545	7.300	1.888	2.789	12.448

Notes: logSO_2int is the log of emission intensity (kg/10,000 yuan). FYP is an indicator variable of the 11$^{\text{th}}$ Five-Year Plan which is equal to 1 if the year is 2006 and afterwards, and 0 otherwise. log$Target$ is the log SO_2 emission target measured by the ratio of the province GDP (yuan) to SO_2 target level (kg) in 2010. log $sales_{it}$ is log of firm sales in 1,000 yuan.

Table B.15. SO_2 emission caps and tariff shocks

SO_2 cap	2000-2005	
$TariffShock_{savg.input}$	-1.293	
	(3.419)	
$TariffShock_{savg.output}$	0.454	
	(1.677)	
$TariffShock_{wavg.input}$		0.107
		(3.629)
$TariffShock_{wavg.output}$		-0.179
		(1.693)
Observations	186	186
R-squared	0.0009	0.0002
Year FE	✓	✓

Notes: Standard errors in parentheses. "savg" and "wavg" represent simple average and weighted average tariffs respectively. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.16. Firm-level SO_2 emission intensity decomposition changes

Year	Within	Across	Entry	Exit	Within+Across	Entry+Exit	Overall change
1999	-5.088	2.496	-0.183	-0.511	-2.592	-0.695	-3.286
	(154.82%)	(-75.96%)	(5.57%)	(15.56%)	(78.86%)	(21.14%)	
2000	-2.353	-0.385	0.052	-1.087	-2.738	-1.036	-3.773
	(62.35%)	(10.20%)	(-1.37%)	(28.81%)	(72.56%)	(27.44%)	
2001	-3.351	-0.368	0.857	-1.286	-3.719	-0.429	-4.148
	(80.79%)	(8.86%)	(-20.65%)	(31.00%)	(89.65%)	(10.35%)	
2002	-4.160	-0.514	0.979	-1.358	-4.674	-0.379	-5.053
	(82.33%)	(10.18%)	(-19.38%)	(26.87%)	(92.51%)	(7.49%)	
2003	-2.460	-2.903	1.407	-1.694	-5.363	-0.287	-5.650
	(43.54%)	(51.37%)	(-24.90%)	(29.98%)	(94.91%)	(5.09%)	
2004	-9.244	3.593	1.492	-1.810	-5.651	-0.318	-5.969
	(154.86%)	(-60.19%)	(-24.99%)	(30.32%)	(94.67%)	(5.33%)	
2005	-9.285	3.280	1.238	-2.057	-6.005	-0.818	-6.823
	(136.08%)	(-48.08%)	(-18.15%)	(30.14%)	(88.01%)	(11.99%)	
2006	-7.095	0.559	1.052	-2.364	-6.537	-1.312	-7.849
	(90.40%)	(-7.12%)	(-13.40%)	(30.12%)	(83.28%)	(16.72%)	
2007	-7.120	-0.062	0.779	-2.138	-7.182	-1.358	-8.540
	(83.36%)	(0.73%)	(-9.13%)	(25.03%)	(84.09%)	(15.91%)	
2008	-10.150	2.612	0.766	-2.329	-7.539	-1.562	-9.101
	(111.53%)	(-28.70%)	(-8.42%)	(25.59%)	(82.83%)	(17.17%)	
2009	-13.404	5.780	0.763	-2.725	-7.624	-1.961	-9.585
	(139.84%)	(-60.30%)	(-7.97%)	(28.43%)	(79.54%)	(20.46%)	
2010	-14.373	6.493	1.000	-2.972	-7.880	-1.972	-9.851
	(145.90%)	(-65.91%)	(-10.15%)	(30.17%)	(79.99%)	(20.01%)	
2011	-24.607	16.030	1.087	-2.377	-8.577	-1.290	-9.867
	(249.39%)	(-162.47%)	(-11.02%)	(24.09%)	(86.93%)	(13.07%)	
2012	-23.371	15.234	1.229	-3.196	-8.137	-1.966	-10.104
	(231.32%)	(-150.78%)	(-12.17%)	(31.63%)	(80.54%)	(19.46%)	

Note: The percentage changes of components relative to overall changes are in parentheses.

Table B.17. Firm-level SO_2 emission intensity decomposition levels

Year	Within	Across	Continue (within+across)	Continue +entry	Continue +entry+exit
1998	52.905	-38.949	13.956	-	14.468
1999	47.818	-36.453	11.365	11.693	11.181
2000	47.915	-37.272	10.643	11.782	10.695
2001	49.980	-40.517	9.463	11.606	10.320
2002	46.138	-37.702	8.436	10.772	9.415
2003	47.011	-39.600	7.410	10.512	8.817
2004	53.145	-46.139	7.006	10.308	8.498
2005	50.954	-44.548	6.406	9.701	7.644
2006	39.634	-34.068	5.567	8.983	6.619
2007	41.423	-36.275	5.148	8.065	5.927
2008	38.709	-34.108	4.600	7.695	5.367
2009	34.285	-30.166	4.119	7.607	4.882
2010	31.806	-28.190	3.616	7.588	4.616
2011	20.815	-17.301	3.514	6.978	4.601
2012	18.265	-15.131	3.135	7.560	4.364

Table B.18. Average pollution elasticity across pollutants

Pollutant	SO_2	NO_x	Smoke dust	COD	NH_3-N	Waste water
Mean pollution elasticity α	0.019	0.035	0.013	0.010	0.009	0.017

Note: The pollutants include sulfur dioxide (SO_2), nitrogen oxides (NO_x) and smoke dust for air pollution, chemical oxygen demand (COD), ammonia nitrogen (NH_3-N) and waste water for water pollution.

Table B.19. Abatement cost and emission reduction

	Shares		Values	
Emission reduction	(1)	(2)	(3)	(4)
Abatement cost	0.508***	0.871***	3.333***	2.965***
	(0.009)	(0.012)	(0.025)	(0.026)
Observations	356,793	356,271	356,792	356,270
R-squared	0.590	0.647	0.742	0.778
Firm FE	✓	✓	✓	✓
Year FE	✓		✓	
Industry FE	✓		✓	
City FE	✓		✓	
Industry-Year FE		✓		✓
City-Year FE		✓		✓

Notes: Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.20. Policy effect on pollution intensity

SO_2int	(1)	(2)	(3)	(4)
Export tariff	1.917***	1.351***		
	(0.369)	(0.321)		
Pollution tax			-0.134***	-0.163***
			(0.020)	(0.018)
Observations	364	364	364	364
Adj. R-squared	0.067	0.312	0.193	0.175
Year FE		✓		✓

Notes: Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

C Trade liberalization and environmental regulation

I run joint regressions of the WTO accession and the 11$^{\text{th}}$ Five-Year Plan following equation (C.1). The results are shown in Table C.1. Reassuringly, the coefficients are very close to the results of the WTO in Table 3 and the 11$^{\text{th}}$ Five-Year Plan in Table 4 separately.

$$\log SO_2int_{it} = \beta_0 + \beta_1\, tariff_s \times WTO_t + + \beta_2 \log Target_p \times FYP_t + \log sales_{it} + \gamma_t + \eta_s + \delta_p + \mu_i + \epsilon_{it} \quad \text{(C.1)}$$

Table C.1. Impact of trade liberalization and environmental regulation on SO_2 pollution intensity

$\log SO_2int$	(1)	(2)	(3)	(4)	(5)	(6)
$tariff_{savg.input} \times WTO$	-0.017***				-0.019***	
	(0.004)				(0.004)	
$tariff_{wavg.input} \times WTO$		-0.014***				-0.016***
		(0.003)				(0.003)
$tariff_{savg.output} \times WTO$			-0.004***		-0.000	
			(0.001)		(0.001)	
$tariff_{wavg.output} \times WTO$				-0.002**		0.000
				(0.001)		(0.001)
$\log Target \times FYP$	-0.092***	-0.093***	-0.101***	-0.101***	-0.097***	-0.098***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)
log *sales*	-0.672***	-0.673***	-0.671***	-0.671***	-0.671***	-0.671***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	560,894	560,894	518,901	518,901	518,901	518,901
Adj. R-squared	0.832	0.832	0.835	0.835	0.835	0.835
Year FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses, clustered at the industry-year and province-year levels. "savg" and "wavg" represent simple average and weighted average tariffs respectively. * significant at 10%, ** significant at 5% , *** significant at 1%.

D Alternative firm-level decomposition

I decompose the firm-level pollution intensity following Martin (2012) to investigate the contribution across and within industries and firms. One can write the aggregate pollution intensity

z as:

$$z = \sum_i \frac{x_{is}}{x} z_{is} = \sum_s \sum_{i \in I_s} \frac{x_s}{x} \frac{x_{is}}{x_s} z_{is} = \sum_s s_s \Phi_s$$
$$= \underbrace{\frac{1}{N} \sum_s \bar{z}_s}_{\text{within}} + \underbrace{\frac{1}{N} \sum_s \sum_{i \in I_s} (s_{is} - \bar{s}_s)(z_{is} - \bar{z}_s)}_{\text{across firms}} + \underbrace{\sum_s (s_s - \bar{s}) \left(\Phi_s - \frac{1}{N} \sum_s \Phi_s \right)}_{\text{across industries}} \tag{D.1}$$

where firm i's share of output within industry s is $s_{is} = \frac{x_{is}}{x_s}$, industry s's share within the economy is $s_s = \frac{x_s}{x}$, each industry's pollution intensity is $\Phi_s = \sum_{i \in I_s} \frac{x_{is}}{x_s} z_{is}$, average firm share within each industry is $\bar{s}_s = \frac{1}{n_s} \sum_{i \in I_s} \frac{x_{is}}{x_s}$, average share of a industry within the economy is $\bar{s} = \frac{1}{N} \sum_s \frac{x_s}{x}$, and average pollution intensity in each industry is $\bar{z}_s = \frac{1}{n_s} \sum_{i \in I_s} z_{is}$. n_s and N represent the number of firms within industry s and the number of industries within the economy, respectively.

The three terms on the right-hand-side of equation (D.1) represent the within-firm, across-firms and across-industries effects. The within-firm component is the average industry mean of pollution intensity and accounts for the contribution of average individual firm pollution intensity. The across-firm component covers the difference in pollution intensity between each firm and the sector mean, taking into consideration firm size. The across-industry component consists of the difference in pollution intensity between each sector and the total industry mean, while including sector size. The decomposition outcome is plotted in Figure D.1. The within-firm scale effect is the highest dashed blue line which raised pollution intensity dramatically after 2000 when China entered the WTO and then declined gradually. The across-firm composition effect represented by the dotted-dash red line decreases the pollution intensity by almost one half, which captures reallocation of market shares towards less polluting firms. The structural change across industries further draws down the pollution intensity by a little, as indicated by the solid green line, consistent with the conclusion from industry-level decomposition that industry structure does not reduce pollution much.

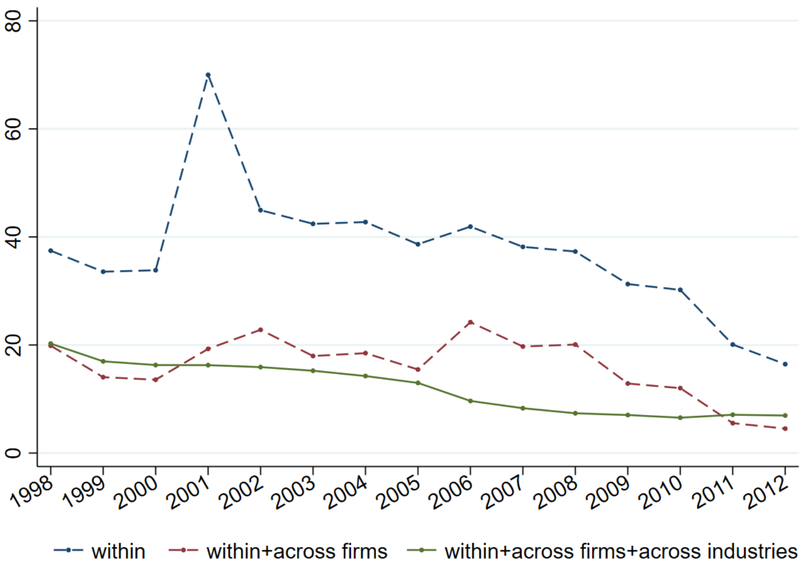


Figure D.1. Firm-level SO_2 emission intensity decomposition

E Proof of comparative statics

First, denote $i_{o,s}(\varphi) = \sum_j z_{oj,s}(\varphi)/\sum_j q_{oj,s}(\varphi)$ as the pollution intensity of a firm with productivity φ, which is pollution emitted per unit of output. $I_{o,s} = Z_{o,s}P_{o,s}/R_{o,s}$ is the pollution intensity of a sector, where $P_{o,s}$ is the sectoral price index, $Z_{o,s}$ is total emissions, and $R_{o,s}$ is total revenue. Next, let $A_{o,s} = E_{o,s}P_{o,s}^{\sigma_s-1}$ be market size, where $E_{o,s}$ is expenditure. Finally, $\lambda_{od,s}$ is a measure of openness to trade, which is the share of country d's expenditure in sector s that is purchased from country o.

Combining equations (20) and (21) gives :

$$\frac{z_{od,s}}{q_{od,s}} = (1 - a_{od,s})^{(1-\alpha_s)/\alpha_s} \tag{E.1}$$

Then $i_{o,s}(\varphi) = \dfrac{\sum_j z_{oj,s}(\varphi)}{\sum_j q_{oj,s}(\varphi)} = \dfrac{\sum_j (1 - a_{od,s})^{(1-\alpha_s)/\alpha_s} q_{oj,s}(\varphi)}{\sum_j q_{oj,s}(\varphi)} = (1-a_{od,s})^{(1-\alpha_s)/\alpha_s} = \left(\dfrac{w_o}{\varphi t_{o,s}}\dfrac{\alpha_s}{1-\alpha_s}\right)^{1-\alpha_s}$ where the last equality is obtained by substituting $1 - a_{od,s}$ with equation (23).

The derivative of pollution intensity with respect to productivity is:

$$\frac{\partial i_{o,s}(\varphi)}{\partial \varphi} = (\alpha_s - 1)\frac{i_{o,s}(\varphi)}{\varphi} < 0$$

given $\alpha_s \in (0, 1)$ and φ, $i_{o,s}(\varphi) > 0$.

Sector-level pollution intensity:

$$I_{o,s} = \frac{Z_{o,s}P_{o,s}}{R_{o,s}} = \frac{\sum_j z_{oj,s}(\varphi)}{\sum_j r_{oj,s}(\varphi)}P_{o,s} = \frac{\alpha_s}{t_{o,s}}\frac{\sigma_s - 1}{\sigma_s}P_{o,s}$$

where the last equality follows by using intensity (E.1), revenue $r_{od,s}(\varphi) = p_{od,s}(\varphi)q_{od,s}(\varphi)$, demand (16), and price (24).

The derivatives are:

$$\frac{\partial I_{o,s}}{\partial t_{o,s}} = \frac{I_{o,s}}{t_{o,s}}(\alpha_s\lambda_{oo,s} - 1) < 0, \quad \frac{\partial I_{o,s}}{\partial b_{o,s}} = -(1-\alpha_s)\frac{I_{o,s}}{b_{o,s}}\lambda_{oo,s} < 0, \quad \frac{\partial I_{o,s}}{\partial \tau_{do,s}} = \frac{I_{o,s}}{\tau_{do,s}}\lambda_{do,s} > 0.$$

given $\alpha_s \in (0, 1)$, $\lambda_{oo,s} \in [0, 1]$, assuming $\theta_s > (\sigma_s - 1)(1 - \alpha_s)$.