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 sulphur dioxide (SO_2) pollution emissions grew at a much lower rate. To study the reasons for this, I focus on the contributions of environmental policy and trade liberalisation, among other factors linked to China's economic development. Combining firm-level data on pollution, production and trade and using China's entry into the World Trade Organisation and the 11$^{\text{th}}$ 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 cleaner 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 liberalisation reduce variable costs of trade and allow firms to abate pollution more.

Keywords: Pollution emission, Environmental regulation, International trade, China.

JEL Codes: F18, F68, L60, Q53, Q56, Q58.

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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 nearly five times from 1998 to 2012. By comparison, the aggregate sulphur dioxide (SO_2) emission in the 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 value) in the blue short-dashed line scaled by the left axis, dropped by around 60%.[1]

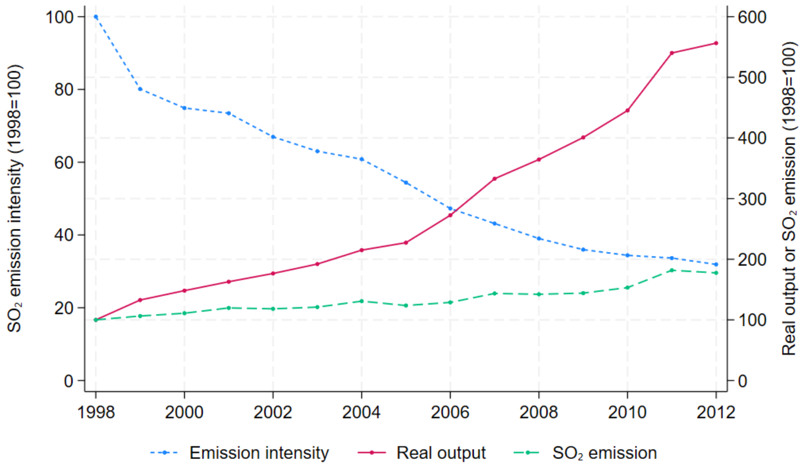


Figure 1. SO_2 emission and real output

Notes: This figure plots the evolution of real manufacturing output, SO_2 total emission and emission intensity (SO_2 per unit of output). The industrial output and 2-digit deflators come from the China Statistical Yearbooks.[2] Firm-level emissions come from the Environmental Statistics Database. The trends of other pollutants show similar patterns and are summarised 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 common in cities. Compared to greenhouse gases with global impact such as carbon dioxide (CO_2), SO_2 is a more local pollutant. It is mainly produced by coal burning, which generated more than 60%

[1]The emission intensity here refers to 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.

[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 incompatible 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.

of electricity in China by 2020, according to the State Council. There are detrimental effects of SO_2 on the environment since it is the primary cause of acid rain, which harms plants and buildings, and can lead to respiratory diseases. The more concentrated the pollutant is, the more harmful it becomes. Therefore, it is very relevant to study the pollution level and the pollution intensity of SO_2 in this paper. The SO_2 emission increased rapidly in China after 2002, from 20 million tons per year to 25.9 million tons in 2006, according to the Ministry of Environmental Protection of China. The amount was higher than all OECD countries combined. Therefore, it was an urgent issue to curb the rapid growth of SO_2 emissions in China. Another reason to study SO_2 is that the regulations set clear targets to reduce SO_2 so that the effectiveness of the environmental policy can be assessed. The data on SO_2 are also recorded with wider coverage of firms and are 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. This paper is among the first to use detailed firm-level pollution data from China, linked to production and trade data, to explore the drivers of industrial pollution emissions. First, it provides descriptive 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 lower pollution intensity. State-owned firms have relatively higher pollution intensity, while foreign-owned firms have relatively lower pollution intensity. Since international trade opportunities give firms incentives to increase production and pollution, while environmental regulations are intended to reduce pollution, the two policies may interact and affect the pollution outcomes. Using China's entry to the WTO and the environmental regulation during the 11^{th} Five-Year Plan as policy shocks, with difference-in-differences (DiD) strategies, I show for the first time that trade liberalisation and pollution policy are jointly 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 total pollution increases more slowly than output. To assess the role of industry structure, I decompose the total pollution level into scale, composition, and technique effects after Copeland and Taylor (1994). 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 the 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. I further apply firm-level decomposition in the spirit of Melitz and Polanec (2015). The results reveal that the reduction in pollution intensity is mainly due to reallocation towards the less pollution-heavy firms within industries, while firm entry and exit play a less important role.

The regression exercises together with the decompositions provide evidence of the channels that drive pollution emissions, such as international trade, environmental regulation, and productivity. However, they are less informative about the aggregate contributions of these forces, nor 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 framework from Shapiro and Walker (2018) and extend it 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, conditional 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 on this aspect through a quantitative model using matched data on pollution, production, and trade of Chinese firms.

The main results suggest that the environmental regulation channel alone would reduce nearly 50% of SO_2 pollution emissions in 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. 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 liberalisation 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 the pollution level, which would be confounded with the technique effect in the conventional decomposition exercise. This indicates that more productive firms reduce pollution more 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 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 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 the most attention are the North American Free Trade Agreement (NAFTA) and China's entry into the World Trade Organisation (WTO). For example, Cherniwchan (2017) estimate the effects of NAFTA on emissions from manufacturing plants in the US and show that two-thirds of particulate matter (PM_{10}) and sulphur dioxide (SO_2) emission reductions between 1994 and 1998 can be attributed to trade liberalisation. For Mexico, Gutiérrez and Teshima (2018) use plant-level data and find that lower tariffs and import competition increase energy efficiency and thus reduce emissions. In another case, Richter and Schiersch (2017) find a negative relation between export intensity and CO_2 emission intensity in Germany. For developing countries such as India, growth in foreign demand led to more carbon dioxide (CO_2) emissions but 40% was mitigated by reduced emission intensity according to 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 labour 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, combining pollution with production and trade at the firm level. As pointed out by Cherniwchan and Taylor (2022), the long-run impact of trade on pollution remains an open question. Rodrigue et al. (2022b) 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 affected pollution emissions. The detailed firm-level data in the regressions are later used in a structural model to consistently quantify different policy effects.

Another line of literature is on environmental regulations. The US enforced the Clean Air Act in the 1990s (Shapiro and Walker, 2018) and the Clean Water Act in 1972 (Keiser and Shapiro, 2018), which substantially abated air and water pollution nationwide. In China, the most frequently mentioned environmental regulation policies were introduced during the 11^{th} Five-Year Plan, covering the period 2006-2010, including both air and water pollutants. Local regulations are effective when supervised by the central government(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).

The evidence confirms 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, specifically, 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 could quantitatively reduce around half of the total emission level.

To disentangle the forces within and across industries that drive the level of pollution emissions, the environmental literature has a long history of decomposition exercises (Copeland and Taylor, 1994; Grossman and Krueger, 1995; Antweiler et al., 2001; Levinson, 2009; Rodrigue et al., 2022a; Barrows and Ollivier, 2018, etc.). In addition to the industry-level decomposition, I decompose the pollution intensity at the firm level, taking into consideration the entry and exit of firms (Melitz and Polanec, 2015). The evidence from industry and firm-level decompositions suggests that within-industry and across-firm production reallocation is a major force that affects pollution levels in China, rather than industry structure change. The results are in line with the Indian case by Barrows and Ollivier (2018) using firm-product level emissions, though it contrasts with the case of Germany, another major country in international trade. 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 has been a small strand of literature using quantitative models to distinguish the contribution of each potential channel to the total level of pollution emissions (Shapiro and Walker, 2018; Shapiro, 2020; Cruz and Rossi-Hansberg, 2023) or to evaluate regulations quantitatively (Duflo et al., 2018; Blundell et al., 2020; Chen et al., 2021). Among them, Shapiro and Walker (2018) develop a two-country, multi-sector model featuring heterogeneous firms in a monopolistic competitive market based on workhorse models from the international (Melitz, 2003) and environmental (Copeland and Taylor, 2003) literature. It is the main structural framework of this paper, which is extended and applied to the Chinese context instead of the original US scenario. The main finding for the US is that environmental regulation, i.e. the Clean Air Act, accounts for most of the emission reductions rather than productivity and trade between 1990 and 2008. Further exploration shows 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 cleaner (Shapiro, 2020). Since China is a much more open economy than the US, and is a developing country that has grown very fast in recent decades, the effects of the channels can be different. Therefore, I extend the analysis and emphasize factors including China's environmental regulation, trade liberalisation and productivity to explore their impacts on pollution emissions. The results show a substantial increase in the implicit pollution tax in China over the sample period. In contrast, an application of the model on German carbon prices (Rottner et al., 2023) shows the implicit carbon price on emission decreased from 2005 to 2019 in most manufacturing sectors.

The different responses to trade liberalisation in countries at various development stages lead to pollution offshoring or the "pollution haven" hypothesis. However, the findings are mixed (Cole and Elliott, 2003; Forslid et al., 2018; Dean et al., 2009; Tanaka et al., 2022; Cherniwchan et al., 2017, Copeland et al., 2022, and Jayachandran, 2022). This paper focuses on the local emission of SO_2, and the answer to the pollution haven hypothesis requires a more comprehensive examination in a separate paper. Finally, there is a growing literature on the labour 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., 2024; Bombardini and Li, 2020). 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 potential effects on health and labour market consequences.

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. 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 at the firm level. The pollution data and the production data start from 1998, and the customs records start in 2000. The common coverage of the three datasets is 2000- 2012. The period of the study covers the fast development since China entered the WTO in 2001 and the implementation of the 11^{th} Five-Year Plan (2006-2010) when the government regulated pollution with specific caps for each province. The majority of the firms in the datasets are concentrated in the manufacturing sectors, which are the focus of this paper. All observations are at the firm level, not plant or establishment, with 4-digit China Industry Classification (henceforth CIC) at each prefecture city.

The reliability of the ESD data is a potential concern, since firms may misreport their emission levels. The ESD is so far the most comprehensive database available on firm-level pollution for China and 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 emissions in each prefecture city. 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 sulphur 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 and private firms with annual sales above 5 million RMB.[3] With the information provided, I can estimate firm-level total factor productivity. 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.

At the aggregate level, I obtain the country-industry production and trade data from the World Input-Output Database (WIOD) for the period 2000-2012 in the structural model estimations. Here I abstract from non-manufacturing industries. The industries are converted from ISIC Revision 4 to CIC 2017 at the 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 the China Statistical Yearbooks and the China Environmental Statistical Yearbooks.

In terms of the industry distribution of SO_2, the manufacturing sector accounts for 53% of total emissions, followed by electricity, heat, gas, and water production and supply, which cover 42% of total emissions in the sample period. Among manufacturing industries, Table B.1 lists the coverage of the firm-level datasets. The pollution data cover 245,475 manufacturing firms between 2000 and 2012. The number shrinks to 130,282 when merged with the ASIF data, accounting for 53% of firms in the pollution data, and 16% of the ASIF data. The number of firms is further reduced to 38,311 when merged with the Customs data, accounting for 29% of firms in the combined pollution and ASIF data. In Section 4.1, I use the pollution data combined with the ASIF and the Customs between 2000 and 2012 to describe the basic patterns of pollution and firm characteristics. In Section 4.2, I use the pollution data starting from 1998, combined with tariff data from the World Integrated Trade Solution (WITS) to evaluate the impact of trade liberalisation. In Section 4.3, I use the pollution data starting from 1998, combined with province regulation targets to assess the effect of environmental regulation. Section 6.2 combines the pollution data and the production data to estimate the model parameters. Finally, Figure A.4 compares the aggregate data from the World Input-Output Table (WIOT), and the EPS firm-level data in terms of production and trade. The firm-level aggregate data closely follow the WIOT data, though slightly lower.

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 played an important role in controlling pollution emissions because there was a specific reduction target of 10% nationwide on pollutants including sulphur dioxide (SO_2) and chemical oxygen demand (COD). The total target was assigned to each province as a pollution quota. The quota was further allocated to cities within each province and large firms.[4] The evaluation of implementation was directly linked to local government performance and the promotion of local leaders. Local governments and firms have strong political incentives to comply with the environmental regulation policy and reduce the pollution emissions to the regional cap. By 2010, most provinces achieved or even exceeded their targets (Shi and Xu, 2018). 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.

[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 exchange rate reported by the Central Bank of China (7.6 RMB per USD in 2007 and 6.5 RMB per USD in 2011).

[4] State-owned enterprises may face more pressure to reduce pollution emissions (e.g. Cui et al., 2020), while foreign-owned firms may be cleaner due to better technology (e.g. Pei et al., 2021). Firms may also change industries or shift production across locations (Chen et al., 2021; Wu et al., 2017). Therefore, in Section 4.2 and Section 4.3, I restrict the sample to firms that remained in the same 4-digit industry or the same prefecture city as robustness checks, which account for 80.34% and 98.36% of firms, respectively.

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 11th Five-Year Plan, there was the 12th 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 11th Five-Year Plan, there are other regional regulations in compliance with the 11th 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).

3.3 China's trade policy

The most important trade policy for China in recent decades is the accession to the World Trade Organisation (WTO) on December 31, 2001. There were significant reductions in tariff rates across all the tradable products, especially in the manufacturing industries. The tariff reductions were bilateral, and following Brandt et al. (2017), I use import tariffs to measure trade openness, because they provide the most accurate and detailed information on the trade reform. The tariff rates on final goods at the 4-digit ISIC level from 1998 to 2011 are retrieved from the World Bank's WITS database. The tariff rates are not available in 2012 for China. I keep both simple average and product line-weighted average tariffs as the output tariffs. The input tariffs are calculated using China's input-output (IO) table in 2002.[5] Specifically, input tariffs are weighted averages of output tariffs, 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). Figures 2b and 2c further show that the simple average input and output tariff levels and tariff changes are positively related to each other. In other words, industries that used to have higher tariff rates experienced more tariff reductions due to the WTO accession.

[5]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 Table B.3 for summary statistics, Figure A.5 for the tariff levels and changes, and Table B.4 for the baseline regression results.

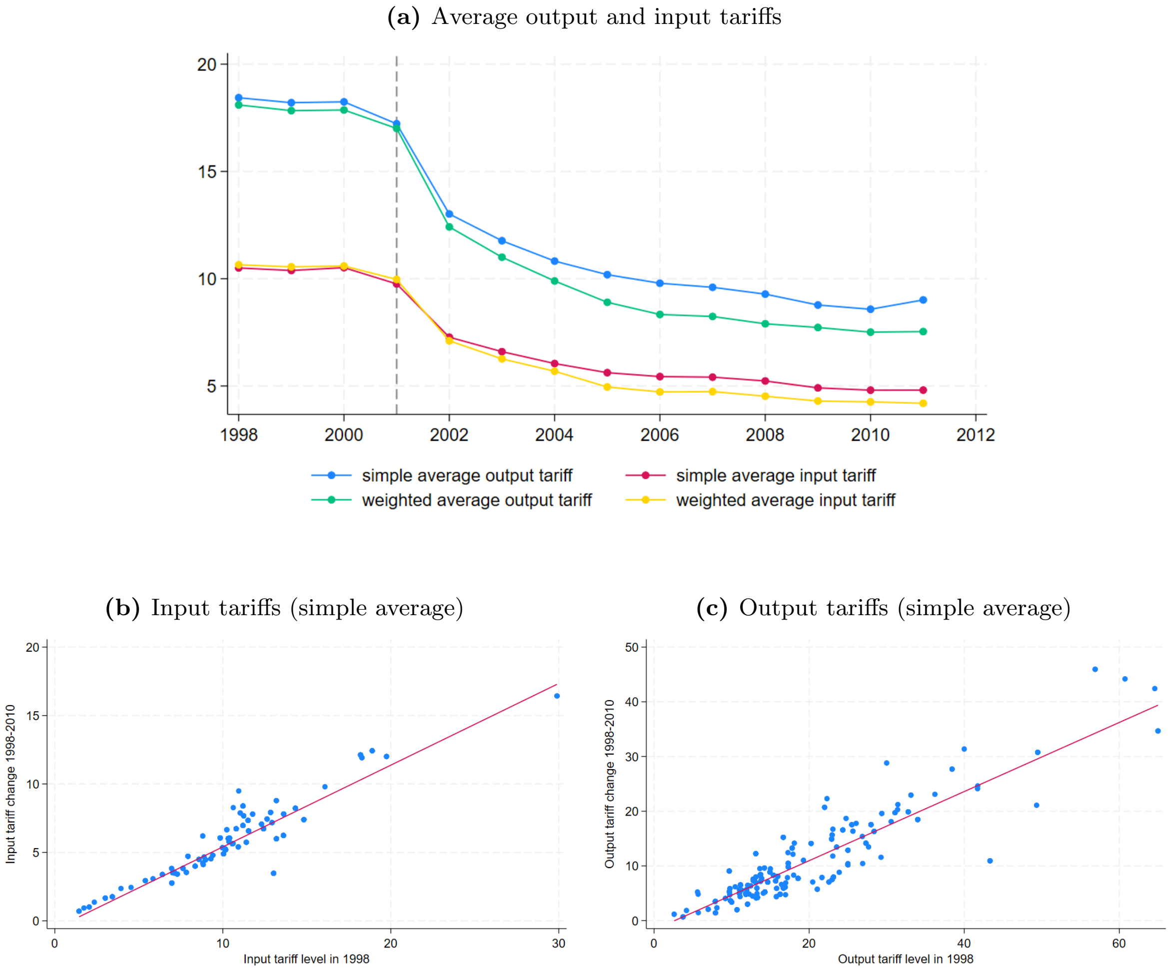


Figure 2. Tariff levels and tariff changes

Notes: These figures plot the simple/weighted average input/output tariffs of 4-digit CIC industries around China's WTO accession on December 31, 2001. Panel (a) plots the tariffs in levels. Panel (b) shows the correlation between the simple average input tariffs and tariff changes since 1998. Panel (c) shows the correlation between the simple average output tariffs and tariff changes since 1998. Each dot represents a 4-digit CIC industry.

4 Firm-level regressions

In this section, I first show some basic patterns of pollution and firm 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 firm-level pollution intensity.

4.1 Pollution and firm characteristics

To begin with, I focus on importers/exporters and see if the amount of international trade affects their pollution outcomes. The specification is the following:

$$y_{it} = \beta_0 + \beta_1 \log Export_{it} + \beta_2 \log Import_{it} + \boldsymbol{\beta_3'} \boldsymbol{X_{it}} + \mu_s + \mu_c + \mu_t + \epsilon_{it} \tag{1}$$

where y_{it} is the outcome variable, which can be log SO_2 emission $\log SO_{2it}$ or emission intensity $\log SO_2int_{it}$. $\log Export_{it}$ and $\log Import_{it}$ are log export and import values in current US dollars, respectively. The control variables $\boldsymbol{X_{it}}$ include the number of employees $labour_{it}$, and firm total factor productivity (TFP) following Levinsohn and Petrin (2003), with Ackerberg et al. (2015) correction.[6] I further include the foreign ownership status dummy FOE and the state ownership status dummy SOE. μ_s, μ_c and μ_t are 4-digit sector, city, and year fixed effects. The summary statistics are shown in Table B.2.

The first column of Table 1 shows that the SO_2 pollution increases with importer and exporter trade values. The second column shows that taking the firm size into consideration, the pollution intensity of exporters and importers decreases with trade values. Column (3) shows that the pollution intensity is positively correlated with firm size, while firms with higher TFP have lower pollution intensity. Column (4) controls for foreign ownership FOE and state ownership SOE. Compared to domestic private-owned firms, foreign-owned firms pollute less intensively, while state-owned firms pollute more intensively.

Table 1. SO_2 pollution and firm characteristics

	(1) logSO_2	(2) logSO_2int	(3) logSO_2int	(4) logSO_2int
log$Export$	0.142***	-0.042***	-0.015*	-0.010
	(0.005)	(0.005)	(0.007)	(0.008)
log$Import$	0.031***	-0.130***	-0.096***	-0.091***
	(0.004)	(0.004)	(0.006)	(0.006)
$labour$			0.006***	0.004***
			(0.001)	(0.001)
TFP			-0.773***	-0.774***
			(0.016)	(0.016)
FOE				-0.318***
				(0.045)
SOE				0.177***
				(0.043)
Observations	51,141	41,645	18,357	18,357
R-squared	0.389	0.465	0.522	0.524
Year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
City FE	yes	yes	yes	yes

Notes: This table presents the correlation between SO_2 emission and importer/exporter firm characteristics. Column (1) shows the results on log SO_2 emission (kg). Columns (2)-(4) show the results on log SO_2 emission intensity (kg/1,000 yuan). Column (3) includes firm size (*labour*) and total factor productivity (TFP) estimated following Levinsohn and Petrin (2003) with Ackerberg et al. (2015) correction. Column (4) includes foreign ownership dummy (FOE) and state ownership dummy (SOE). Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

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 liberalisation

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. All the manufacturing industries experienced some bilateral tariff reduction, thus, there is no control group that had

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

no industrial tariff change. The research design leverages 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:

$$\log SO_2int_{it} = \beta_0 + \beta_1\ tariff_s^{1998} \times WTO_t + \log\ sales_{it} + \eta_s + \delta_{ct} + \mu_i + \epsilon_{it} \tag{2}$$

where $\log SO_2int_{it}$ denotes log 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 firm sales in 1,000 yuan. η_s, δ_{ct}, and μ_i are 4-digit CIC industry, city-year, and firm fixed effects. ϵ_{it} is the error term. The standard errors are clustered at the industry-year level.

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. Following Cui et al. (2020), I do not use tariffs in the current year because they may be endogenous to the pollution outcome. Lagged tariffs also suffer from the problem. As pointed out by Lu and Yu (2015) and shown in Figure 2, the pre-accession tariff is a good predictor of future tariff reduction and import growth, and is not subject to reverse causality after the WTO accession. Therefore, I use the tariff levels in 1998 to measure the impact of trade liberalisation in the baseline. Table B.3 presents the summary statistics of the key variables.

The estimation results of Equation (2) are presented in Table 2. The tariff reduction after the WTO accession 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 1.3% on average in the following years. The results on firms that remained in the same 4-digit industry are reported in Table B.5. The coefficients are consistent with the baseline but larger in magnitude, suggesting that there is reallocation across industries and that the baseline is a lower-bound effect of trade liberalisation.

Table 2. Impact of trade liberalisation on SO_2 pollution intensity

$\log SO_2int$	(1)	(2)	(3)	(4)	(5)	(6)
$tariff^{1998}_{savg.input} \times WTO$	-0.013***				-0.013***	
	(0.002)				(0.002)	
$tariff^{1998}_{wavg.input} \times WTO$		-0.011***				-0.011***
		(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*	-0.683***	-0.683***	-0.681***	-0.681***	-0.680***	-0.680***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	560,858	560,858	518,866	518,866	518,866	518,866
Adj. R-squared	0.846	0.846	0.848	0.848	0.848	0.848
Firm FE	✓	✓	✓	✓	✓	✓
4-digit Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: This table reports the impact of trade liberalisation on SO_2 pollution intensity following Equation (2). The outcome variable $\log SO_2int$ is log SO_2 pollution intensity (kg/1,000 yuan). $tariff^{1998}_{savg.input}$, $tariff^{1998}_{wavg.input}$, $tariff^{1998}_{savg.output}$, $tariff^{1998}_{wavg.output}$ are simple average input, weighted average input, simple average output, and weighted average output tariffs at 4-digit CIC industry level in 1998, respectively. WTO is a dummy variable for China's WTO accession which is equal to 1 after 2001 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the industry-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

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

$$\log SO_2int_{it} = \beta_0 + \sum_t \beta_t\ tariff^{1998}_s \times D_t + \log\ sales_{it} + \eta_s + \delta_{ct} + \mu_i + \epsilon_{it} \qquad (3)$$

where D_t is the year dummy, and the year of the WTO accession 2001 is omitted. The estimation results are plotted in Figure 3. Consistent with the regressions, the 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 reversed in the last few years of the sample period, potentially because tariff rates stabilised and were sufficiently low to further influence pollution emissions.

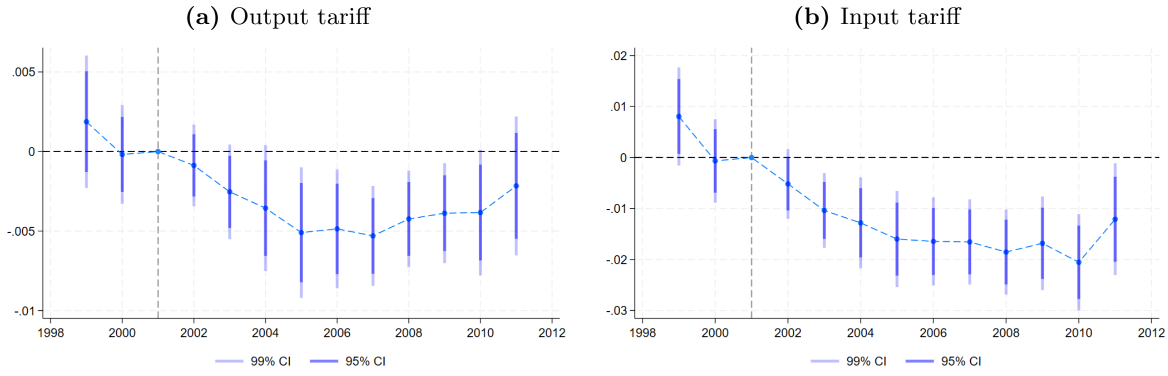


Figure 3. Impact of trade liberalisation on SO_2 pollution intensity (simple average tariffs)

Notes: These figures plot the estimates of trade liberalisation effects over time following Equation (3), along with the 95% and 99% confidence intervals. The vertical dashed line indicates the year of China's WTO accession.

Following Shapiro (2020), I further differentiate industries by dirty and clean. Dirty industries have pollution per unit cost above average, while clean industries are below average. Dirty industries include industries with 2-digit code 22 (Manufacture of paper and paper products), 26 (Manufacture of raw chemical materials and chemical products), 28 (Manufacture of chemical fibres), 30 (Manufacture of non-metallic mineral products), 31 (Smelting and pressing of ferrous metals), 32 (Smelting and pressing of non-ferrous metals), consistent with the structural parameters in Table 5. The baseline regression results by dirty and clean industries are in Table B.6. Compared to all industries, the effect of trade liberalisation on SO_2 pollution intensity is larger in dirty industries and smaller in clean industries, suggesting that trade liberalisation reduced pollution intensity mainly within dirty industry categories.

To check the robustness of the baseline results, in the spirit of Brandt et al. (2017), I use tariffs before the WTO accession in 1998 as instruments for the one-year lag tariffs with two-stage least-squares (2SLS) regressions. This could reduce endogeneity concerns such as reverse causality between tariffs and the outcome variable. The first-stage results are in Table B.7. There is a strong and positive correlation between the instrument and the tariff changes. The second-stage results are in Table B.8. 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 1.8% to 2.2% on average in the following years.

The results on other pollutants are summarized in Table B.9. I replicate the baseline regressions of sulphur dioxide (SO_2) on chemical oxygen demand (COD), waste gas (WasteGas), and waste water (WasteWater). The data are not available for nitrogen oxides (NO_x) before 2006 and for ammonia nitrogen (NH_3-N) before 2001, so they are not included in this exercise. The effects of trade liberalisation on COD are negative but not statistically significant. The effects on waste gas are negative and statistically significant in input tariffs with magnitudes similar to SO_2. The effect on waste water is only negative and statistically significant in simple average input tariffs and the magnitude is much smaller than SO_2. The event study graphs on waste gas and waste water are in Figure A.6. The effects of tariffs on pollution intensity are not statistically significant before the WTO accession and become statistically significant afterwards.

4.3 Environmental regulation

Next, I use different emission caps across provinces during the 11th Five-Year Plan to measure the effect of environmental regulation on firm SO_2 emission. Similar 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 faces no environmental regulation. The research design leverages 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 generalized difference-in-differences (DiD) specification:

$$\log SO_2int_{it} = \beta_0 + \beta_1 \log Target_p \times FYP_t + \log\ sales_{it} + \delta_p + \eta_{st} + \mu_i + \epsilon_{it} \tag{4}$$

where $\log SO_2int_{it}$ is the log 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.[7] 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 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.10. The regression results are shown in Table 3. If the provincial $Target$ increases by 1 %, the firm-level pollution intensity would decrease by around 0.07% to 0.09%. The results on firms that remained in the same city are reported in Table B.12. The coefficients are consistent with the baseline but slightly smaller in magnitude, suggesting that there is pollution reallocation across locations and that the baseline may overestimate the effect of the environmental regulation.

Again, I run the regression by year following the event study specification:

$$\log SO_2int_{it} = \beta_0 + \sum_t \beta_t \log Target_p \times D_t + \log\ sales_{it} + \delta_p + \eta_{st} + \mu_i + \epsilon_{it} \tag{5}$$

where D_t is the year dummy, and the year before the 11^{th} Five-Year Plan 2005 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.

[7] I can use an alternative environmental regulation target measured by the log of the ratio between the SO_2 emission target during the 10^{th} Five-Year Plan and the 11^{th} Five-Year Plan. The summary statistics are shown in Table B.10. The regression results are reported in Table B.11 and are consistent with the baseline measure. For ease of comparison between the empirical evidence and the model counterfactual, I keep the baseline measure henceforth.

Table 3. 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	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Year FE	✓	✓		
2-digit Industry FE	✓			
4-digit Industry FE		✓		
2-digit Industry-Year FE			✓	
4-digit Industry-Year FE				✓

Notes: This table presents the impact of environmental regulation on SO_2 emission intensity following Equation (4). The outcome variable $\log SO_2int$ is log SO_2 pollution intensity (kg/1,000 yuan). $\log Target$ is the log SO_2 emission target measured by the ratio of the province GDP (yuan) to SO_2 target level (kg) in 2010. A higher emission target indicates more strict regulation. FYP is a dummy variable of the 11$^{\text{th}}$ Five-Year Plan which is equal to 1 after 2005 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the province-year level. * significant at 10%, ** significant at 5% , *** significant at 1%. The number of observations is smaller in Column (4) than in the previous columns because more singleton observations are dropped when controlling for 4-digit Industry-Year FE.

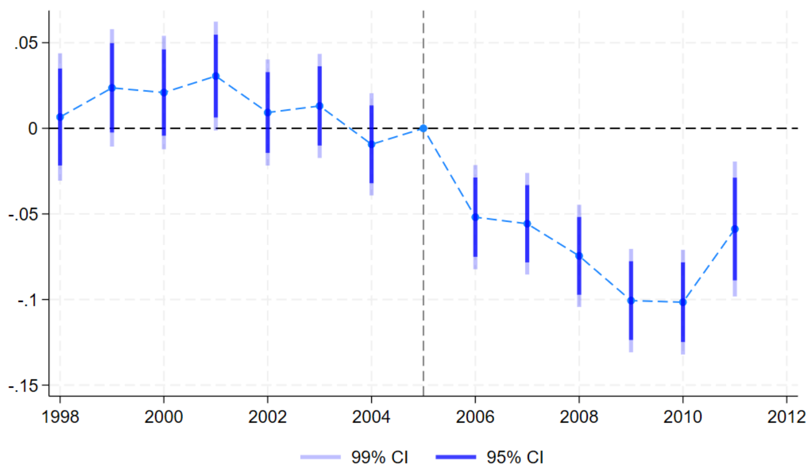


Figure 4. Impact of environmental regulation on SO_2 pollution intensity

Notes: This figure plots the estimates of environmental regulation effects over time following Equation (5), along with the 95% and 99% confidence intervals. The vertical dashed line indicates the year before China's 11$^{\text{th}}$ Five-Year Plan.

One concern of the DiD exercises is that trade reform and 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.

Since the WTO accession and the 11^{th} 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.

Another concern with the DiD regressions is that the pollution targets may be correlated with some time-varying province characteristics that bias the results. Therefore, following Shi and Xu (2018) who studied the regional SO_2 regulation during the 10^{th} 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:

$$\log SO_2int_{it} = \beta_0 + \beta_1 \log Target_p \times FYP_t \times \log SO_2int_{sector} + \log\, sales_{it} + \gamma_{pt} + \delta_{ps} + \eta_{st} + \mu_i + \epsilon_{it} \quad (6)$$

where $\log SO_2int_{it}$ is the log 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 11^{th} Five-Year Plan which is equal to 1 if the year is 2006 and afterwards, and 0 otherwise. $\log SO_2int_{sector}$ is the log SO_2 emission to GDP ratio of each 2-digit industry in 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 4. Consistent with the DiD regression results, more stringent pollution regulation during the 11^{th} Five-Year Plan decreases firm pollution intensity, especially in industries with high SO_2 pollution emission intensities.

Table 4. Impact of environmental regulation on SO_2 pollution intensity (triple differences)

$\log SO_2int$	(1)	(2)	(3)	(4)
$\log Target \times FYP \times \log SO_2int_{sector}$	-0.053***	-0.016*	-0.040***	-0.017***
	(0.015)	(0.009)	(0.012)	(0.005)
log *sales*	-0.498***	-0.668***	-0.497***	-0.671***
	(0.008)	(0.009)	(0.004)	(0.005)
Observations	628,682	576,121	619,121	569,315
Adj. R-squared	0.536	0.830	0.704	0.832
Province-Year FE	✓			
Province-Industry FE	✓		✓	
Industry-Year FE	✓	✓	✓	✓
City-Year FE		✓		
City-Industry FE		✓		✓
Firm FE			✓	✓

Notes: This table presents the impact of environmental regulation on SO_2 pollution intensity following Equation (6). The outcome variable $\log SO_2int$ is log SO_2 pollution intensity (kg/1,000 yuan). $\log Target$ is the log SO_2 emission target measured by the ratio of the province GDP (yuan) to SO_2 target level (kg) in 2010. A higher emission target indicates more strict regulation. FYP is a dummy variable of the 11^{th} Five-Year Plan which is equal to 1 after 2005 and 0 otherwise. $\log SO_2int_{sector}$ is the log SO_2 emission to GDP ratio of each 2-digit industry in 2005. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the province-industry level. * significant at 10%, ** significant at 5% , *** significant at 1%.

The results on other pollutants are summarized in Table B.13. I redo the baseline exercises of sulphur dioxide (SO_2) on chemical oxygen demand (COD) and ammonia nitrogen (NH_3-N). The COD targets are province total quotas similar to SO_2, and the NH_3-N targets cover only industry and household. There were no emission targets on nitrogen oxides (NO_x), waste gas (WasteGas), and waste water (WasteWater) during the 11^{th} Five-Year Plan, so they are not included in this exercise. The effects of environmental regulation on COD and NH_3-N are negative and statistically significant with magnitudes even larger than SO_2. The event study graphs are in Figure A.7. The effects of environmental regulation on pollution intensity are not statistically significant before the 11$^{\text{th}}$ Five-Year Plan and become statistically significant afterwards.

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

5 Decomposition

This section conducts the decomposition exercises 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:

$$Z = \sum_s z_s = \sum_s x_s e_s = X \sum_s \kappa_s e_s \tag{7}$$

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 value. If each sector's share of total output is denoted as $\kappa_s = x_s/X$, Z equals the final term of Equation (7). Put in vector forms:

$$Z = X\boldsymbol{\kappa}'\boldsymbol{e} \tag{8}$$

Totally differentiating equation (8) yields:

$$dZ = \underbrace{\boldsymbol{\kappa}'\boldsymbol{e}dX}_{\text{scale}} + \underbrace{X\boldsymbol{e}'d\boldsymbol{\kappa}}_{\text{composition}} + \underbrace{X\boldsymbol{\kappa}'d\boldsymbol{e}}_{\text{technique}} \tag{9}$$

The three terms on the right-hand-side of equation (9) 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 (9), while the output is deflated with 2-digit industry-year specific indices from the China Statistical Yearbooks.[8]

The decomposition 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 was at work. The red short-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

[8]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.

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 the scale effect alone, as in Cole and Zhang (2019) and Rodrigue et al. (2022a), whereas the technique effect greatly reduces pollution.[9,10]

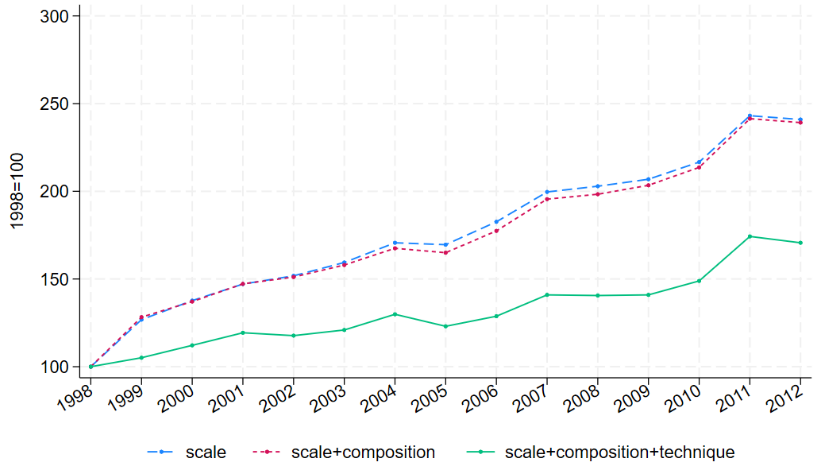


Figure 5. Industry-level SO_2 emission decomposition

Note: This figure plots the industry-level decomposition results following Equation (9).

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 by more than half over 20 years. The combined scale and composition effects are also different between China and the US, with China more than doubled and the US less than 40% growth. For both the US and China, the technique effect significantly drives down total pollution.

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 e over time (from $t = 1$ to 2) can be decomposed into three groups of firms,

[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 the 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.8. In either case, the magnitudes are similar.

[10] 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 firm-level emission intensities at 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. 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. The results are summarized in Figure A.9. 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 shows a slightly higher scale effect as well as the combination of scale and composition effects, but the overall trends remain close.

namely, continuing (C), entering (E), and exiting (X) firms:

$$\begin{aligned} e_1 =& s_{C1}e_{C1} + s_{X1}e_{X1} &= e_{C1} + s_{X1}(e_{X1} - e_{C1}) = \bar{e}_{C1} + \text{cov}_{C1} + s_{X1}(e_{X1} - e_{C1}) \\ e_2 =& s_{C2}e_{C2} + s_{E2}e_{E2} &= e_{C2} + s_{E2}(e_{E2} - e_{C2}) = \bar{e}_{C2} + \text{cov}_{C2} + s_{E2}(e_{E2} - e_{C2}) \end{aligned} \tag{10}$$

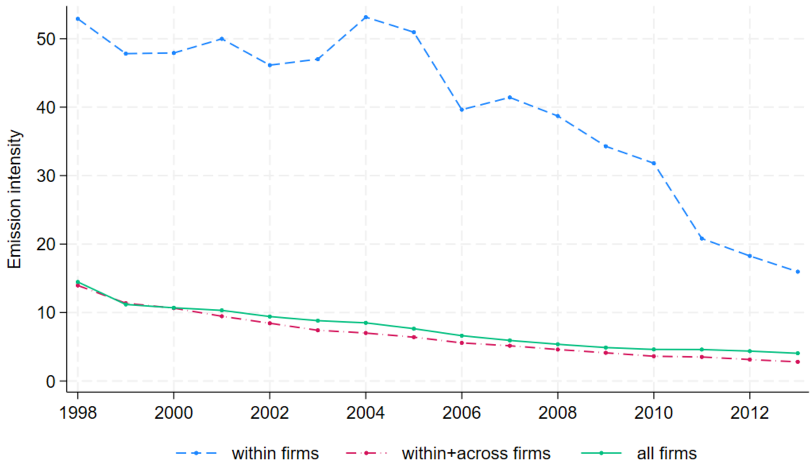
The pollution intensity expressed in change Δe is:

$$\begin{aligned} \Delta e &= (e_{C2} - e_{C1}) + s_{E2}(e_{E2} - e_{C2}) + s_{X1}(e_{C1} - e_{X1}) \\ &= \underbrace{\underbrace{\Delta\bar{e}_C}_{\text{within-firm}} + \underbrace{\Delta\text{cov}_C}_{\text{across-firm}}}_{\text{continuing firms}} + \underbrace{s_{E2}(e_{E2} - e_{C2})}_{\text{entering firms}} + \underbrace{s_{X1}(e_{C1} - e_{X1})}_{\text{exiting firms}} \end{aligned} \tag{11}$$

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 $e_{Gt} = \sum_{i \in G}(s_{it}/s_{Gt})e_{it}$ is the group's weighted average emission intensity. Among continuing firms, the first term $\bar{e}_C = \frac{1}{n}\sum_{i=1}^{n} e_i$ is the unweighted mean firm emission intensity. The second term $\text{cov}_C = \sum_i (s_i - \bar{s})(e_i - \bar{e})$ 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 the year 1998 as the initial period $t = 1$ and all the changes are relative to this baseline year.

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 are 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 detail. Firm entry increases pollution intensity while firm exit reduces pollution intensity. I also conduct the firm-level decomposition by sector and then calculate sector averages of each component. The results are plotted in Figure A.10 and are qualitatively similar.

(a) Within and across continuing firms



(b) Entry and exit

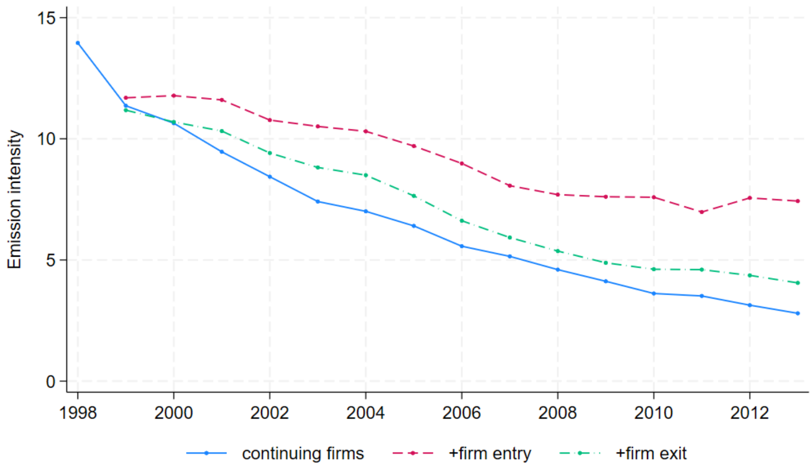


Figure 6. Firm-level SO_2 emission intensity decomposition

Note: These figures plot the firm-level decomposition results following Equation (11).

The evidence from the regressions and decompositions show the following stylized facts: (i) Firms in industries with more trade liberalisation pollute less intensively. (ii) Firms in provinces with more stringent environmental regulations pollute less intensively. (iii) Higher TFP and better technology help firms reduce pollution emissions. (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. The model features firms that differ in productivity, and choose different pollution abatement costs. Labour 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. One can derive analytical solutions from the model to guide the counterfactual analysis. I first introduce the key setup of the model in Section 6.1, and then estimate the key parameters using China's firm-level data in Section 6.2, and recover some historical values in Section 6.3 before the counterfactual exercises in Section 7.

6.1 Setup

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

$$U_d = \prod_s \left(\left[\sum_o \int_{\omega \in \Omega_{o,s}} q_{od,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right]^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\beta_{d,s}} \tag{12}$$

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.

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:

$$\pi_{o,s}(\varphi) = \sum_d \pi_{od,s}(\varphi) - w_o f^e_{o,s} \tag{13}$$

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

where $p_{od,s}(\varphi)$ is the price, w_o is the wage of labour $l_{od,s}(\varphi)$, $t_{o,s}$ 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:

$$G(\varphi; b_{o,s}) = 1 - \left(\frac{\varphi}{b_{o,s}} \right)^{-\theta_s} \tag{14}$$

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.

Production and pollution Firms sell the number of units:

$$q_{od,s}(\varphi) = (1 - a_{od,s}(\varphi))\varphi l_{od,s}(\varphi) \tag{15}$$

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 emissions:

$$z_{od,s}(\varphi) = (1 - a_{od,s}(\varphi))^{\frac{1}{\alpha_s}} \varphi l_{od,s}(\varphi) \tag{16}$$

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).

Intermediate results Combing equations (15) and (16), one can write the output as a Cobb-Douglas function of pollution emissions and productive factors:

$$q_{od,s} = (z_{od,s})^{\alpha_s}(\varphi l_{od,s})^{1-\alpha_s} \tag{17}$$

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

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

$$1 - a_{od,s} = \left(\frac{w_o}{\varphi t_{o,s}} \frac{\alpha_s}{1-\alpha_s}\right)^{\alpha_s} \tag{18}$$

These results will be used later for comparative statics and parameter estimates.

Competitive equilibrium There are two conditions for a competitive equilibrium. The first condition is on labour market clearing, where labour supply must equal labour demand in each country. The second condition is that the expected profit must equal the fixed cost of drawing productivity.

Comparative statics Before carrying out the quantitative analysis, it is useful to show the effects of pollution taxes, productivity, and trade liberalisation analytically to better understand the implications of the model. The proofs of the propositions are detailed in the appendix of Shapiro and Walker (2018).

PROPOSITION 1:

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

The reason is that firms with higher productivity invest more in pollution abatement to maximize profit, as shown in the first-order condition (18).

PROPOSITION 2:

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

The intuition is that pollution tax makes firms invest more in pollution abatement as shown in Equation (18). 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.

Method of counterfactual analysis To analyze counterfactual pollution emissions, one can 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 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, and 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 the world is considered foreign. The equilibrium conditions can be expressed in changes as follows:[11]

$$1 = \psi_o \left(\frac{\sum_s \hat{M}^e_{o,s} R_{o,s} \frac{(\sigma_s - 1)(\theta_s - \alpha_s + 1)}{\sigma_s \theta_s} + \eta'_o}{\sum_s R_{o,s} \frac{(\sigma_s - 1)(\theta_s - \alpha_s + 1)}{\sigma_s \theta_s} + \eta_o} \right) \tag{19}$$

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

$$\hat{w}_o = \sum_d \frac{\zeta_{od,s}\hat{w}_o^{-\theta_s}\hat{\Gamma}_{od,s}}{\sum_o \lambda_{od,s}\hat{M}^e_{o,s}\hat{w}_o^{-\theta_s}\hat{\Gamma}_{od,s}} \hat{\beta}_{d,s} \frac{R'_d - NX'_d}{R_d - NX_d} \tag{20}$$

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, one 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:

$$\hat{Z}_{o,s} = \frac{\hat{M}^e_{o,s}\hat{w}_o}{\hat{t_{o,s}}} \tag{21}$$

where $\hat{M}^e_{o,s}$ and $\hat{w}_o$ are endogenous variables that depend on changes in foreign and home market competitiveness, expenditure shares and pollution tax $\{\hat{\Gamma}_{od,s}, \hat{\beta}_{d,s}, \hat{t}_{o,s}\}$. I then extend the analysis to include additional channels relevant to the Chinese economy and pollution. Specifically, I extract the variable trade cost and productivity $\hat{\tau}_{od,s}$ and $\hat{b}_{o,s}$ from home market competitiveness $\hat{\Gamma}_{od,s}$ to look at counterfactual pollution outcomes.

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. I combine the firm-level pollution data from the ESD and the production data from the ASIF to estimate the model parameters.

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 the lack of precise abatement cost information and prefecture-level regulation stringency is neither readily available nor comprehensive.[12] Therefore, I estimate equation (17) 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), with Ackerberg et al. (2015) correction.[13] I then rewrite the equation into the following econometric specification:

$$\ln q_{it} = \alpha \ln z_{it} + (1-\alpha)\ln(\varphi l_{it}) + \nu_t + \nu_c + \nu_s + \epsilon_{it} \tag{22}$$

[12] Rodrigue et al. (2022b) instead measures emission output abatement rather than abatement cost.

[13] Specifically, the TFP is measured by the log output minus a weighted sum of log labour, 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 the 2-digit industry-specific producer price index, the capital is deflated with the provincial fixed assets investment price index, the materials are deflated with the annual purchasing price index, and the energy input is measured by industrial coal consumption. Coal is the major source of energy and SO_2 emissions 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 the China Statistical Yearbooks.

where the pollution elasticity α is the estimated average coefficient of pollution emission z_{it} for all manufacturing firms, q_{it} and l_{it} are output and labour employment of firm i respectively.[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 5. The estimated pollution elasticity for each 2-digit sector s is listed in Column (2) of Table 5. 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.

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

Table 5. 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
All	Mean	1.18	0.019	0.79	6.07	7.51

Alternatively, I can estimate the production function taking into consideration labour, capital, materials, energy input, and pollution emission together to simultaneously obtain the pollution elasticity and productivity, the result is an estimated average pollution elasticity $\alpha = 0.022$, 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 both close to the baseline estimate. In addition to the baseline SO_2 pollution elasticity, I also estimate the pollution elasticities of other pollutants as reported in Table B.14, 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 it with some related statistics. According to the China Environmental Statistical Yearbooks, the average pollution abatement investment as a percentage of the GDP of each province is 1.6 percent, 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 (15) and (16) to get $\frac{z_{od,s}}{q_{od,s}} = (1 - a_{od,s})^{(1-\alpha_s)/\alpha_s}$ 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.11 compares the abatement cost in industrial waste gas summed by province according to the China Environmental Statistical Yearbooks and the abatement cost implied by the model. The trends are very similar between the data and the model.

One assumption of the model is that firms spend a fraction a of input on pollution abatement, while the remaining $1 - a$ is used on production. The higher the pollution abatement cost a, the more emissions 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 emission abatement using the difference between the emission generated and the emission reduction. Figure A.12 shows the correlation between the emission reduction and abatement cost by industry across time. The left panel shows the correlation in shares and the right panel shows the correlation in values. In any case, the emission reduction and the abatement cost are positively correlated, which supports the implication of the model.

6.2.2 The elasticity of substitution

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

$$w_o L^p_{o,s} = (1 - \alpha_s)\frac{\sigma_s - 1}{\sigma_s} R_{o,s} \tag{23}$$

where w_o is the nominal wage of the origin country, $L^p_{o,s}$ is the labour 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:

$$\sigma_s = (1 - \alpha_s)/(1 - \alpha_s - w_o L^p_{o,s}/R_{o,s}) \tag{24}$$

where $w_o L^p_{o,s}/R_{o,s}$ is the sector input share reported in Column (3) of Table 5. The method 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 ASIF to estimate this set of parameters and the results are listed in Column (4) of Table 5. The cross-sector mean is 6.07. The sector with the largest elasticity of substitution is "Processing of petroleum, coking, and nuclear fuel" (σ=11.18), which has more homogeneous products and the sector with the smallest elasticity of substitution is "Manufacture of tobacco" (σ=1.81) followed by "Manufacture of medicines" (σ=2.37), which have relatively more differentiated products. The industries are comparable to the estimates in Shapiro and Walker (2018). In their paper, the elasticity of substitution is highest for "Coke refined petroleum, and nuclear fuels sector" (σ=8.18), while the elasticity of substitution is smallest for "Medical, precision, and optical products sector" (σ=2.89), with a cross-sector mean of 4.76.

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:

$$\ln(Pr\{x > X_{i,s}\}) = \gamma_{0,s} + \gamma_{1,s}\ln(X_{i,s}) + \epsilon_{i,s} \tag{25}$$

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 sector are used because the Pareto distribution best fits the right tail of the firm distribution. The results are in Column (5) of Table 5. 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 countries. I recover the historical values of these variables to prepare for the counterfactual analysis. In addition, I extend the analysis and extract variable trade cost and productivity from home competitiveness to specifically examine the impact of trade liberalisation and technology improvement, corresponding to the empirical findings.

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 of interest 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 behaviour 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:

$$\hat{t}_{o,s} = \frac{\hat{M}^e_{o,s}\hat{w}_o}{\hat{Z}_{o,s}} \tag{26}$$

where $\hat{Z}_{o,s}$ 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

[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 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 elasticity of substitution in the counterfactual section and show that the results are qualitatively robust.

by the change in the mass of firm entry, factor price, and pollution emission, which reflects the overall level of regulation on SO_2. The recovered trend is shown in Figure 7.

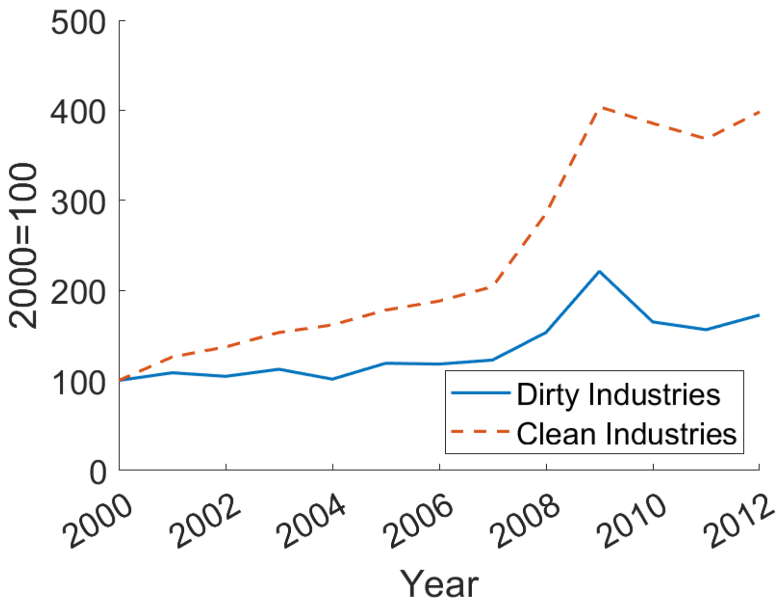


Figure 7. Implicit pollution tax of SO_2 (model-implied)

Note: This figure plots the implicit pollution tax of SO_2 emissions $\hat{t}_{o,s}$ recovered from Equation (26). The 2-digit CIC industries are aggregated into dirty and clean industries. Dirty industries have pollution elasticity α_s above average, while clean industries are below average, weighted by the baseline output of each industry.

The dirty industries are those with pollution elasticity above the sector mean and the clean industries are below the mean pollution elasticity.[16] The two groups of industries are weighted by baseline industry revenue from the World Input-Output Tables (WIOT). The implicit pollution tax on SO_2 increased significantly during the sample period, with clean industries higher than dirty industries. I plot the implied pollution tax for other pollutants in Figure A.13. The implicit pollution taxes on the other pollutants also increased significantly during the sample period.

There is no direct pollution tax for firms since local governments may implement policies at different times and policy details. One can think of the pollution tax as a measure of the 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/kg to 1.26 yuan/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 the change in SO_2 emission divided by the change in output before and after the 11^{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.[17] 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.

[16] The dirty industries include industries with 2-digit code 22 (Manufacture of paper and paper products), 26 (Manufacture of raw chemical materials and chemical products), 28 (Manufacture of chemical fibres), 30 (Manufacture of non-metallic mineral products), 31 (Smelting and pressing of ferrous metals), and 32 (Smelting and pressing of non-ferrous metals). The rest are relatively clean industries.

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

The results are plotted in Figure A.14. High-regulation provinces face a 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 the following:

$$\hat{\beta}^*_{d,s} = \frac{\sum_o X'_{od,s} / \sum_{o,s} X'_{od,s}}{\sum_o X_{od,s} / \sum_{o,s} X_{od,s}} \tag{27}$$

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 is the same as above, where dirty industries have above-average pollution elasticities and clean industries below average. The two groups are aggregated using unweighted means. The rest of the world apart from China is aggregated into Foreign as one destination. In both panels, the change in dirty industries is higher in general than in clean industries. There are drops in expenditure shares of dirty industries after the 2008 financial crisis and increases in expenditure shares of clean industries.

6.3.3 Market competitiveness

The third group of historical values is foreign and Chinese market competitiveness. Here, Chinese "competitiveness" refers to the ability of Chinese firms selling 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:

$$\hat{\Gamma}_{od,s} = (1/\hat{b}_{o,s})^{-\theta_s} (\hat{\tau}_{od,s})^{-\theta_s/(1-\alpha_s)} (\hat{f}_{od,s})^{1-\theta_s/(\sigma_s-1)(1-\alpha_s)} (\hat{t}_{o,s})^{-\alpha_s\theta_s/(1-\alpha_s)} \tag{28}$$

$$= \frac{\hat{\lambda}_{od,s}}{\hat{M}^e_{o,s} \hat{w}_o^{-\theta_s}}, \; o \neq \text{China} \tag{29}$$

$$\hat{\Gamma}_{od,s} = (1/\hat{b}_{o,s})^{-\theta_s} (\hat{\tau}_{od,s})^{-\theta_s/(1-\alpha_s)} (\hat{f}_{od,s})^{1-\theta_s/(\sigma_s-1)(1-\alpha_s)} \tag{30}$$

$$= \hat{t}_{o,s}^{\frac{\alpha_s\theta_s}{1-\alpha_s}} \frac{\hat{\lambda}_{od,s}}{\hat{M}^e_{o,s} \hat{w}_o^{-\theta_s}}, \; o = \text{China} \tag{31}$$

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.

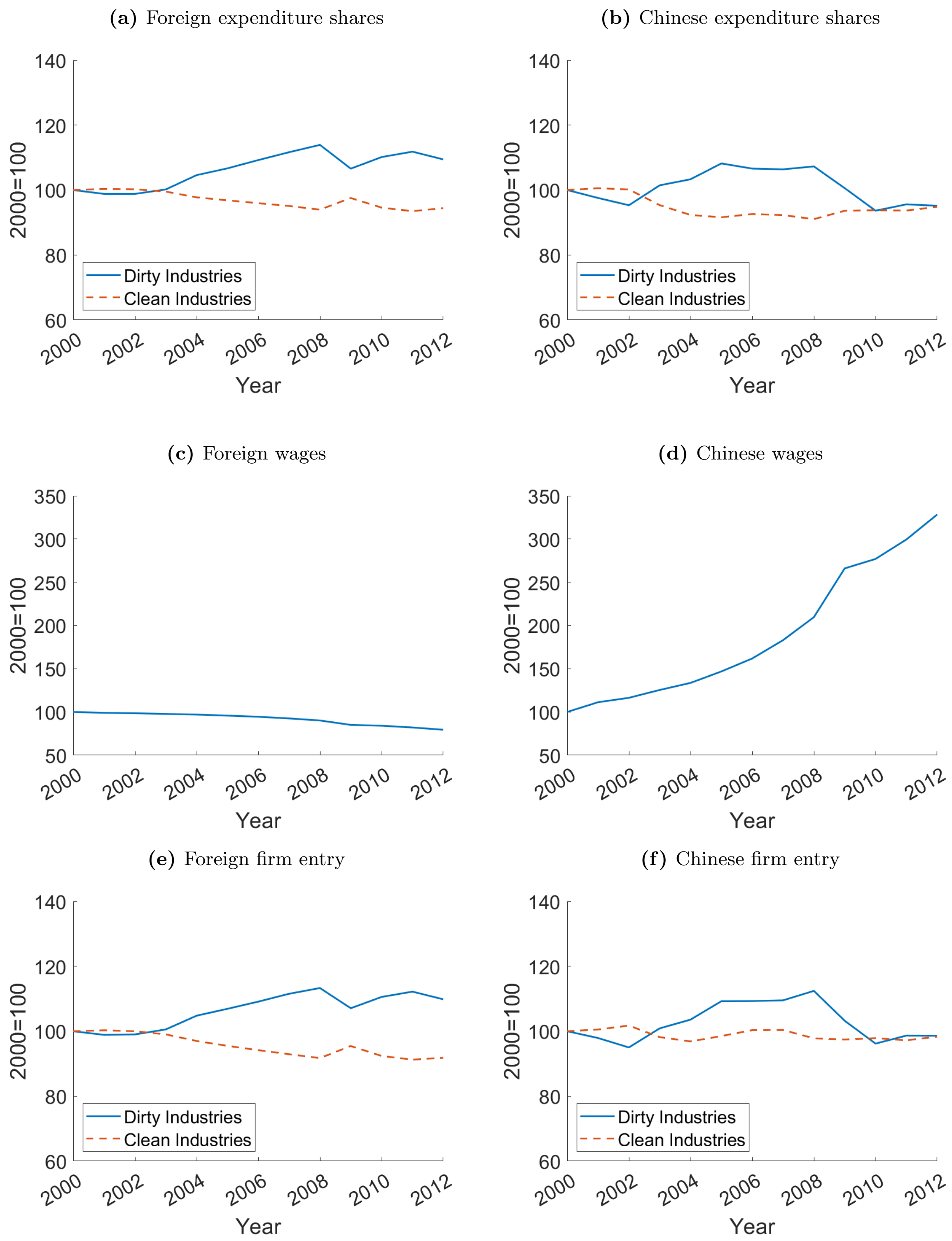


Figure 8. Historic values

Notes: These figures plot the historical values of key variables from the model. Panels (a) and (b) plot the foreign and Chinese expenditure shares $\hat{\beta}_{d,s}$ from Equation (27). Panels (c) and (d) plot the foreign and Chinese wages $\hat{w}_o$ solved from equilibrium conditions (19) and (20). Panels (e) and (f) plot the foreign and Chinese firm entry $\hat{M}^e_{o,s}$ solved from equilibrium conditions (19) and (20). The 2-digit CIC industries are aggregated into dirty and clean industries in panels (a), (b), (e), and (f). Dirty industries have pollution elasticity α_s above average, while clean industries are below average, unweighted mean.

It is not very informative to plot the market competitiveness per se, so I plot the historical values of some sum-components of the market competitiveness, namely, the Foreign and Chinese wages, as well as firm entry in Figure 8.

The wages recovered from the model show that the nominal wages for countries outside of China dropped gradually after 2000 to reach a level of 80% of its initial value. In contrast, the nominal wages for China increased to over 300% of their level in 2000. To make sense of the foreign wage changes from the model, 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 the world grew by less than 20%. For China, the US accounts for a large share of foreign wages, which corresponds to the model-implied mild decline in foreign wages. On the other hand, for the US, the rapid wage increase in China contributes to the wage growth of the rest of the world.

To verify the Chinese wage changes solved from the model, I compare the results to wage data from other sources. One source is the average wage bill from financial accounts of industrial firms in the ASIF database, weighted by the annual firm employment. Figure A.15 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 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.15 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 for the retrieved values from the model, however, they offer a reasonable range where the endogenous wages 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 rapid growth 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 A.16 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 a certain threshold and are not the universe of firms. However, the positive correlation reflects that the model captures the variances across industry and time in the data.

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 (30) into export tariff $\hat{\tau}_{od,s}$ which is the variable cost of trade, and sector productivity measured by the Pareto location parameter $\hat{b}_{o,s}$. Since China is more open than the US economy, it is likely that trade liberalisation affects production and pollution more in China. Therefore, it is useful to specifically evaluate the effect of tariff reduction. This would also link the model to the regression analysis and allow for checks on the pollution response to policy interventions.

I use effective applied (AHS) simple average export tariff data for China from the World Bank's WITS database at 4-digit ISIC Revision 3 level and convert to CIC 2-digit level to account for tariff $\tau_{od,s}$ in the model. The Pareto location parameter $b_{o,s}$ can be obtained along with the estimation of the Pareto shape parameter θ_s. 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 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. The retrieved historical values of the additional set of variables are shown in Figure 9. I can then look at counterfactual pollution emissions if each of these variables alone follows the historical values.

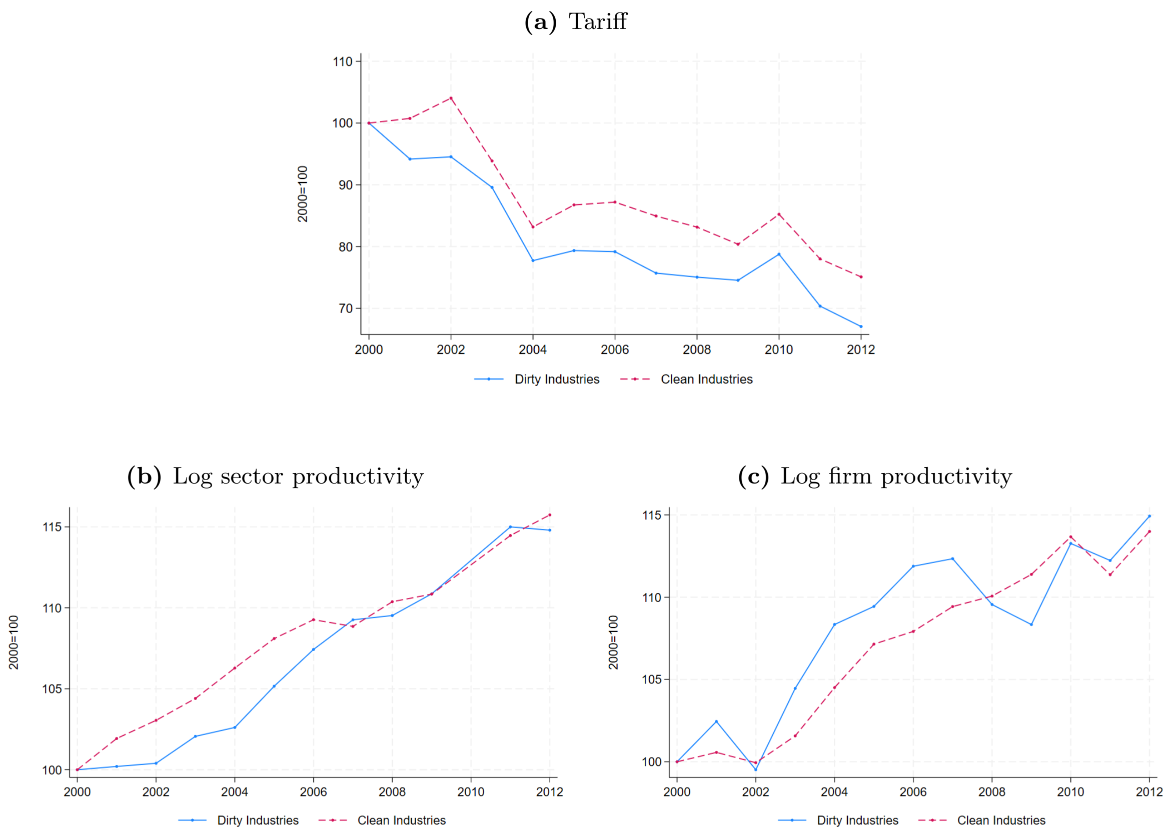


Figure 9. Historic values of additional variables

Notes: These figures plot the historical values of additional variables for the counterfactual. Panel (a) plots the tariff $\tau_{od,s}$ using the effective applied (AHS) simple average export tariff data for China from the World Bank's WITS database at 4-digit ISIC Revision 3 level and converted to CIC 2-digit level. Panel (b) plots the log sector productivity from the Pareto location parameter $b_{o,s}$ in the model. Panel (c) plots the log firm productivity from the production function estimation following Levinsohn and Petrin (2003), with Ackerberg et al. (2015) correction. 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. I then extend the exercise to variable trade costs and productivity to assess their effects on total pollution. Section 7.2 shows other counterfactual results such as the effects of a single channel and pollution intensity outcomes. Section 7.3 compares the magnitudes of the model and data in terms of policies on trade liberalisation and environmental regulation. I then calculate the economic cost of environmental regulation, before experimenting with other counterfactual policies. Section 7.4 conducts sensitivity analyses of the model. Finally, Section 7.5 summarizes the counterfactual emissions of other pollutants.

7.1 Baseline results

The baseline counterfactual results are plotted in Figure 10. 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 the year 2000. The figure shows that Chinese competitiveness would greatly increase the total SO_2 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 much.

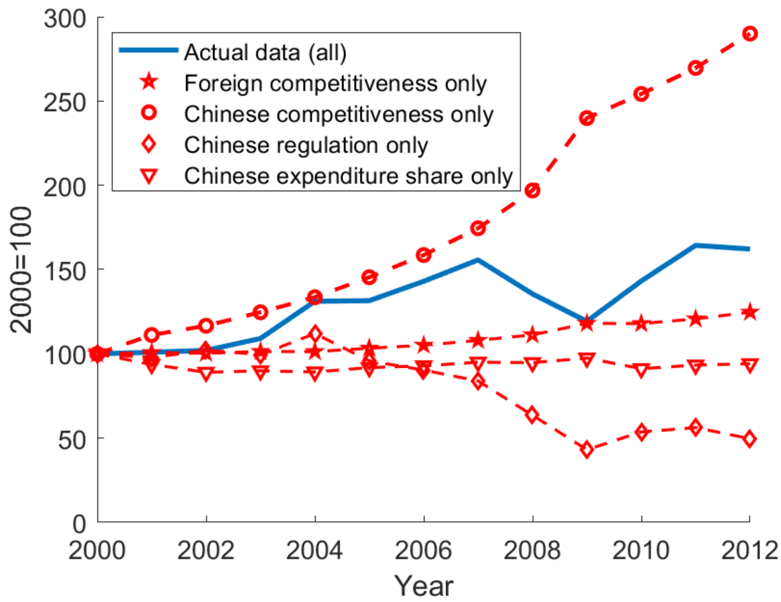


Figure 10. Counterfactual Chinese manufacturing pollution emissions

Notes: This figure plots the counterfactual Chinese manufacturing pollution emissions of foreign competitiveness, Chinese competitiveness, Chinese regulation and Chinese expenditure share, respectively. The solid blue line is the data when all channels are included. The dashed red lines are counterfactual pollution emissions when only one channel follows the historical values while the other variables are at the initial values in 2000.

The additional counterfactual results by decomposing Chinese competitiveness are plotted in Figure 11. The blue dashed lines show that the tariff changes would reduce the total SO_2 pollution emission level by the most among other channels since 2004, later surpassed by Chinese regulation since 2008. While the sector productivity would reduce the pollution level, however, the magnitudes are moderate.

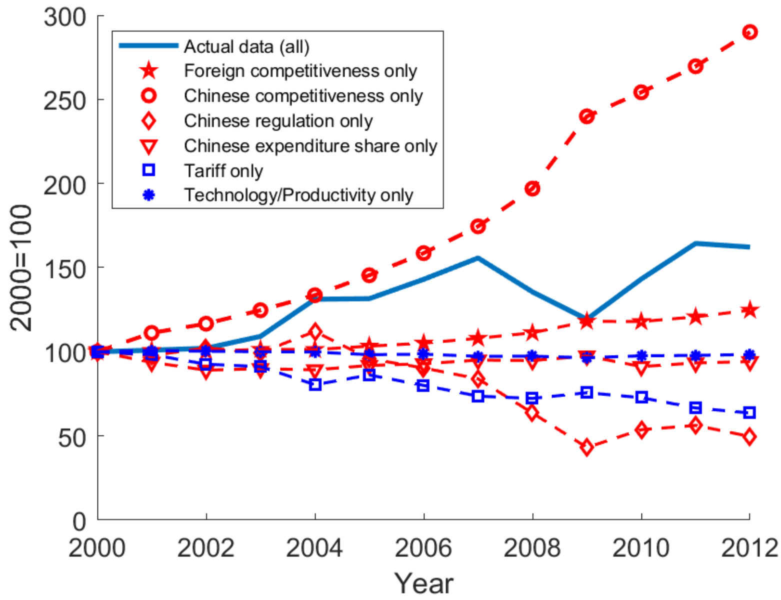


Figure 11. Additional counterfactuals (decomposed Chinese competitiveness)

Notes: This figure plots the additional counterfactual Chinese manufacturing pollution emissions by decomposing Chinese competitiveness to tariff and productivity, respectively. The solid blue line is the data when all channels are included. The dashed red and blue lines are counterfactual pollution emissions when only one channel follows the historical values while the other variables are at the initial values in 2000.

In the benchmark counterfactual results, I aggregate firm-level pollution merged with production information used for parameter estimates, so there is a dip in the 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 the 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 tariffs is more pronounced than in the benchmark.

7.2 Other counterfactuals

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

7.2.1 Effect of a single channel

The baseline counterfactual results are structural decompositions when one variable follows the historical values, and the other variables remain at the initial values. Alternatively, one can evaluate the counterfactual effect of a single channel (e.g. flat pollution tax or no environmental policy), computed by keeping one variable at the initial value, and the other variables follow their historical values. The results 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 2000, which is much higher than the actual pollution level at 162%. If the level of trade liberalisation 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 Pollution intensity

In terms of pollution intensity, Figure A.19 shows that it dropped over the period to less than 50% of the initial value, corresponding to Figure 1 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 liberalisation 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 estimates from the regressions to check the external validity of the model predictions. Specifically, I look at the "elasticity" of pollution intensity to trade liberalisation and environmental regulation, which are the main forces to reduce pollution in the model. I then calculate the economic cost of environmental regulation, before experimenting with counterfactual policies.

7.3.1 Trade liberalisation

Recall that in Table 2, a 1% point reduction in input tariff would reduce firm SO_2 intensity by 1.1% to 1.3% on average. I then regress the industry-specific counterfactual pollution intensity from the model on average industry tariff. The first two columns in Table B.15 show that a 1% tariff cut would reduce pollution intensity by 1.4% to 1.9%, which is of similar magnitude to the estimate from the regressions.

7.3.2 Environmental regulation

Table 3 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. Columns (3) and (4) in Table B.15 show that a 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 11th Five-Year Plan, while there might be other local policies that are not included in the DiD analysis but captured in the structure model. 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, the economic cost of SO_2 emission was 20,000 yuan per ton in 2005.[18] 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

[18]The economic cost of emission per ton of SO_2 estimated by the European Commission for the EU25 Member States is 5,600 EUR at a lower bound in 2005, which is equivalent to 53,200 RMB at the exchange rate of 1 EUR=9.5 RMB in 2005. The value is much higher than the cost in China. However, the GDP per capita in the EU25 Member States was significantly higher than in China. Given that the GDP per capita is positively related to the economic cost of pollution, the economic costs of pollution in the EU and China are incompatible. Therefore, I do not directly use the EU standard in the calculation of the economic cost of pollution.

of SO_2 emission (5.7 million tons $\times$112%), equal to 127.68 billion RMB in 2005 (6.384 million tons $\times$ 20,000 RMB/ton), roughly 0.68% of annual GDP in 2005.[19]

7.3.4 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.20a displays the scenario when all industries receive the same level of environmental regulation so that they face a 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 the actual level, SO_2 emissions would further decrease to 25% of the initial level.

One can also examine the counterfactual pollution emissions due to alternative tariff rates. Figure A.20b shows that if tariff costs were reduced by half, SO_2 emissions would further decrease to 38% of the initial level. The results indicate that trade conflicts such as the US-China trade war would have inverse effects on pollution emissions. As tariff costs increase, firms are left with little room to abate pollution, and as a result, emission levels will rise.

Finally, combining the trade policy and the environment policy has synergy effects in Figure A.20c and further reduces the total SO_2 pollution to roughly 27% of the 2000 level.

7.4 Sensitivity analyses

I conduct a series of sensitivity analyses on the main counterfactuals in this section. The first row of Table 6 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 11. 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 using trade data and 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 6. Compared to the main counterfactuals, this exercise provides very similar results, except that the change in tariff is 10% 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, such as the top 25% and 50% instead of 10% in the baseline. 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 when the parameter is halved or doubled. The counterfactuals are a bit more volatile to changes in parameter α, 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 nearly one-half.

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

Table 6. Sensitivity analysis

	Foreign competitiveness	Chinese competitiveness	Chinese expenditure shares	Chinese environmental regulation	Tariff	Technology/ productivity
1. Actual change			162.180			
2. Main estimate	124.726	289.988	94.147	49.662	63.566	98.361
3. σ: Feenstra	124.289	292.573	94.124	49.768	73.522	96.444
4. θ: top 25 %	124.646	290.096	94.136	49.800	71.307	95.794
5. θ: top 50 %	124.452	288.870	49.916	94.119	72.038	93.669
6. α: $\times$ 0.5	124.443	285.067	50.323	94.139	71.442	97.976
7. α: $\times$ 2	125.592	343.825	94.181	44.728	75.548	99.519
8. Partial equilibrium	100.000	100.000	100.000	50.815	100.000	100.000

Notes: This table presents the sensitivity analysis of the main model counterfactual SO_2 emissions between 2000 and 2012. The SO_2 emission at the beginning of the period is set to 100. Row 1 reports the actual change in the data, which means at the end of the period in 2012, the SO_2 emission from the Chinese manufacturing industries increased by 62.18%. Row 2 shows the main estimate corresponding to the baseline counterfactual Figure 10. Row 3 uses an alternative method to estimate the elasticity of substitution σ following Soderbery (2015). Rows 4 and 5 estimate the Pareto shape parameter θ using the top 25% and 50% tails respectively, instead of the 10% tail in the baseline. Rows 6 and 7 change the estimated pollution elasticity α by half or double. Row 8 presents partial equilibrium where there is no change in factor prices or firm entry: $\hat{w}_o = \hat{M}^e_{o,s} = 1$.

7.5 Counterfactuals for other pollutants

Apart from SO_2, I reproduce the counterfactual analysis with regard to other pollutants following the same procedure of 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 of 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 a comparable assessment of the effect of policies. The counterfactual exercises are summarized in Figure A.21. 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 more stringent environmental policies. In terms of other air pollutants, environmental regulations would have reduced NO_x (nitrogen oxides) emissions by around 50%, while almost all smoke dust emissions could be reduced. These results indicate that there is a 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 in reducing 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 levels 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 using matched data on China's firm-level financial statistics, trade, and pollution emissions. I find that large firms pollute more, but the more firms import and export, the less pollution-intensive they are. Higher total factor productivity and foreign ownership are associated with lower pollution intensity while state-owned firms have higher pollution intensity. Policies such as international trade liberalisation and environmental regulation can effectively 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, rather than industry structural change or firm entry and exit.

To structurally estimate the effects from the regressions and decompositions and to conduct counterfactual analysis, I adopt the quantitative framework of Shapiro and Walker (2018) to derive the contribution of each 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 are estimated by sector 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 and 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. I further single out two additional channels, namely, the variable trade costs measured by tariffs and productivity. The results show that tariff cuts from trade liberalisation are the force second to environmental regulation to drive down pollution levels. Meanwhile, productivity alone would reduce pollution only moderately. Finally, I compare the magnitudes from the regressions with the implications from the model, and explore some alternative environmental policies and tariff costs to derive the counterfactual emission outcomes.

The findings of this paper highlight the importance of environmental and trade policies in reducing pollution emissions. Regulations can be important 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 has been discussed in this paper, including greenhouse gases (GHG) such as 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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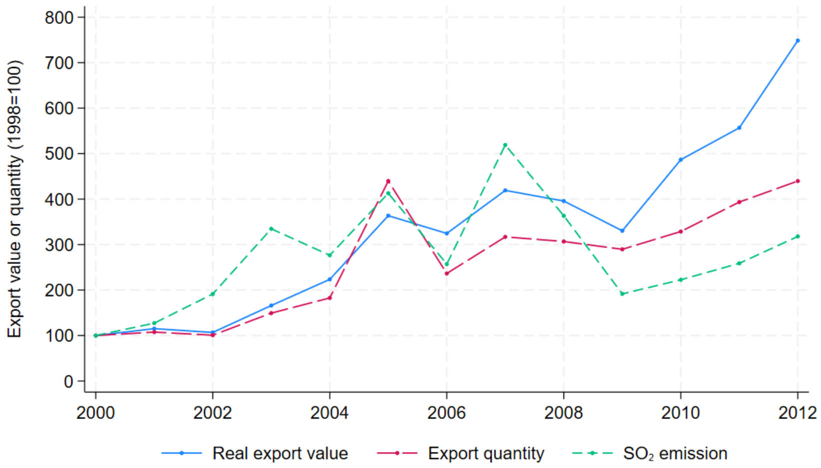
Appendix

A Additional figures

(a) Export and emission



(b) Revenue and physical emission intensities

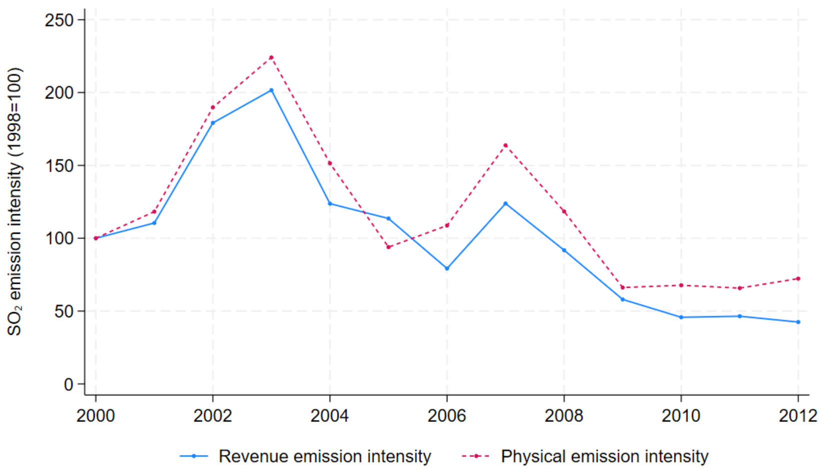


Figure A.1. Export emission intensities

Notes: Panel (a) plots the export value, quantity and SO_2 emission by combining production data with trade data, assuming that emission is proportional to production. Panel (b) plots The revenue and physical emission intensities, respectively. The export data come from the customs, the pollution data come from the Ministry of Environment Protection.

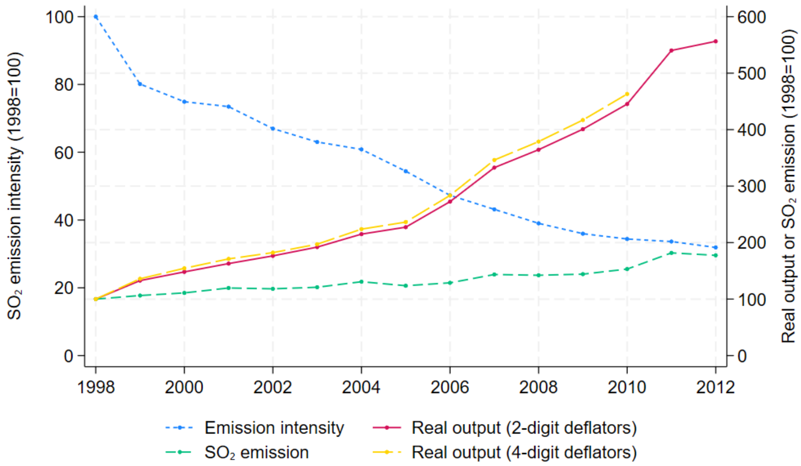


Figure A.2. SO_2 emissions and real output (different deflators)

Notes: This figure plots the evolution of real manufacturing output, SO_2 total emission and emission intensity (SO_2 per unit of output value). The real manufacturing output is deflated with 2-digit and 4-digit deflators, respectively. The industrial output and 2-digit deflators come from the China Statistical Yearbooks. I alternatively use 4-digit 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 incompatible with previous years, so I do not extend the deflators after 2010. The real output deflated at 4-digit industries closely follows the trend deflated at 2-digit industries. Firm-level emissions come from the Environmental Statistics Database.

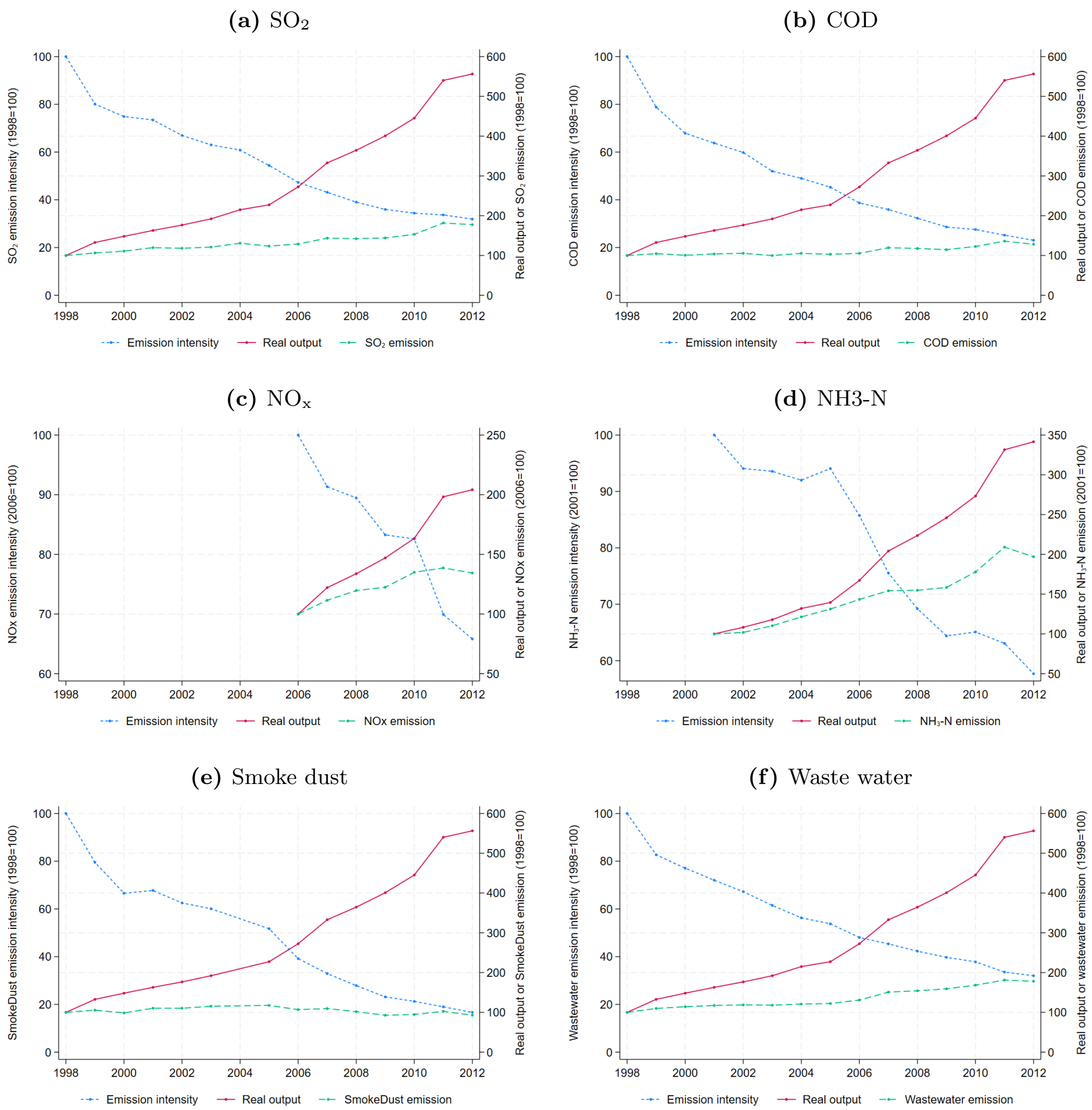
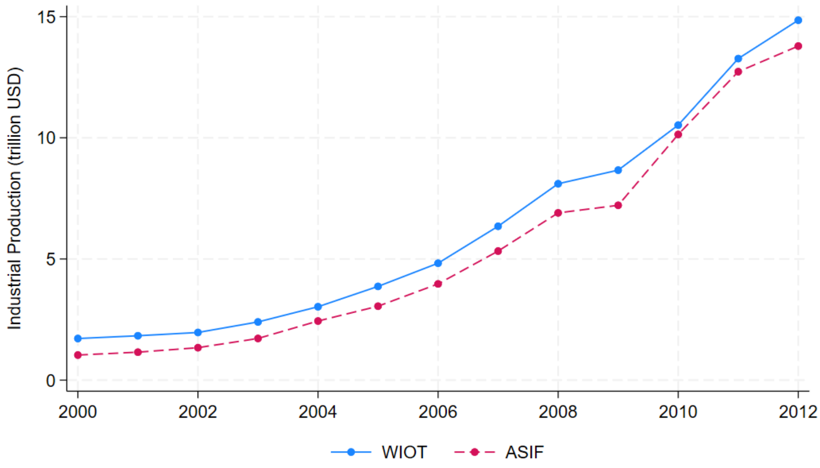


Figure A.3. Pollution emissions and real output (other pollutants)

Notes: These figures plot the evolution of real manufacturing output, total emission and emission intensity (emission per unit of output value) across pollutants. The industrial output and 2-digit deflators come from the China Statistical Yearbooks. Firm-level emissions come from the Environmental Statistics Database. The pollutants include sulphur 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) Production

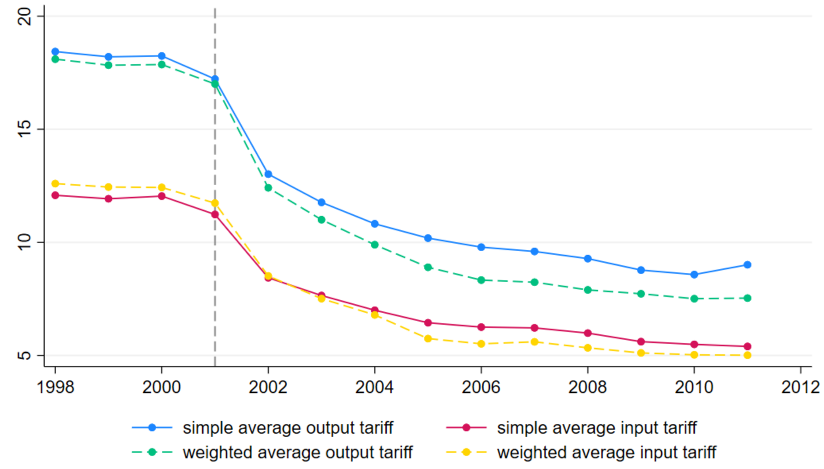
(b) Export

(c) Import

Figure A.4. Data match

Note: These figures plot the match between the WIOT data and the EPS firm-level data between 2000 and 2012.

(a) Average output and input tariffs



(b) Input tariffs (simple average)

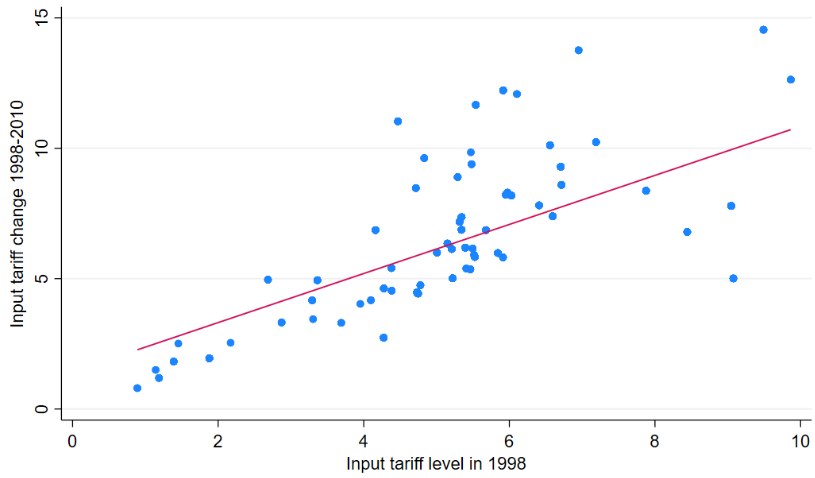


Figure A.5. Tariff levels and tariff changes (1997 input-output table)

Notes: These figures plot the simple/weighted average input/output tariffs of 4-digit CIC industries around China's WTO accession on December 31, 2001, using the input-output table of 1997 to derive the input tariffs from output tariffs. Panel (a) plots the tariffs in levels. Panel (b) shows the correlation between simple average input tariffs and changes in tariffs since 1998. Each dot represents a 4-digit CIC industry.

(a) Waste gas (b) Waste water

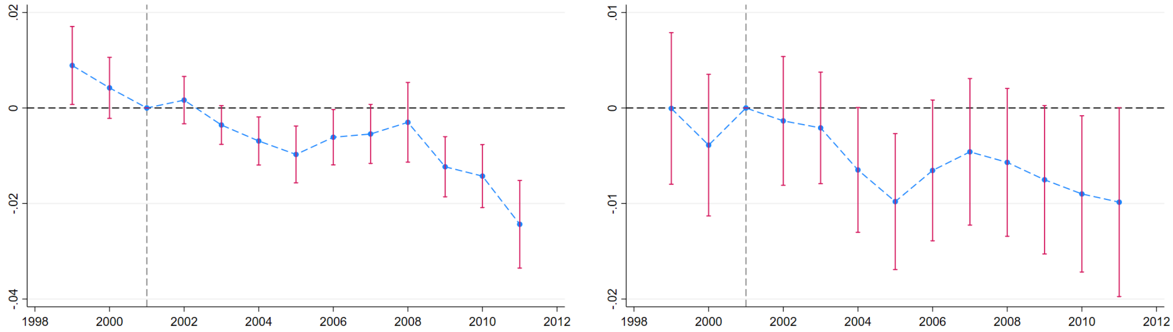


Figure A.6. Impact of trade liberalisation on pollution intensity (simple average input tariffs, other pollutants)

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

(a) COD (b) NH_3-N

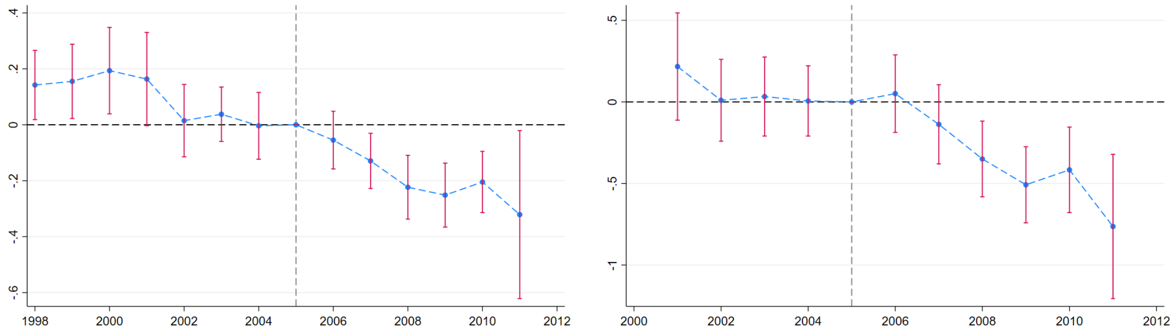


Figure A.7. Impact of environmental regulation on pollution intensity (other pollutants)

Notes: These figures plot the estimates of environmental regulation effects over time, along with the 95% confidence intervals. The pollutants are chemical oxygen demand (COD) and ammonia nitrogen (NH_3-N), respectively. The vertical dashed line indicates the year before China's 11th Five-Year Plan.

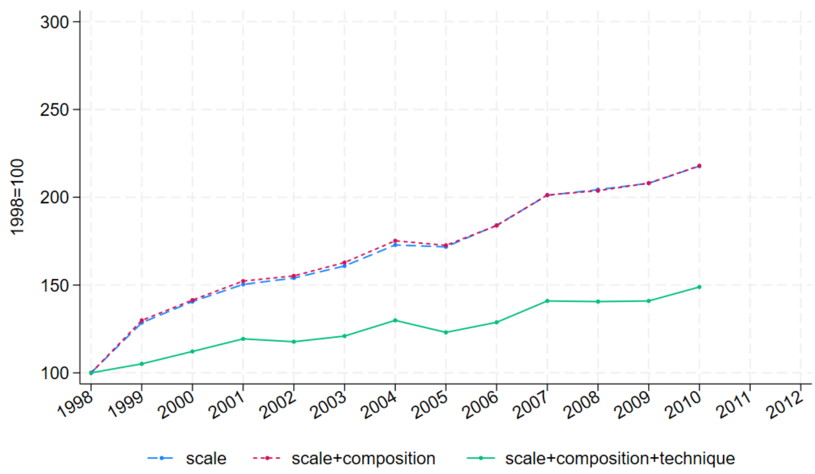
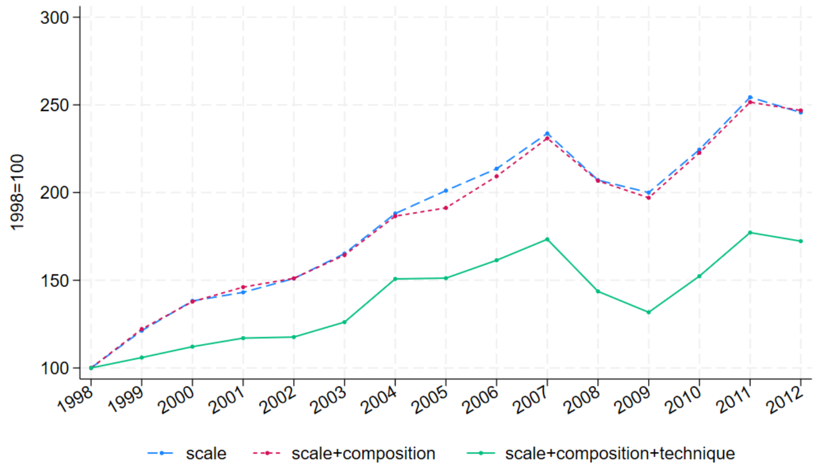


Figure A.8. Industry-level SO_2 emission decomposition (alternative deflator)

Notes: This figure plots the industry-level decomposition results following Equation (9) at 4-digit industries with 4-digit deflators from Brandt et al. (2017) instead of decomposition at 2-digit industries. The sample with 4-digit deflators covers 1998-2010 due to the compatibility of deflators.

(a) Revenue shares



(b) Cost shares

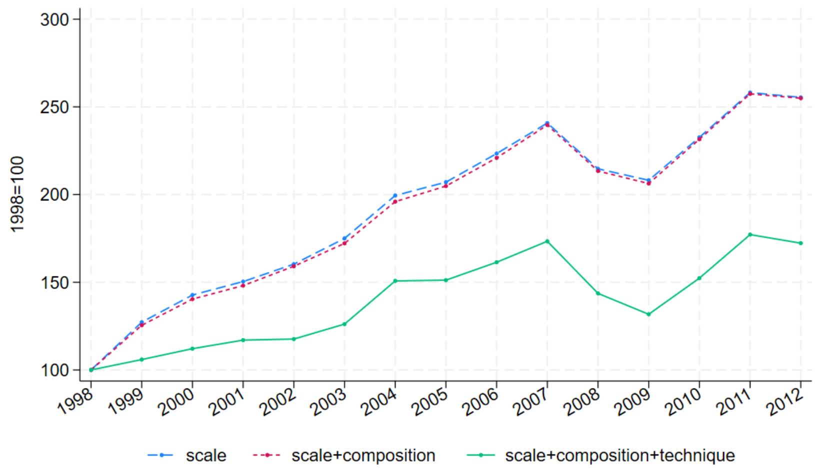


Figure A.9. Industry-level SO_2 emission decomposition (alternative shares)

Notes: These figures plot the industry-level decomposition results following Equation (9). To mitigate the bias of markups, I follow Rodrigue et al. (2022a) and use cost shares in Panel (b) instead of revenue shares in Panel (a) to aggregate emission intensities to the industry level.

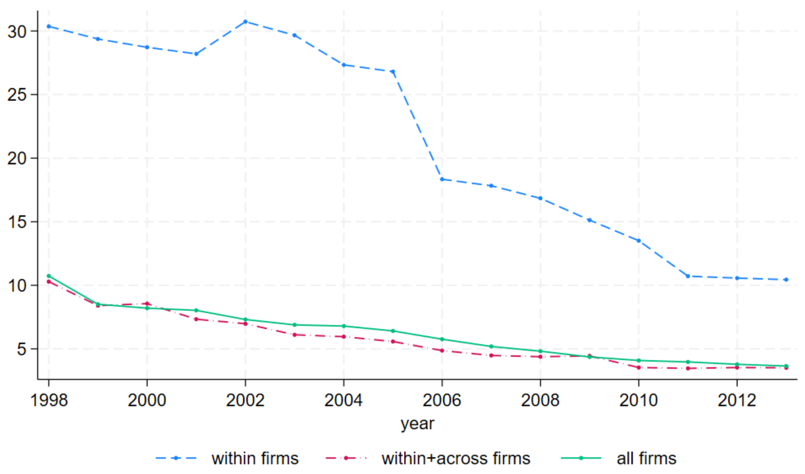


Figure A.10. Firm-level SO_2 emission intensity decomposition (by industry)

Notes: This figure plots the firm-level decomposition results following Equation (11). I conduct the firm-level decomposition by sector and then calculate sector averages of each component.

(a) Abatement cost from data

(b) Abatement cost from model

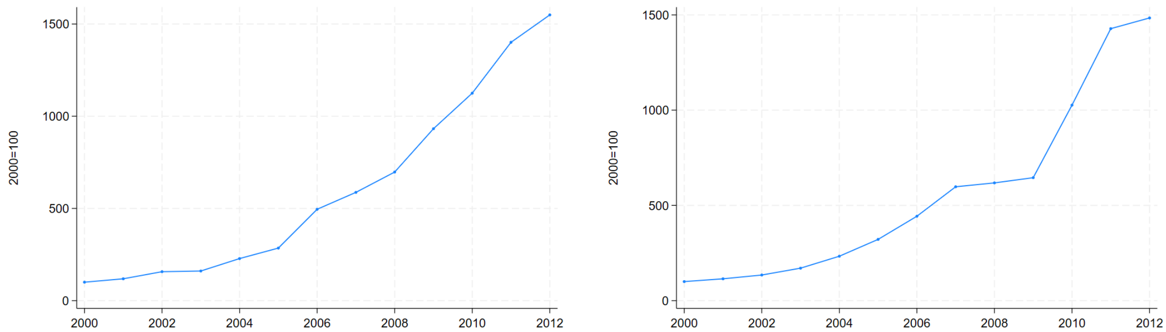


Figure A.11. Abatement cost data and model

Notes: These figures compare the abatement cost data in industrial waste gas summed by province according to the China Environmental Statistical Yearbooks in Panel (a) and the abatement cost implied by the model $a_{od,s}$ in Panel (b).

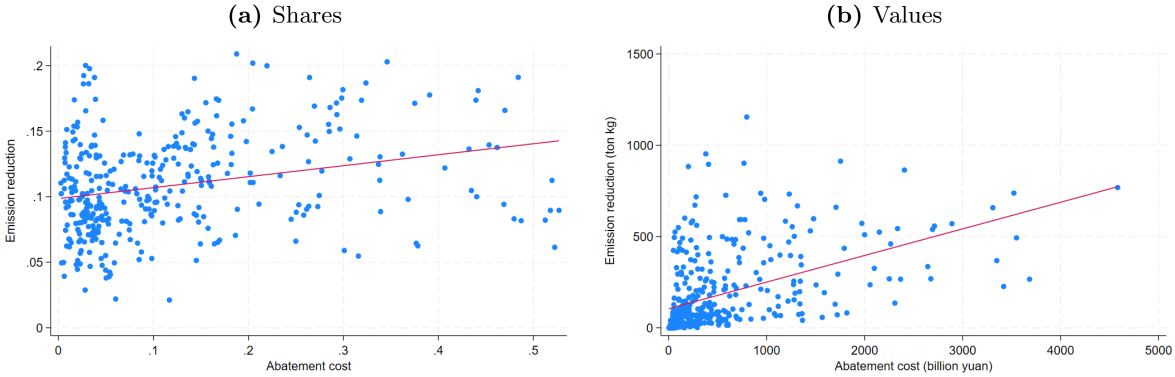


Figure A.12. Correlation between abatement cost and emission reduction

Notes: These figures show the correlation between the emission reduction share and abatement cost share by industry across time in Panel (a), and the levels of emission reduction (ton) with abatement cost (billion yuan) in Panel (b). 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.

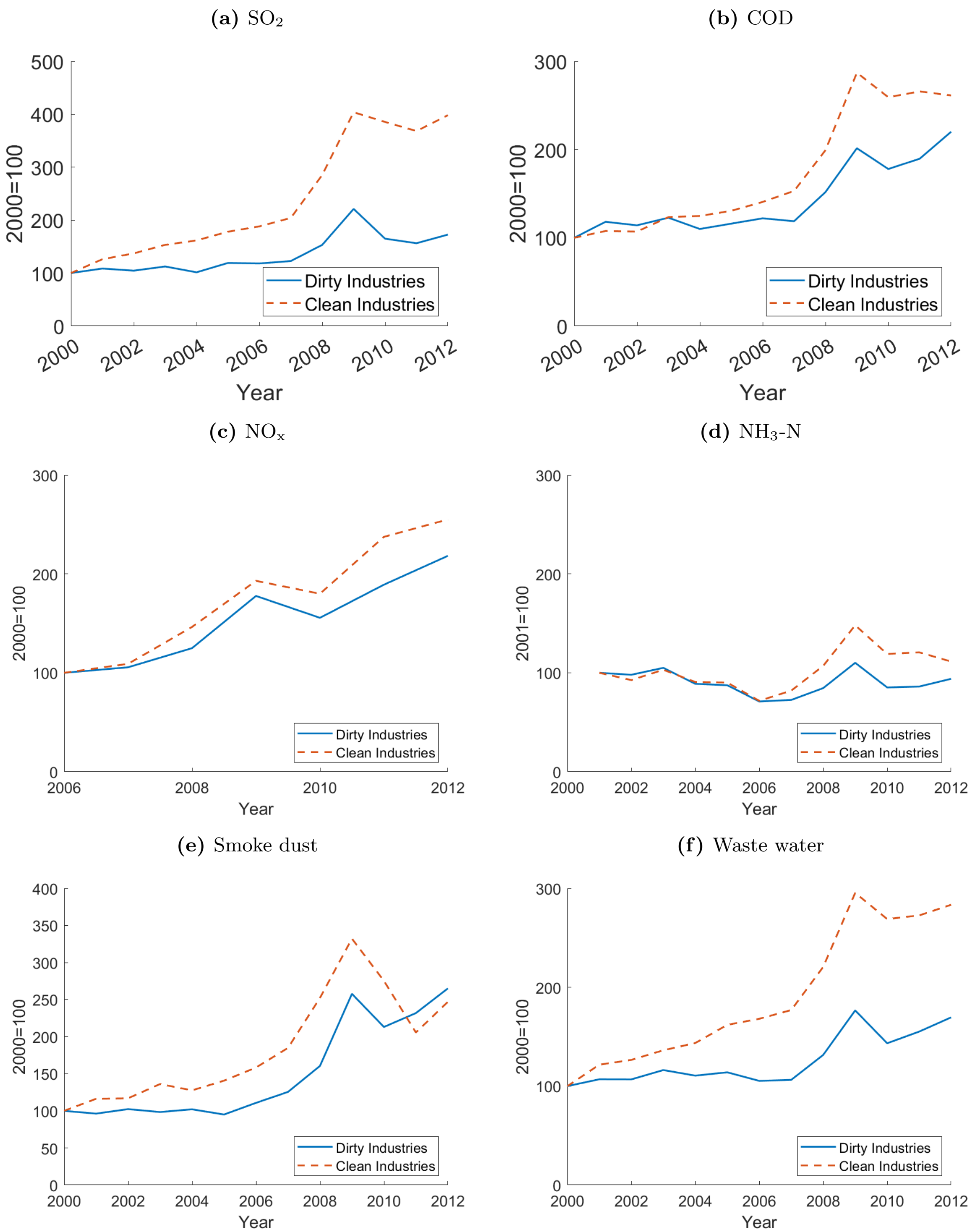


Figure A.13. Implicit pollution tax across pollutants

Notes: These figures plot the implicit pollution tax of emissions $\hat{t}_{o,s}$ recovered from Equation (26). The 2-digit CIC industries are aggregated into dirty and clean industries. Dirty industries have pollution elasticity α_s above average, while clean industries are below average, weighted by the baseline output of each industry. The pollutants include sulphur 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.

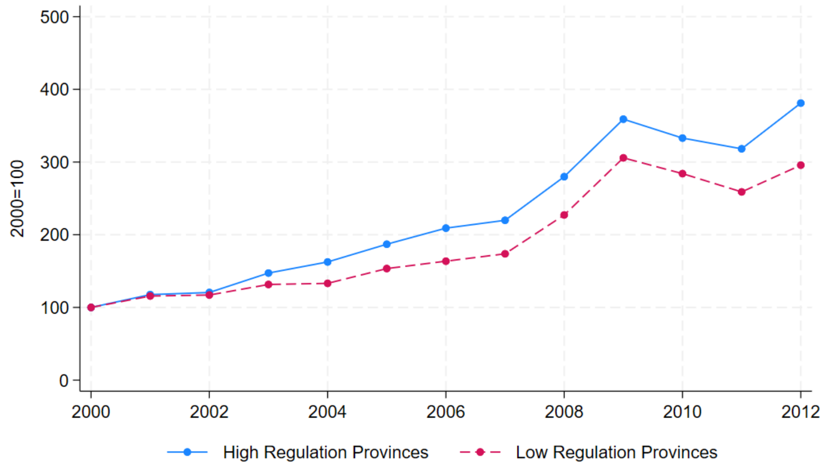


Figure A.14. Implicit pollution tax by province

Notes: This figure plots the implicit pollution tax by high and low regulation provinces. The province pollution tax is the weighted average of the implicit pollution tax by industry $\hat{t}_{o,s}$ recovered from Equation (26) and taking industry output share in the initial year as weights. High regulation provinces have above average change in SO_2 cap over the change in GDP between 2005 and 2010, while low regulation provinces are below average.

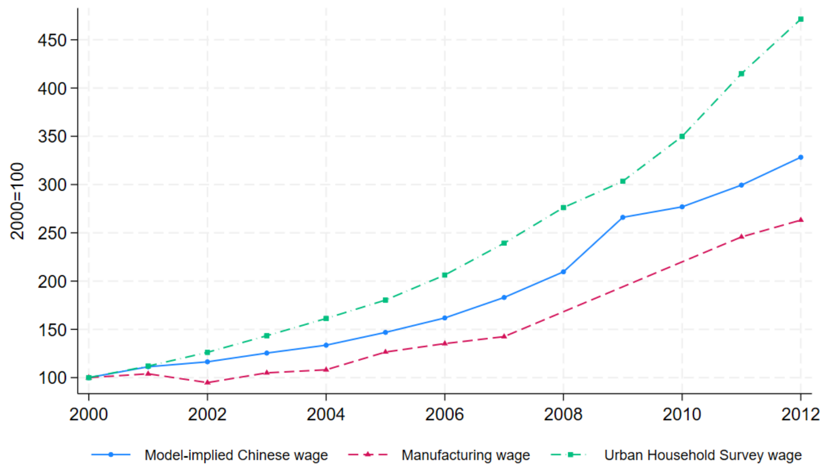


Figure A.15. Chinese wages

Note: This figure plots the Chinese wage implied by the model, from the manufacturing survey and urban household survey, respectively.

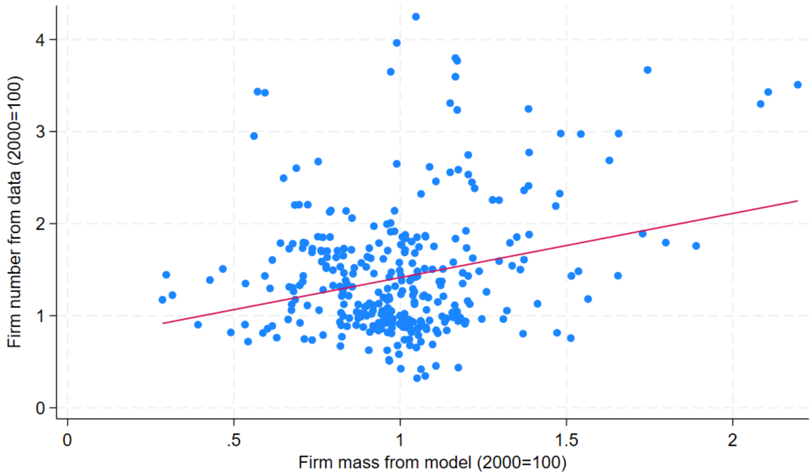


Figure A.16. Correlation between firm number and firm mass

Note: This figure plots the correlation between firm number from the annual survey data and the mass of firms from the model $\hat{M}^e_{o,s}$. Each point represents an industry-year level observation.

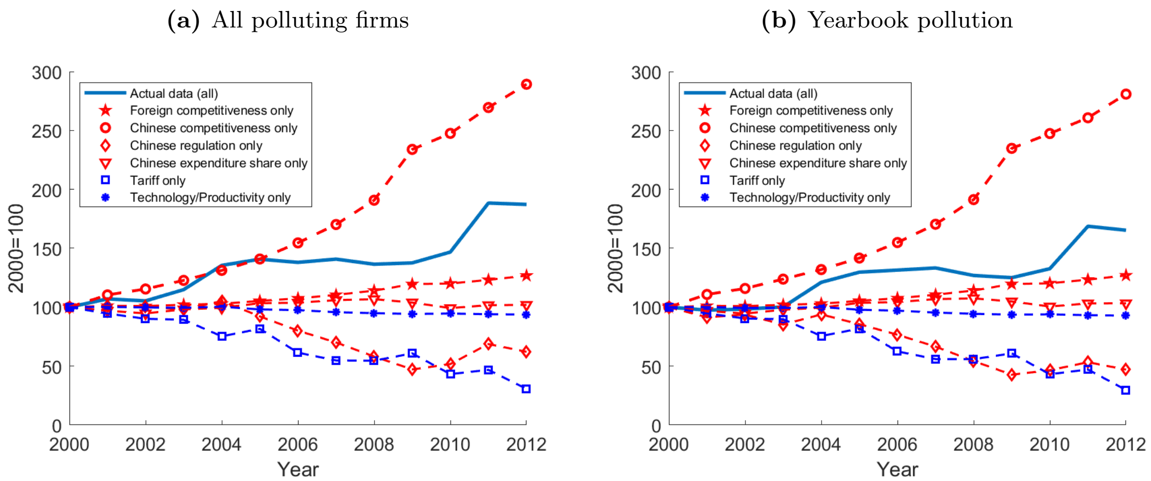


Figure A.17. Additional counterfactuals with alternative pollution data

Notes: This figure plots the counterfactual Chinese manufacturing pollution emissions. Figure (a) uses data on all polluting firms without matching with firm production. Figure (b) uses pollution data from the yearbooks. The solid blue line is the data when all channels are included. The dashed red and blue lines are counterfactual pollution emissions when only one channel follows the historical values while the other variables are at the initial values in 2000.

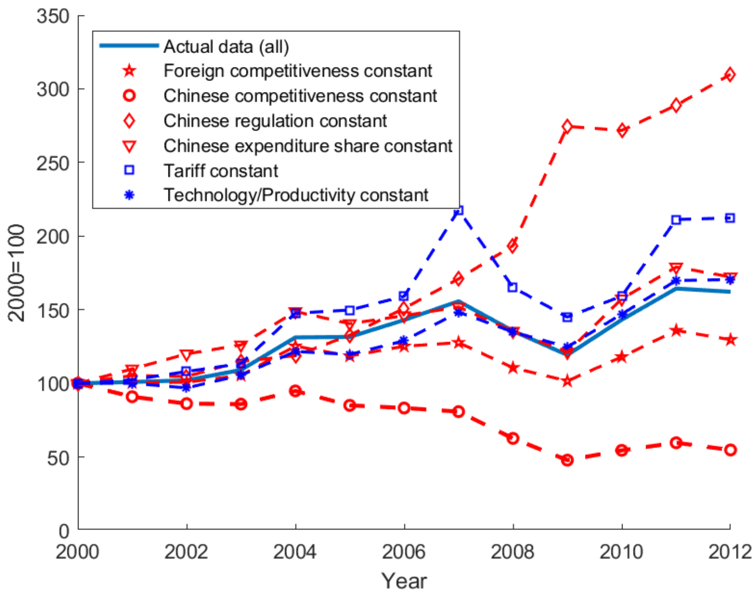


Figure A.18. Counterfactual Chinese manufacturing pollution emissions (single channel)

Notes: This figure plots the counterfactual Chinese manufacturing pollution emissions through a single channel. The solid blue line is the data when all channels are included. The dashed lines are counterfactual pollution emissions when keeping one channel at the initial value in 2000, while the other variables follow the historical values.

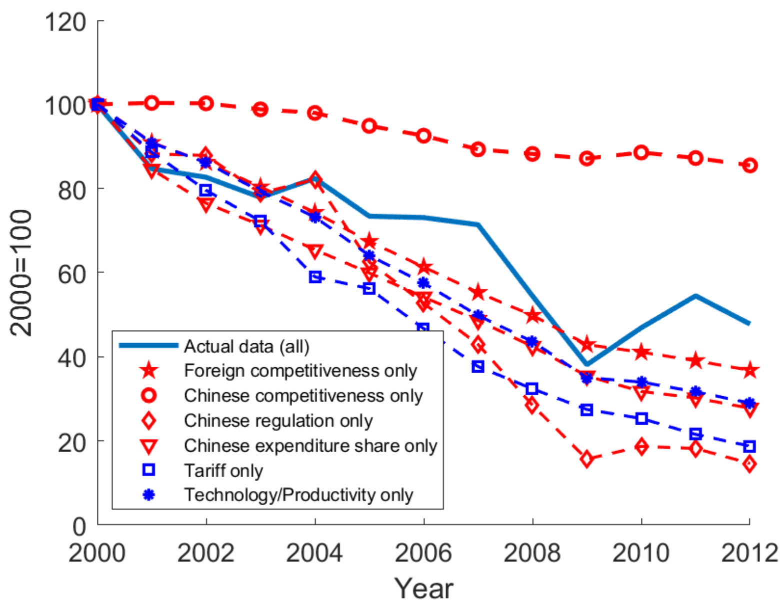
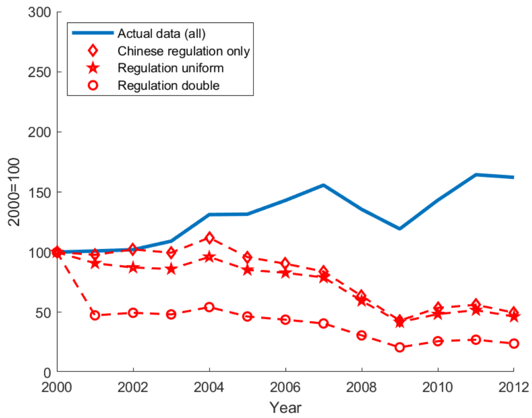


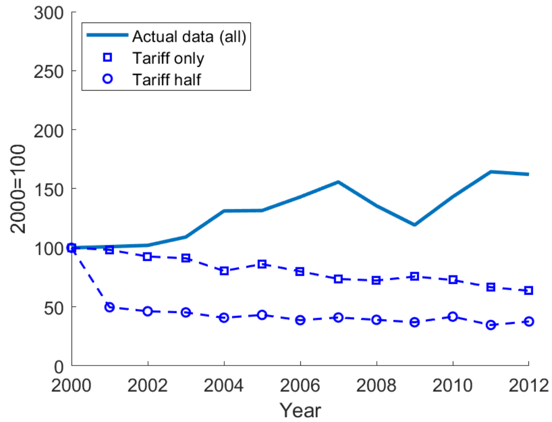
Figure A.19. Counterfactual Chinese manufacturing pollution intensities

Notes: This figure plots the counterfactual Chinese manufacturing pollution intensities. The solid blue line is the data when all channels are included. The dashed lines are counterfactual pollution intensities when only one channel follows the historical values while the other variables are at the initial values in 2000.

(a) Pollution regulations



(b) Tariffs



(c) Trade and environmental policies

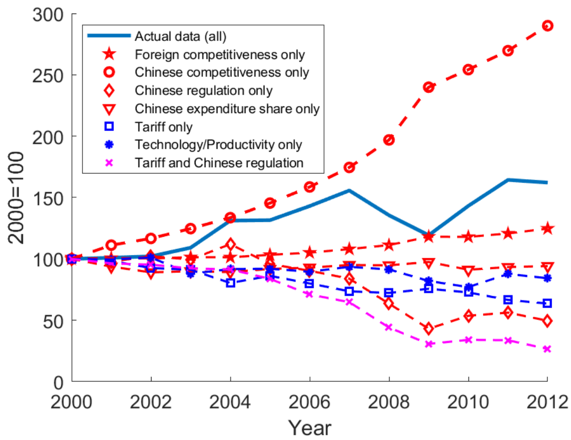


Figure A.20. Counterfactual SO_2 emissions of alternative policies

Notes: These figures plot the counterfactual Chinese manufacturing pollution emissions due to pollution regulations and tariffs, respectively. The solid blue line is the data when all channels are included. In Panel (a), the red dashed lines are counterfactual pollution emissions when only Chinese regulation follows the historical values while the other variables are at the initial values in 2000. In Panel (b), the blue dashed lines are counterfactual pollution emissions when only tariffs follow the historical values while the other variables are at the initial values in 2000. In Panel (c), the pink dashed line is the counterfactual pollution emissions when tariff and Chinese regulation are combined and follow their historical values while the other variables are at the initial values in 2000.

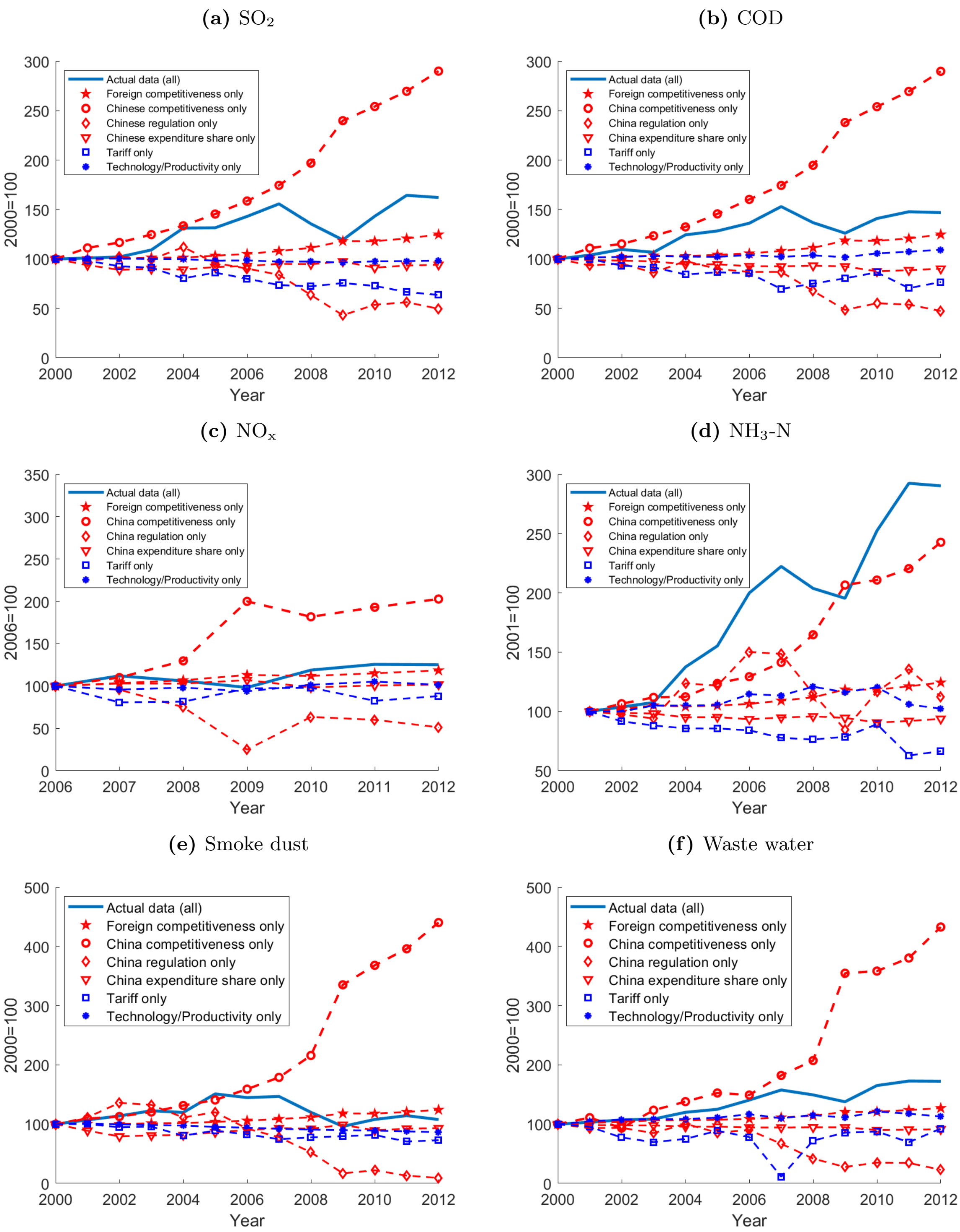


Figure A.21. Counterfactuals of other pollutants

Notes: These figures plot the counterfactual Chinese manufacturing pollution emissions. The solid blue line is the data when all channels are included. The dashed red and blue lines are counterfactual pollution emissions when only one channel follows the historical values while the other variables are at the initial values in 2000. The pollutants include sulphur 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. Data coverage

CIC Code	Pollution	ASIF	Pollution +ASIF	% in Pollution	% in ASIF	Pollution +ASIF +Customs	% in Pollution +ASIF
13	70,693	212,260	36,925	52%	17%	9,190	25%
14	34,448	78,755	19,711	57%	25%	6,099	31%
15	31,354	53,784	16,397	52%	30%	2,764	17%
16	2,123	2,587	1,263	59%	49%	47	4%
17	85,515	287,939	48,231	56%	17%	16,505	34%
18	11,892	159,383	6,730	57%	4%	3,462	51%
19	15,184	78,234	7,760	51%	10%	3,596	46%
20	14,340	81,147	7,953	55%	10%	1,601	20%
21	3,280	44,350	2,177	66%	5%	1,279	59%
22	57,645	92,344	27,421	48%	30%	3,738	14%
23	5,805	61,416	3,688	64%	6%	743	20%
24	3,818	42,513	2,304	60%	5%	1,609	70%
25	12,879	23,054	7,517	58%	33%	564	8%
26	104,791	252,863	66,904	64%	26%	17,849	27%
27	31,393	65,739	22,378	71%	34%	5,699	25%
28	4,016	18,476	2,875	72%	16%	1,269	44%
29	12,012	40,008	5,758	48%	14%	2,512	44%
30	67,953	163,462	8,946	13%	5%	3,346	37%
31	160,239	286,930	78,550	49%	27%	8,350	11%
32	33,860	76,074	21,673	64%	28%	2,992	14%
33	35,685	58,413	14,564	41%	25%	3,099	21%
34	51,241	199,088	21,047	41%	11%	6,588	31%
35	31,109	286,914	23,500	76%	8%	7,531	32%
36	16,423	150,824	10,113	62%	7%	3,384	33%
37	23,582	163,012	18,935	80%	12%	7,644	40%
39	19,861	191,137	12,331	80%	6%	5,048	41%
40	16,762	131,558	15,355	92%	12%	9,300	61%
41	8,513	56,626	4,840	57%	9%	2,288	47%
42	8,050	63,832	6,270	78%	10%	3,365	54%
43	3,265	19,667	1,978	61%	10%	833	42%
Total obs.	977,731	3,442,389	524,094	54%	15%	142,294	27%
No. of firms	245,475	806,324	130,219	53%	16%	38,311	29%

Notes: This table lists the coverage of observations for Chinese manufacturing firms across datasets by industry between 2000 and 2012, after merging the pollution dataset with the ASIF dataset and the Customs dataset.

Table B.2. Summary statistics of importers/exporters

Variable	Obs	Mean	Std. Dev.	Min	Max
logSO_2	116,813	9.421	2.224	2.485	15.011
logSO_2int	85,185	0.357	2.340	-10.523	9.734
log$Export$	168,758	14.545	2.223	7.746	19.612
log$Import$	125,847	13.606	2.883	5.375	19.891
$labour$	82,805	7.348	10.306	0.310	80.190
TFP	64,199	0.216	0.993	-11.497	9.161
FOE	142,415	0.162	0.369	0	1
SOE	142,415	0.113	0.317	0	1

Notes: This table summarizes the statistics of Table 1. logSO_2 is log SO_2 emission (kg), logSO_2int is log SO_2 emission per unit of output value (kg/1,000 yuan). log$Export$ and log$Import$ are log export and import values in current US dollars. $labour$ is the number of employment (in 100). TFP is firm total factor productivity. FOE is the foreign ownership status dummy. SOE is the state ownership status dummy.

Table B.3. Summary statistics of trade liberalisation

Variable	Obs	Mean	Std. dev.	Min	Max
logSO_2int	641,278	2.355	2.175	-8.641	11.290
log$CODint$	579,722	0.670	2.490	-10.118	10.963
log$WasteGasint$	674,134	0.181	2.100	-9.880	9.707
log$WasteWaterint$	662,471	2.648	2.092	-7.844	11.628
log $sales$	861,545	7.300	1.888	2.789	12.448
WTO	14	0.714	0.469	0	1
$tariff^{1998}_{savg.output}$	420	18.434	10.423	2.590	65
$tariff^{1998}_{wavg.output}$	420	18.100	11.751	3.700	107.060
$tariff^{1998}_{savg.input}$	429	10.501	3.627	1.443	29.893
$tariff^{1998}_{wavg.input}$	429	10.649	3.960	1.468	29.419
$tariff^{1998\_IO97}_{savg.input}$	429	12.083	3.909	1.692	24.037
$tariff^{1998\_IO97}_{wavg.input}$	429	12.598	4.846	1.550	24.902

Notes: This table summarizes the statistics of trade liberalisation in Table 2, Table B.4, and Table B.9. logSO_2int, log$CODint$, log$WasteGasint$, and log$WasteWaterint$ are log sulphur dioxide (SO_2), chemical oxygen demand (COD), waste gas (WasteGas), and waste water (WasteWater) emission per unit of output value (kg/10,000 yuan), respectively. log $sales_{it}$ is log 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. $tariff^{1998}_{savg.input}$, $tariff^{1998}_{wavg.input}$, $tariff^{1998}_{savg.output}$, $tariff^{1998}_{wavg.output}$ are simple average input, weighted average input, simple average output, and weighted average output tariffs at 4-digit CIC industry level in 1998, respectively. $tariff^{1998\_IO97}_{savg.input}$, $tariff^{1998\_IO97}_{wavg.input}$ are simple average input and weighted average input tariffs calculated using the input-output table of 1997.

Table B.4. Impact of trade liberalisation on SO_2 pollution intensity (1997 input-output table)

logSO_2int	(1)	(2)	(3)	(4)	(5)	(6)
$tariff^{1998\_IO97}_{savg.input} \times WTO$	-0.012***				-0.015***	
	(0.002)				(0.002)	
$tariff^{1998\_IO97}_{wavg.input} \times WTO$		-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	560,858	560,858	518,866	518,866	518,866	518,866
Adj. R-squared	0.846	0.846	0.848	0.848	0.848	0.848
Firm FE	✓	✓	✓	✓	✓	✓
4-digit Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: This table reports the impact of trade liberalisation on SO_2 pollution intensity following Equation (2) and using tariffs from the 1997 input-output table. The outcome variable logSO_2int is log SO_2 pollution intensity (kg/1,000 yuan). $tariff^{1998\_IO97}_{savg.input}$, $tariff^{1998\_IO97}_{wavg.input}$, $tariff^{1998}_{savg.output}$, $tariff^{1998}_{wavg.output}$ are simple average input, weighted average input, simple average output, and weighted average output tariffs in 1998 at 4-digit CIC industry level, respectively. The input tariffs are calculated using the input-output table of 1997. WTO is a dummy variable for China's WTO accession which is equal to 1 after 2001 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the industry-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.5. Impact of trade liberalisation on SO_2 pollution intensity (same industry)

logSO_2int	(1)	(2)	(3)	(4)	(5)	(6)
$tariff^{1998}_{savg.input} \times WTO$	-0.022***				-0.020***	
	(0.003)				(0.003)	
$tariff^{1998}_{wavg.input} \times WTO$		-0.018***				-0.018***
		(0.003)				(0.003)
$tariff^{1998}_{savg.output} \times WTO$			-0.005***		-0.002	
			(0.001)		(0.001)	
$tariff^{1998}_{wavg.output} \times WTO$				-0.003***		-0.001
				(0.001)		(0.001)
log *sales*	-0.663***	-0.663***	-0.661***	-0.661***	-0.661***	-0.661***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	378,551	378,551	357,516	357,516	357,516	357,516
Adj. R-squared	0.852	0.852	0.853	0.853	0.853	0.853
Firm FE	✓	✓	✓	✓	✓	✓
4-digit Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: This table reports the impact of trade liberalisation on SO_2 pollution intensity following Equation (2), when firms do not change 4-digit industry. The outcome variable logSO_2int is log SO_2 pollution intensity (kg/1,000 yuan). $tariff^{1998}_{savg.input}$, $tariff^{1998}_{wavg.input}$, $tariff^{1998}_{savg.output}$, $tariff^{1998}_{wavg.output}$ are simple average input, weighted average input, simple average output, and weighted average output tariffs at 4-digit CIC industry level in 1998, respectively. WTO is a dummy variable for China's WTO accession which is equal to 1 after 2001 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the industry-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.6. Impact of trade liberalisation on SO_2 pollution intensity (dirty and clean industries)

	All industries		Dirty industries		Clean industries	
logSO_2int	(1)	(2)	(3)	(4)	(5)	(6)
$tariff^{1998}_{savg.input} \times WTO$	-0.013***		-0.019***		-0.004*	
	(0.002)		(0.006)		(0.003)	
$tariff^{1998}_{wavg.input} \times WTO$		-0.011***		-0.023***		-0.001
		(0.002)		(0.006)		(0.002)
$tariff^{1998}_{savg.output} \times WTO$	-0.001		-0.002		0.000	
	(0.001)		(0.002)		(0.001)	
$tariff^{1998}_{wavg.output} \times WTO$		-0.000		-0.000		-0.001
		(0.001)		(0.001)		(0.001)
log *sales*	-0.680***	-0.680***	-0.608***	-0.608***	-0.754***	-0.754***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.005)	(0.005)
Observations	518,866	518,866	280,190	280,190	235,935	235,935
Adj. R-squared	0.848	0.848	0.816	0.816	0.837	0.837
Firm FE	✓	✓	✓	✓	✓	✓
4-digit Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: This table reports the impact of trade liberalisation on SO_2 pollution intensity by dirty and clean industries. Following Shapiro (2020), dirty industries have pollution per unit cost above average, while clean industries are below average. Dirty industries include industries with 2-digit code 22 (Manufacture of paper and paper products), 26 (Manufacture of raw chemical materials and chemical products), 28 (Manufacture of chemical fibres), 30 (Manufacture of non-metallic mineral products), 31 (melting and pressing of ferrous metals), 32 (Smelting and pressing of non-ferrous metals), consistent with the structural parameters in Table 5. The outcome variable logSO_2int is log SO_2 pollution intensity (kg/1,000 yuan). $tariff^{1998}_{savg.input}$, $tariff^{1998}_{wavg.input}$, $tariff^{1998}_{savg.output}$, $tariff^{1998}_{wavg.output}$ are simple average input, weighted average input, simple average output, and weighted average output tariffs at 4-digit CIC industry level in 1998, respectively. WTO is a dummy variable for China's WTO accession which is equal to 1 after 2001 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the industry-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.7. First-stage regressions of tariffs (2SLS)

	(1) $tariff^{lag}_{savg.input}$ $\times WTO$	(2) $tariff^{lag}_{wavg.input}$ $\times WTO$	(3) $tariff^{lag}_{savg.output}$ $\times WTO$	(4) $tariff^{lag}_{wavg.output}$ $\times WTO$
$tariff^{1998}_{savg.input}$ $\times WTO$	0.615***			
	(0.002)			
$tariff^{1998}_{wavg.input}$ $\times WTO$		0.611***		
		(0.002)		
$tariff^{1998}_{savg.output}$ $\times WTO$			0.563***	
			(0.002)	
$tariff^{1998}_{wavg.output}$ $\times WTO$				0.502***
				(0.003)
K-P F-stat.	143,443	133,235	68,408	28,386

Notes: This table reports the first-stage regressions using tariffs before the WTO accession in 1998 as instruments for the actual tariff changes from 1998. In practice, the tariffs interact with the WTO dummy in the first stage. $tariff^{lag}_{savg.input}$, $tariff^{lag}_{wavg.input}$, $tariff^{lag}_{savg.output}$, $tariff^{lag}_{wavg.output}$ are one-year lag simple average input, weighted average input, simple average output, and weighted average output tariff at 4-digit CIC industry level, respectively. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the industry-year level. Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.8. Impact of trade liberalisation on SO_2 pollution intensity (2SLS)

logSO_2int	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{tariff}^{lag}_{savg.input} \times WTO$	-0.022***				-0.022***	
	(0.002)				(0.002)	
$\widehat{tariff}^{lag}_{wavg.input} \times WTO$		-0.018***				-0.019***
		(0.002)				(0.002)
$\widehat{tariff}^{lag}_{savg.output} \times WTO$			-0.006***		-0.001*	
			(0.001)		(0.001)	
$\widehat{tariff}^{lag}_{wavg.output} \times WTO$				-0.004***		-0.001
				(0.001)		(0.001)
log *sales*	-0.683***	-0.683***	-0.681***	-0.681***	-0.680***	-0.681***
	(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	✓	✓	✓	✓	✓	✓
4-digit Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: This table reports the impact of trade liberalisation on SO_2 pollution intensity following Equation (2) and using tariffs before the WTO accession in 1998 as instruments for the tariff changes. The outcome variable logSO_2int is log SO_2 pollution intensity (kg/1,000 yuan). $\widehat{tariff}^{lag}_{savg.input}$, $\widehat{tariff}^{lag}_{wavg.input}$, $\widehat{tariff}^{lag}_{savg.output}$, $\widehat{tariff}^{lag}_{wavg.output}$ are predicted one-year lag simple average input, weighted average input, simple average output, and weighted average output tariff at 4-digit CIC industry level, respectively. WTO is a dummy variable for China's WTO accession which is equal to 1 after 2001 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the industry-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.9. Impact of trade liberalisation on pollution intensity (other pollutants)

	(1)	(2)	(3)	(4)	(5)	(6)
	log$CODint$		log$WasteGasint$		log$WasteWaterint$	
$tariff^{1998}_{savg.input} \times WTO$	-0.000		-0.011***		-0.005**	
	(0.002)		(0.002)		(0.003)	
$tariff^{1998}_{wavg.input} \times WTO$		-0.003		-0.008***		0.002
		(0.002)		(0.002)		(0.002)
$tariff^{1998}_{savg.output} \times WTO$	-0.001		-0.000		0.005***	
	(0.001)		(0.001)		(0.001)	
$tariff^{1998}_{wavg.output} \times WTO$		-0.001		-0.000		0.002***
		(0.001)		(0.001)		(0.001)
log $sales$	-0.726***	-0.726***	-0.650***	-0.650***	-0.699***	-0.700***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)
Observations	446,216	446,216	546,037	546,037	511,956	511,956
Adj. R-squared	0.798	0.798	0.861	0.861	0.814	0.814
Firm FE	✓	✓	✓	✓	✓	✓
4-digit Industry FE	✓	✓	✓	✓	✓	✓
City-Year FE	✓	✓	✓	✓	✓	✓

Notes: This table reports the impact of trade liberalisation on pollution intensity of other pollutants. The outcome variables are log pollution intensity (kg/1,000 yuan) of chemical oxygen demand (COD), waste gas (WasteGas), and waste water (WasteWater). The data are not available for nitrogen oxides (NO_x) before 2006 and for ammonia nitrogen (NH_3-N) before 2001, so they are not included in the table. $tariff^{1998}_{savg.input}$, $tariff^{1998}_{wavg.input}$, $tariff^{1998}_{savg.output}$, $tariff^{1998}_{wavg.output}$ are simple average input, weighted average input, simple average output, and weighted average output tariffs at 4-digit CIC industry level in 1998, respectively. WTO is a dummy variable for China's WTO accession which is equal to 1 after 2001 and 0 otherwise. log $sales$ is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the industry-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.10. Summary statistics of environmental regulation

Variable	Obs	Mean	Std. dev.	Min	Max
logSO_2int	641,278	2.355	2.175	-8.641	11.290
log$CODint$	579,722	0.670	2.490	-10.118	10.963
logNH_3Nint	278,156	-2.033	2.542	-12.526	8.093
log $sales$	861,545	7.300	1.888	2.789	12.448
FYP	14	0.429	0.514	0	1
log$Target$	31	12.210	0.882	10.594	14.747
log$Target_{alt}$	31	0.104	0.077	0	0.300
log$CODTarget$	31	12.664	0.526	11.531	14.170
log$NH_3NTarget$	31	14.593	0.429	13.870	15.968

Notes: This table summarizes the statistics of environmental regulation in Table 3, Table B.13, and Table B.11. logSO_2int, log$CODint$, and logNH_3Nint are log sulphur dioxide (SO_2), chemical oxygen demand (COD), and ammonia nitrogen (NH_3-N) emission per unit of output value (kg/10,000 yuan), respectively. FYP is an indicator variable of the 11^{th} Five-Year Plan which is equal to 1 if the year is 2006 and afterwards, and 0 otherwise. log$Target$, log$CODTarget$, and log$NH_3NTarget$ are the log emission targets of sulphur dioxide (SO_2), chemical oxygen demand (COD), and ammonia nitrogen (NH_3-N) measured by the ratio of the province GDP (yuan) to the emission target level (kg) in 2010, respectively. log$Target_{alt}$ is the log of the ratio between the SO_2 emission target during the 10^{th} Five-Year Plan and the 11^{th} Five-Year Plan. log $sales_{it}$ is log firm sales in 1,000 yuan.

Table B.11. Impact of environmental regulation on SO_2 emission intensity (alternative regulation measure)

logSO_2int	(1)	(2)	(3)	(4)
log$Target_{alt} \times FYP$	-1.712***	-1.716***	-1.653***	-1.682***
	(0.215)	(0.214)	(0.209)	(0.211)
log *sales*	-0.676***	-0.676***	-0.673***	-0.674***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	588,157	588,157	588,157	587,870
Adj. R-squared	0.832	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: This table presents the impact of environmental regulation on SO_2 emission intensity following Equation (4). The outcome variable logSO_2int is log SO_2 pollution intensity (kg/1,000 yuan). log$Target_{alt}$ is the log of the ratio between the SO_2 emission target during the 10th Five-Year Plan and the 11th Five-Year Plan. A higher emission target indicates more strict regulation. FYP is a dummy variable of the 11th Five-Year Plan which is equal to 1 after 2005 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the province-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.12. Impact of environmental regulation on SO_2 emission intensity (same city)

logSO_2int	(1)	(2)	(3)	(4)
log$Target \times FYP$	-0.077***	-0.079***	-0.064***	-0.073***
	(0.025)	(0.025)	(0.024)	(0.024)
log *sales*	-0.677***	-0.677***	-0.674***	-0.674***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	569,953	569,953	569,953	569,661
Adj. R-squared	0.833	0.834	0.835	0.836
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: This table presents the impact of environmental regulation on SO_2 emission intensity following Equation (4), when firms do not change prefecture city. The outcome variable logSO_2int is log SO_2 pollution intensity (kg/1,000 yuan). 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. A higher emission target indicates more strict regulation. FYP is a dummy variable of the 11th Five-Year Plan which is equal to 1 after 2005 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the province-year level. * significant at 10%, ** significant at 5% , *** significant at 1%. The number of observations is smaller in Column (4) than in the previous columns because more singleton observations are dropped when controlling for 4-digit Industry-Year FE.

Table B.13. Impact of environmental regulation on emission intensity (other pollutants)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\log CODint$				$\log NH_3Nint$			
$\log CODTarget \times FYP$	-0.153***	-0.155***	-0.196***	-0.225***				
	(0.040)	(0.040)	(0.038)	(0.037)				
$\log NH_3NTarget \times FYP$					-0.277***	-0.278***	-0.267***	-0.303***
					(0.078)	(0.078)	(0.076)	(0.077)
log *sales*	-0.711***	-0.712***	-0.712***	-0.713***	-0.731***	-0.732***	-0.732***	-0.733***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.009)	(0.009)	(0.009)
Observations	531,667	531,666	531,667	531,466	246,441	246,439	246,439	246,109
Adj. R-squared	0.784	0.785	0.786	0.788	0.761	0.762	0.762	0.765
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓			✓	✓		
2-digit Industry FE	✓				✓			
4-digit Industry FE		✓				✓		
2-digit Industry-Year FE			✓				✓	
4-digit Industry-Year FE				✓				✓

Notes: This table presents the impact of environmental regulation on emission intensity other pollutants. The outcome variables are log pollution intensity (kg/1,000 yuan) of chemical oxygen demand (COD) and ammonia nitrogen (NH_3-N). The COD targets are province total quotas similar to SO_2, and the NH_3-N targets cover only industrial and household. $\log CODTarget$ and $\log NH_3NTarget$ are the log emission targets measured by the ratio of the province GDP (yuan) to the emission target level (kg) in 2010. There were no emission targets on nitrogen oxides (NO_x), waste gas (WasteGas), and waste water (WasteWater) during the 11^{th} Five-Year Plan, so they are not included in the table. A higher emission target indicates more strict regulation. FYP is a dummy variable of the 11^{th} Five-Year Plan which is equal to 1 after 2005 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the province-year level. * significant at 10%, ** significant at 5% , *** significant at 1%.

Table B.14. Average pollution elasticity by pollutant

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

Notes: This table reports the average pollution elasticity at 2-digit CIC industry level by pollutant. The pollutants include sulphur 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.15. Policy effect on pollution intensity

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

Notes: This table reports the effects of trade and environmental policies on SO_2 pollution intensity from the model. Columns (1) and (2) regress the industry-specific counterfactual pollution intensity from the model on average industry export tariff. Columns (3) and (4) regress the industry-specific counterfactual pollution intensity on the average pollution tax from the model. Standard errors in parentheses. * significant at 10%, ** significant at 5% , *** significant at 1%.

C Trade liberalisation and environmental regulation

I run joint regressions of the WTO accession and the 11$^{\text{th}}$ Five-Year Plan following equation (C.1). I control for the year, 4-digit CIC industry, province, and firm fixed effects γ_t, η_s, δ_p, and μ_i, respectively. The standard errors are clustered at the 4-digit industry-year and province-year levels. The results are shown in Table C.1. Reassuringly, the coefficients are very close to the results of the WTO in Table 2 and the 11$^{\text{th}}$ Five-Year Plan in Table 3 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 liberalisation and environmental regulation on SO_2 pollution intensity

logSO_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
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
4-digit Industry FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓

Notes: This table reports the impact of trade liberalisation and environmental regulation on SO_2 pollution intensity following Equation (C.1). The outcome variable logSO_2int is log SO_2 pollution intensity (kg/1,000 yuan). $tariff^{1998}_{savg.input}$, $tariff^{1998}_{wavg.input}$, $tariff^{1998}_{savg.output}$, $tariff^{1998}_{wavg.output}$ are simple average input, weighted average input, simple average output, and weighted average output tariffs at 4-digit CIC industry level in 1998, respectively. WTO is a dummy variable for China's WTO accession which is equal to 1 after 2001 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. A higher emission target indicates more strict regulation. FYP is a dummy variable of the 11$^{\text{th}}$ Five-Year Plan which is equal to 1 after 2005 and 0 otherwise. log *sales* is log firm sales in 1,000 yuan. Standard errors in parentheses, clustered at the industry-year and province-year levels. * significant at 10%, ** significant at 5% , *** significant at 1%.