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// LEI LI, ANDREAS LÖSCHEL, JIANSUO PEI,
BODO STURM, AND ANQI YU

Trade Liberalization and SO_2 Emissions: Firm-level Evidence from China's WTO Entry

Trade liberalization and SO_2 emissions: Firm-level evidence from China's WTO entry

Lei Li (Nankai University, China), Andreas Löschel (Westfälische Wilhelms-Universität Münster, ZEW Mannheim, Germany, UIBE, China), Jiansuo Pei (UIBE, China), Bodo Sturm (HTWK Leipzig, ZEW Mannheim, Germany), and Anqi Yu (UIBE, China)

Abstract: Is trade liberalization contributing to cleaner production amongst manufacturing firms? Theoretical predictions and empirical evidences are mixed. This study utilizes China's dual trade regime and China's WTO entry in 2001 to construct a unique micro dataset on manufacturing firms for China for the period 2000-2007, and performs a difference-in-difference estimation strategy to directly examine this issue. Specifically, normal exporters that saw tariff changes during the same period form the treatment group; while processing exporters that enjoy tariff-exemptions both pre- and post-WTO entry serve as the control group. Results show that China's WTO entry contributed to a lower SO_2 emission intensity for normal exporting firms. We further examine the mechanism and show that the productivity channel accounted for the observed pattern. Specifically, more efficient normal exporters saw greater decline of SO_2 emission intensity than average normal exporters. This study contributes to a better understanding of the impact of trade on the environment, especially in developing countries. It also complements the literature in terms of providing China's micro evidence on the impact of trade liberalization on firm's environmental performance.

Keywords: WTO; trade liberalization; dual trade regime; SO_2 emission intensity; China

JEL codes: F18; Q53; Q56

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1. Introduction

The degradation of the environment in developing countries has been one of the most challenging policy issues of recent times. The massive growth in world trade might be the main source of this problem. On the one hand, there are theoretical and empirical concerns that the developing world acts as a "pollution haven" for the developed world (e.g., Copeland and Taylor, 2004; Kellenberg, 2009). In addition, empirical evidence shows that trends of local pollution in developed countries are declining strongly (e.g. WIOD 2013 & 2016). On the other hand, trade may lead to structural changes, efficiency gains and technological improvements which could contribute to less pollution in developing countries.

China is not only key to understanding whether trade is good or bad for the environment in developing countries, it is also the most prominent example both in terms of export growth and growth in sulfur dioxide (SO_2) emissions,[1] especially after its accession to the World Trade Organization (WTO). From 2001 till 2007 (before the financial crisis in 2008/09), the trade volume soared from about half trillion RMB (i.e., 51 million USD in 2001) to 1.8 trillion RMB in 2007; and during the same period, SO_2 emissions grew from 21.9Mt to 27.9Mt. China now is one of the world's biggest SO_2 emitters and simultaneously plays an important and increasing role in trade. Will this exacerbate the problem or bring improvements in SO_2 pollution?

Answering this question is central to understanding the environmental effects of trade liberalization. For instance, one strand of research argues that international trade is not conducive to improvements in environmental quality or at best the effect is ambiguous. Classical discussions date back to Leontief (1970). More recently, Cole et al. (2006) used energy consumption as the main dependent variable (rather than

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[1] There are several reasons why a focus on SO_2 is warranted. SO_2 emissions are primarily industry-driven (rather than generated by transportation or household activity) and the corresponding negative effects are local (rather than trans-boundary or global). Furthermore, different abatement technologies exist. In fact, China ranks the first for total SO_2 emissions in the world, and emitted 30.8Mt in 2010 (Klimont et al., 2013). The SO_2 emission intensity (measured by SO_2 emissions per unit of total output), however, gradually declined from 13.60t/million dollars in 1997 to 1.45t/million dollars in 2014 or respectively by about 12 percent per year (Source: WIOD 2013 & 2016; National Bulletin of Environmental Statistics of China, various years).

various pollutants) and found a positive correlation between the degree of trade openness and per capita energy consumption. Recently, Shapiro and Walker (2018) report a large role of technique effects and very small trade-induced composition effects. In contrast, Cherniwchan (2017), who uses NAFTA as a policy shock to examine the effects of trade liberalization and the pollution emitted by US manufacturing plants, shows that ratification of NAFTA accounted for a substantial decline of particulate matter and SO_2 emissions from affected US manufacturing plants. In other words, trade liberalization is found to be an important driving force for reductions of pollution for manufacturing plants. In this vein, *World Development Report 2020*, the flagship report by the World Bank, recognizes the ambiguous effects of international trade on the environment (see Chapter 5).

To examine this problem, relying on aggregate data (either industry and/or region) as a standard practice has provided robust empirical evidence on the differential effects of trade liberalization across heterogeneous regions and sectors (see Dean and Lovely, 2010).[2] However, these studies do not offer much insight on the behavior of individual polluters within each industry. In this paper, we move beyond the relationship between trade and aggregate pollution levels and study the firms' responses (in terms of pollution behavior, measured by emissions per unit of total output) to China's WTO entry, a trade shock that accounts for the increase in market competition in China. Specifically, we focus on SO_2 emissions, one of the main local pollutants with severe negative effects for the environment and human health in China (HEI, 2016).

This paper builds on a unique dataset to investigate the manufacturing firms' environmental responses to trade liberalization. Specifically, we utilized data during the period 2000-2007, and took China's WTO entry in 2001 as a quasi-experimental setting, to perform a difference-in-difference (DID) estimation. In this way, we are able to directly examine the impact of trade liberalization on firms' environmental performance. To that end, we combined and merged three rich firm-level datasets for

[2] They point out the heterogeneous performance of different firms, an important aspect that will be further considered in our study.

China, namely the National Bureau of Statistics' annual survey of industrial production (ASIP), which shows firm-level production information; the Chinese environmental statistics database (CESD) obtained from the Ministry of Ecology and Environment; and customs data provided by China Customs plus tariff data obtained from WITS (World Integrated Trade Solution, developed and maintained by UNCTAD and World Bank). A total of 13,641 manufacturing observations were successfully matched. To the best of our knowledge, it is the first time that this unique dataset has been constructed and used in this line of research.

The identification in this paper is made possible due to China's dual trade regime. In addition to the normal trade regime, there is a special treatment of processing trade. Specifically, processing trade refers to a trade mode in which firms import raw materials, or parts and components from other countries, combining with their own land or labor resources, process them into final products and then export. In fact, processing exports accounted for over half of China's total exports for the period 1996-2007 (see Yu, 2015; Dietzenbacher et al., 2012).

The tariff reduction after China joined the WTO has had different effects on the enterprises engaged in processing trade and normal trade (in several aspects, e.g. declining input costs). Theoretically speaking, for the enterprises participating in processing trade, the impact of trade liberalization on their environmental performances should be relatively small, as processing trade enjoys tax-free treatment both before and after the trade shock (i.e., these firms were not directly affected by the shock). While the firms engaged in normal trade did not enjoy a preferential tariff before China's accession to the WTO, yet saw an import tariff decline after China's accession to the WTO (i.e., these firms were directly affected by the shock). Therefore, it is expected that the impact of trade liberalization on pollutant discharges of normal trade enterprises is greater compared to processing trade enterprises.

Using processing exporters that enjoy tariff-exemptions both pre- and post-WTO entry as the control group and normal exporters that saw tariff changes during the same period as the treatment group, our empirical findings can be summarized as follows. China’s WTO entry contributed to lower SO_2 emission intensity for normal exporters. Specifically, compared with processing exporters that are not directly affected by trade liberalization, SO_2 emission intensity of normal exporters is statistically significantly reduced by roughly 6% after China's accession to WTO. Hence, China’s WTO entry accounted for a lower SO_2 emission intensity for normal exporters, which is in line with previous evidence reported for developed economies (see Cherniwchan, 2017). In order to provide supportive evidence for our approach, we conducted a falsification test, in which hybrid exporters (performing both processing and normal exports) replaced the pure normal exporters. As expected, the impact of China's accession to the WTO on the SO_2 emission intensity of hybrid exporters is no longer statistically significant. We also study possible confounding effects of two policy reforms, i.e. the reform of state-owned enterprises and the relaxation of regulations on the entry of foreign invested enterprises. China's accession to the WTO still has a significantly negative impact on the SO_2 emissions intensity. We show that these effects vary across ownership in different regions.

In theory, there are several potential mechanisms which may be accountable for this pattern, our focus here however is on the ones described by Melitz (2003) model with heterogeneous firms. China's accession to the WTO might impact enterprises engaged in normal export via different channels: First, through the productivity channel, i.e. lower input costs (due to lower import tariffs) result in higher productivity, and productivity is negatively related to firms’ emission intensity (Forslid et al., 2018). Second, through the dynamics of firm entry and exit, i.e. the reallocation of market shares, trade openness increases local competition and forces the least productive (also the most polluting) firms to exit the exporting market, and non-exporters to scale down their production. Previous studies have shown that more productive firms are cleaner for a given productivity level since they find it profitable to make larger fixed investments in clean technology (e.g., due to more stringent environmental regulations) (see e.g., Forslid et al., 2018). We observe that these properties are consistent with Chinese manufacturing survey data, which contains rich information at the firm level. Indeed, our results show that especially more productive normal exporters became cleaner (with lower SO_2 emissions per output) after China's accession to the WTO.

We make three main contributions to the literature: first, relative to other recent micro data work on environmental effects of trade liberalization in developed countries, we constructed a unique dataset for China from the merger of three rich firm-level datasets. It allows us to conduct in-depth study for the environmental performance (i.e., SO_2 emission intensity) of Chinese firms due to trade shocks. Second, we study the impact of trade liberalization on the environment at granular firm level, taking advantage of China's dual trade regime (processing vs. normal exports). Third, we make use of China's accession to the WTO in 2001 as a semi-natural policy shock to perform a DID estimation strategy that directly tackles the potential endogeneity problem (i.e., the simultaneity issue),[3] which is key in order to correctly estimate whether trade liberalization contributes to cleaner manufacturing production.

Our paper provides novel evidence on firms' environmental reactions in China due to the trade liberalization shock and discusses the underling driving forces of these reactions. It relates to the long-time debate on whether trade is good or bad for the environment, most notably Cherniwchan (2017) (see also *World Development Report 2020*; Forslid et al., 2018; Cui et al., 2012; Cole and Elliott, 2003; Antweiler et al., 2001; Copeland and Taylor, 1994; Grossman and Krueger, 1991).[4] Our paper also

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[3] Generally speaking, there are three main sources of endogeneity: first, policy endogeneity; second, omitting variables; and third, reverse causality. This could occur if there were to be measurement errors concerning estimates of the possible interaction between trade and the environment. Previous studies have contributed to investigations along this vein (see e.g., Baghdadi et al., 2013; Löschel et al., 2013; Managi et al., 2009; Gamper-Rabindran, 2006). In our case, it is more about simultaneity, i.e. did trade increase productivity which reduced pollution, or did productivity increase trade and reduce pollution simultaneously? Therefore, the WTO accession in our setting could work as a quasi-experiment.

[4] The availability of micro-level data allows for a better understanding of firms' heterogeneity with regard to their environmental performance (Bernard and Jensen, 1999; Tybout, 2001). More recent empirical studies seek to explore the firm-level relationship between export status and environmental performance, and the mechanisms at play. For example, British exporting firms are found to contribute to better environmental performance because they innovate more (Girma et al., 2008). Similar results are obtained for Ireland (Batrakova and Davies, 2012), Sweden (Forslid et al., 2018), and the US (Holladay, 2016). Clearly, most research focuses on developed countries, while evidence from developing economies is scant. The main reasons for the relatively small amount of literature for developing countries seem to be lacking data availability, and poor data quality, in particular

relates to a fast-growing strand of literature that studies the impact of China's entry into WTO on firm performances, e.g. total factor productivity (TFP); mark-up (Brandt et al., 2012; 2017) and innovation (Liu et al., 2016). Moreover, discussions on environmental policy issues have been growing in China (Xu, 2011), and trade policies are often adopted to address such issues (Eisenbarth, 2017). Our paper complements these studies and also relates to Brandt et al. (2017) who study the effects of trade liberalization on firms' mark-up changes.

The paper proceeds as follows: Section 2 describes the dataset and presents some stylized facts. Section 3 formally introduces the econometric models and conducts the empirical investigation on trade liberalization and SO_2 emission intensity for manufacturing firms. Section 4 discusses potential explanations for the observed pattern. Section 5 concludes.

2. Data and background

2.1 Data overview

Our dataset is derived from three rich firm-level data sources: i) the annual survey of industrial production (ASIP) maintained by National Bureau of Statistics (NBS); ii) China's environmental statistics database (CESD) provided by Ministry of Ecology and Environment (formerly known as Ministry of Environmental Protection); and iii) customs trade database collected by China Customs. Further, we obtain tariff data from WITS (i.e., World Integrated Trade Solution) maintained by the World Bank. These four datasets are matched and merged.

ASIP database records annual firm-level data for the period 2000-2007, covering all state-owned enterprises, and other firms with sales above 5 million RMB. These data are derived from annual surveys conducted by NBS, and widely used in economics studies. The original ASIP data set includes the mining, manufacturing and public utilities industries; however, as most of the merchandise trade occurs in

concerning the firm-level data characterizing heterogeneity of firms within industry.

manufacturing, we only consider the data from the manufacturing industry. Following common practice dealing with China's ASIP (see e.g., Yu, 2015; Feenstra et al., 2014; and Brandt et al., 2012), as a first step, observations that reported missing or negative values for any of the following variables were omitted from the study: total sales, total revenue, total employment, fixed capital, export value, intermediate inputs; as well as those where export values exceeds total sales, and/or if share of foreign assets exceeded one. Thereafter, we also omitted observations with less than eight employees (which are not likely to have reliable accounting capacity). Further, as the data ranges from 2000 to 2007, corresponding to two different versions of industry classifications, we map the data for 2000 and 2001 (based on the 1994 standard) to the 2002 version of the China Standard Industrial Classification.

The CESD is the most extensive nationwide environmental dataset in China provided by the Ministry of Ecology and Environment, and just recently made available to researchers (see Pei et al., 2019; Wang et al., 2018 for recent contributions using the dataset). Due to the strict data quality control procedures, the CESD is arguably the most reliable dataset in China recording plant-level environmental performance. In fact, the CESD collects annual emissions data for three industrial sectors, namely mining, manufacturing, and electricity, heat and water production and supply, covering 39 two-digit National Standard Industrial Classification (SIC) industries. According to the authority, all plants within each county are first ordered from highest to lowest according to their annual discharges of pollutants and waste, such as Chemical Oxygen Demand (COD), NH_3, SO_2, NOx, and Total Suspended Particulate (TSP). Then, the plants in each county that account for 85% of the annual discharges of one or more pollutants in the same county are included in the CESD. The variables included in the annual CESD are 1) basic information of the enterprise (e.g., name, address); 2) basic production information (e.g., total output); 3) pollutants (e.g., SO_2, COD); 4) pollution abatement equipment (e.g., investment in abatement).

Customs data is provided by China Customs. This database covers all trading firms with trade related indicators and spans from 2000 to 2007. It covers the entire sample of China's exporters and importers, and contains disaggregate product level information of firms' trading price, quantity and value at the HS eight-digit level. Importantly, this data also provides information on trade mode, i.e. whether a firm is conducting processing export or normal export, allowing us to construct firms' status as to processing and/or normal traders. Following previous research for matching and merging China's micro data, we first match the ASIP and the CESD. The matching and merging process is roughly divided into two main steps (see Pei et al., 2019 for a related discussion regarding the year 2007). And then, the merged data are matched with Customs data, resulting in an unbalanced panel from 2000 to 2007 with 13,641 observations (plus 10,412 observations for hybrid firms; and for identification consideration, the 13,641 observations of pure processing and normal exporters are used in subsequent analysis, if not otherwise stated). Details are provided in the Appendix A1.

2.2 Policy background

In order to attract foreign invested enterprises and accumulate foreign reserve (via trade surplus), among other motives, China started processing trade (i.e., imports to exports) after her opening-up policy in 1978. Like many other economies, where preferential measures such as duty-free when enterprises import raw materials, components or other investment goods are only applicable to strictly controlled export processing zones, China designated several areas (mainly along the coastal regions, e.g. Guangdong Province) as the processing zones. For management concern, originally the idea was to put all the processing firms in processing zones, but this was not very successful (in fact, less than one third of processing trade is conducted within officially defined processing zones).

One major obstacle for this practice is that, the firms will not be able to exploit the full potential of China's relative low cost (e.g., labor cost). Then, in parallel to normal trade regime, China Customs implemented a processing trade regime which traced the processing imports virtually all over China until they are re-exported. Although the special economic zones (SEZs) attracted a lot of attention and are located near important economic centers in southern coastal China, they did not determine the scope of the export processing regime. Rather the definition of the processing zone is not geographical, but formed on the legal status of enterprises (as long as they have foreign orders specified as processing trade). In essence, China has created a huge export processing zone.

The processing traders, which can be foreign invested enterprises (FIEs), private, or state owned enterprises (SOEs), are tariff-exempt (Naughton et al., 1996), and can perform the production activities virtually anywhere within China (i.e. they are not restricted to processing zones, in contrast to typical cases in many other economies). Compared with normal trade, the typical feature of processing trade is that it is duty free, that is, the imported inputs are exempted from import tariff (plus value-added tax applicable). Further, processing trade is also subject to tax rebate policy, i.e. domestic materials and parts used in the processing process can be refunded when exporting. In sum, no tariff and value-added tax (VAT) must be paid in China when processing imported materials and parts, but all final products must be exported.[5] In sharp contrast, firms engaged in normal trade are required to pay import tariff and VAT; even if VAT may be refunded, it is only partially reimbursed.

China formally joined the WTO on December 11, 2001. It took about 15 years since the negotiation started, whose exact timing can be regarded as an unpredictable. Moreover, the ratification is depending on factors outside China such as the negotiations between China and WTO member economies like the US and EU. More specifically, from China's perspective, it is exogenous and out of control though China has devoted a lot of effort, e.g. before the establishment of WTO, it was hoped to regain the status of founding member of GATT but not successful, and it took another 6 years to get a ticket entering WTO in 2001. From the US perspective, it also

[5] It was strictly implemented before 2008 (when global financial crisis started) that processing trade must be exported. After 2008, acknowledging the difficult situation of exports plus the pressure of rebalancing and China's own structural reform towards more domestic consumption, the processing trade was allowed to sell domestically given that the tax was properly paid.

comes as a surprise, e.g. Schott and Pierce (2016) attribute the decline of US manufacturing jobs to US (unexpectedly) granted permanent MFN to China in 2000; ADH (2013) directly link the job losses to China's (unexpected) accession to WTO. In this regard, the exact timing of China's entry into WTO is arguably unpredictable, thus can be considered as a policy shock.

2.3 Variable construction

In what follows, we construct relevant variables (based on the merged dataset) for the empirical study.

Dummy normal variable

In our sample, trade mode is a variable in the data (see Table 1 for summary statistics). In fact, there are several categories of trade mode in the raw data, including: processing and assembling (no ownership changes), processing trade with imported materials (with ownership changes), normal trade, and other forms of trade (a small proportion of trade). Following relevant regulations and official definitions, the mode of processing trade consists of processing and assembling and the processing trade with imported materials, while the mode of normal trade refers to the remaining modes of trade.

In addition, we observe that there are enterprises performing both processing trade and normal trade. These enterprises are termed as hybrid type of trading firms. For specification and identification consideration, we focus on firms engaging in one single trade mode, i.e. either pure processing trade or pure normal trade. Therefore, the main results in the paper do not include the hybrid trading firms (10,142 observations).

As previously stated, the final dataset is an unbalanced panel from 2000 to 2007 with a total of 13,641 observations. To facilitate our analysis, we generate a new dummy variable (*normal*) from the unbalanced panel dataset; 11,875 out of 13,641 observations are assigned the dummy variable *normal*, which equals 1, while the rest (i.e., the remaining 1,766 observations) equals zero.

The lower panel of Table 1 presents several key statistics for the raw data from ASIP and CESD (served as the population). Due to different coverage of firms in different surveys, the merged sample is a subset of the raw data. Nonetheless, some preliminary comparisons between the sample and the raw data can be seen. It is observed that the merged dataset in general is larger in average total output and employs more workers, while emits less SO_2 than the raw data. A simple calculation shows that the average SO_2 emission intensity of the merged dataset is lower than that of the raw data, so we interpret our subsequent empirical results as a lower bound estimation.

Table 1: Observations of different trade modes and statistics for the raw data

Trade mode/dataset	Observations	Total output (simple mean in million RMB)	SO_2 emissions (simple mean in tonnes)	Employment (simple mean in thousand)
Normal trade	11,875	269.273	169.152	0.844
Processing trade	1,766	316.118	117.127	0.814
Hybrid	10,142	549.181	109.229	1.049
ASIP	1,777,293	80.852	n.a.	0.267
CESD	599,035	125.807	197.757	n.a.
Exporters in ASIP and CESD	29,245	451.265	120.946	1.039

Source: Authors' own illustration based on raw data and the matched dataset. ASIP = annual survey of industrial production maintained by National Bureau of Statistics of China; CESD = China environmental statistics database maintained by Ministry of Ecology and Environment.

SO_2 emission intensity

We use the ratio of sulfur dioxide emissions to total output, and then add 1 to calculate the sulfur dioxide emission intensity (to facilitate our analysis when taking logarithms, as some firms may report zero emissions).[6]

Real total output, real intermediate input and real value added

The World Input-Output Table of 1998-2007 from the WIOD database (see Timmer et

[6] In the sample, the number of observations with no reporting SO_2 emissions value is 3,617, accounting for 26.52% of the total observations.

al., 2015) provides annual data for China. The data include the total output and intermediate input in current prices, and there are also data of total output and intermediate input in previous year's price. The ratio of the two different output values gives the total output price index, which can be used to estimate the real total output value of each year at 1998 constant prices. Likewise, the ratio of the two versions of intermediate inputs gives the price index of the intermediate inputs, which can be used to derive the intermediate input value at 1998 constant prices. Ultimately, real value added can be obtained (as a residual) by subtracting the real intermediate input value from the real total output value.

Real Capital Stock

We use the standard perpetual inventory method to calculate capital stocks. This variable is used to estimate productivity. In the calculation process, it was necessary to ensure the availability of the initial capital stock of each enterprise, the real investment of fixed assets and depreciation value in each year were available. We use the net value of fixed assets of each enterprise in 1998, or the net value of fixed assets corresponding to the year when the enterprise first appears in the database, to convert it into the actual value in 1998 as the initial capital stock of each enterprise.

Although ASIP database does not directly report the fixed asset investment at the enterprise level, it reports the original value of fixed assets in each year. The difference between the original values of fixed assets in the next two years is the nominal investment of the enterprise in each year. Then, according to the price index of fixed asset investment, it can be converted into the real investment value. ASIP database directly reports the depreciation amount of each enterprise in the current year, and then using the fixed asset investment price index as a deflator, we can calculate the real depreciation value. Finally, we can obtain the real capital stock at firm level.

TFP (ACF), TFP (OP) and TFP (OLS)

There are several methods to estimate total factor productivity (TFP), and each of them addresses certain issues pertaining to the data. For the sake of completeness, we briefly discuss the main approaches, and how we apply those methods in our data. The baseline estimation for TFP normally starts with OLS estimation of a production function. However, (for the econometrician unobserved) productivity shocks may influence inputs and output leading to simultaneity bias (e.g. Griliches and Mairesse, 1995). To reckon with the simultaneity problem, Olley and Pakes (1996) proposed to use the current investment of enterprises as a proxy variable of the impact of unobservable productivity; alternatively, Levinsohn and Petrin (2003) chose to rely on the intermediate input as a proxy variable of the unobservable productivity impact.

Moreover, according to Ackerberg et al. (2015), both OP (Olley and Pakes, 1996) and LP (Levinsohn and Petrin, 2003) methods have the problem of "function correlation", that is, the labor input is a certain function of other variables, so the coefficient of labor input cannot be estimated directly. They therefore proposed a method to solve the "function correlation". Specifically, they introduce labor input into the function of investment demand or intermediate demand, so as to obtain a consistent estimation of production function, making the estimation result preferred. In this regard, we use the ACF method (Ackerberg et al. 2015) to calculate TFP. In addition, the OP and OLS are employed to re-estimate TFP as robustness tests. A summary of the variables is given in Table 2.

Table 2: Variable definition

Variables	Description
Normal	A dummy variable. If an enterprise engaged in normal trade, the value is 1; otherwise 0.
Post2002	A dummy variable. For 2002 and later years, the value is 1; or otherwise 0.
SO_2 emissions	Total sulfur dioxide emissions in ton per year by enterprises
SO_2 emission intensity	The ratio of sulfur dioxide emissions in ton to total industrial output value in mRMB +1
Employment	Average number of employees per year
TFP(ACF)	Total factor productivity calculated using ACF method
TFP(OLS)	Total factor productivity calculated using OLS method
TFP(OP)	Total factor productivity calculated using OP method
Intermediate ratio	The ratio of intermediate input value in mRMB to total industrial output value in mRMB
Wage ratio	The ratio of employees' wage in mRMB to main business revenue in mRMB

Source: Authors' own illustration.

3. Statistical analysis

3.1 Descriptive statistics

Table 3 shows descriptive statistics for the whole sample; Tables 4 and 5 for normal and processing exporters respectively. The observation that processing exporters on average are cleaner than normal exporters is not surprising given that the production of processing trade is more labor-intensive than normal trade, and usually capital-intensive production is positively associated with heavy pollution.

Table 3: Whole sample including normal and processing exporters

Variable	Observations	Mean	Sd	Med	iqr	Min	Max
SO_2 emission intensity (t/mRMB)	13,641	1.618	1.298	1.114	0.585	1	8.431
Normal × Post2002	13,641	0.711	0.453	1	1	0	1
Employment	13,641	839.990	1739.234	375	665	8	44233
TFP (ACF)	13,641	0.414	0.180	0.391	0.210	0.054	1.118
Intermediate ratio	13,641	0.760	0.118	0.772	0.144	0.360	0.981
Wage ratio	13,641	0.078	0.065	0.060	0.069	0.005	0.346

Source: Authors' calculation based on the merged dataset.

Table 4: The sample of normal exporters

Variable	Observations	Mean	Sd	Med	iqr	Min	Max
SO_2 emission intensity (t/mRMB)	11,875	1.650	1.335	1.128	0.626	1	8.431
Employment	11,875	843.784	1742.083	380	670	11	44233
TFP (ACF)	11,875	0.416	0.180	0.393	0.210	0.054	1.118
Intermediate ratio	11,875	0.758	0.118	0.769	0.145	0.360	0.981
Wage ratio	11,875	0.077	0.063	0.059	0.067	0.005	0.346

Source: Authors' calculation based on the merged dataset.

More specifically processing trade involves fabrication activities (e.g., the assembly of iPhone by Foxconn in China, hardly generate emissions directly), whereas normal trade consists of production both for intermediate and final goods (typically associated with emissions). From a production chain point of view, processing trade has a shorter production chain than that for normal trade (see a thorough discussion in Yang et al., 2015), thus *c.p.* generates less emissions in China.

Table 5: The sample of processing exporters

Variable	Observations	Mean	Sd	Med	iqr	Min	Max
SO_2 emission intensity (t/mRMB)	1,766	1.403	0.983	1.032	0.338	1	8.431
Employment	1,766	814.477	1720.225	340	629	8	37530
TFP (ACF)	1,766	0.400	0.181	0.376	0.208	0.054	1.118
Intermediate ratio	1,766	0.776	0.119	0.791	0.138	0.360	0.981
Wage ratio	1,766	0.088	0.077	0.065	0.083	0.005	0.346

Source: Authors' calculation based on the merged dataset.

3.2 The environmental effects of trade shocks on exporting firms

As stated above, processing trade is a typical arrangement in developing countries, taking advantage of cheap labor combined with technology and markets in developed economies. That said, this form of trade is not unique to China, and is also existing in other East Asian countries (e.g., Indonesia and Viet Nam) and Mexico (being the three most prominent examples).

Governments in developing countries usually encourage the development of various types of processing trade as a means to participate in global production (see e.g., *World Development Report 2020*), where imported intermediates such as parts and components are usually tax-free. Hence, during the process of trade liberalization (mainly in the form of import tariff reduction), the enterprises engaging in processing trade are not (or to a lesser extent) affected compared with the enterprises conducting normal trade. Therefore, it is hypothesized that, the environmental effects of trade liberalization on the pollutants discharged by heterogeneous enterprises will differ, depending on whether processing trade accounts for a large proportion of a firm's total trade. Precisely, in order to investigate the impact of trade liberalization on firm's environmental performance, we take advantage of China's processing trade and WTO entry. Normal traders face different tariff rates pre- and post-WTO serving as the treatment group; while processing exporters subject to tariff-exempt both pre- and post-WTO are the control group.

3.2.1 Regression analysis

To the best of our knowledge, this study is amongst the first to focus on the environmental performance due to China's accession to WTO as it differentiates between normal trade and processing trade. Recent studies investigated the differential productivity effects of trade liberalization on processing trade and normal trade. For instance, Yu (2015) found that tariff reduction had a significant positive effect on the productivity of normal trade enterprises, and the higher the share of processing trade enterprises, the smaller the benefit from tariff reduction. Our main departure from this line of research is that we focus on the differential environmental effects of trade liberalization across processing exporters and normal exporters. In what follows, we will test this hypothesis empirically.

Our focus is on the impact of China's accession to WTO and on the differential environmental performance of normal trade enterprises and processing trade enterprises. To tackle potential endogeneity issues, we use China's WTO entry in 2001 as a quasi-experiment to perform a DID estimation. Here, we take processing exporters as the control group that enjoys tariff-exempt both pre- and post-WTO entry; while normal exporters saw tariff reductions during the same period, forming the treatment group. In this way, we can directly evaluate the impact of trade liberalization on firm's environmental performances. Following Liu et al. (2017), our DID estimation is specified below:

$$\boldsymbol{log(SO2\ intensity)_{ijt} = \alpha_i + \gamma_{jt} + \beta_1 Normal_i \times Post2002_t + \beta_2 Control_{ijt} + \varepsilon_{ijt}} \quad \textbf{(1)}$$

Where *i* indexes enterprises, *j* refers to 2-digit industries, and *t* indexes years. $Normal_i$ equals 1 if an enterprise engages in normal trade; otherwise it equals to 0. $Post2002_t$ takes 1 for the years 2002 till 2007; otherwise it takes 0. $Normal_i \times Post2002_t$ is the interaction term between the $Normal_i$ and $Post2002_t$.

The estimator β_1 is of interest, it captures the average differential change in SO_2 emission intensity of normal exporters (due to the policy shock) relative to the control group (i.e., processing exporters). If β_1 is significantly negative, then we can infer that China's accession to WTO led to a lower SO_2 emission intensity of normal exporters. Following usual practice (see e.g., Forslid et al., 2018; Liu et al., 2016; Holladay, 2016; Wang et al., 2018; Kee and Tang, 2016), $Control_{ijt}$ represents other firm-specific control variables, such as total factor productivity (TFP), employment, wage ratio and intermediate ratio.

In addition, we take advantage of the nature of our panel data by including enterprise fixed effects (α_i) and industry-time fixed effects (γ_{jt}) in our baseline specification. The inclusion of the industry-time and enterprise fixed effects means that we control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant (see also Wang et al., 2018). ε_{ijt} is the usual idiosyncratic error term.

3.2.2 The baseline results

One of the preconditions for a validity of DID estimation is that the treatment group and the control group meet the same trend hypothesis before being processed (Bertrand, 2004). In general, there are two basic assumptions that should be satisfied when using the DID model, namely *parallel trend assumption*,[7] and *no association between temporary shocks* (the stochastic error) *and policy dummy variables*.

DID allows selection to be based on individual characteristics, as long as the characteristics do not change with time; as such, an advantage of using DID is that it addresses the endogeneity issue due to possible "selection bias". The result of parallel pre-trend hypothesis is presented below.

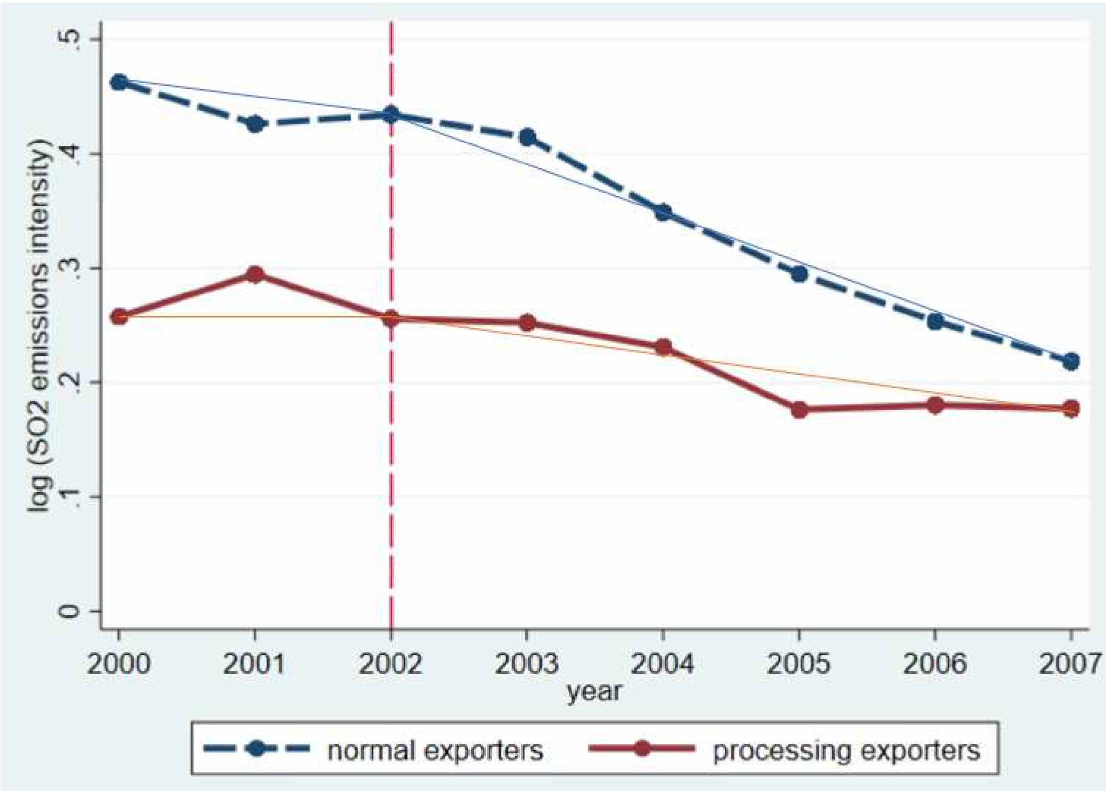

Figure 1: China's dual trade regime: processing trade vs. normal trade
Note: Mean values of *log(SO_2 emissions intensity)*. See Table 2 for variable definition.

Before China's accession to the WTO (i.e., before 2002), the SO_2 emission intensity of the treatment group and the control group exhibited are not statistically different. In fact, the dynamic regression analysis (given later in Table 8) reveals that, relative to 2000, firms engaged in normal trade did not exhibit significantly lower SO_2 emission

[7] The DID method does not require that the treatment group and the control group are identical, and there may be some differences between the two groups; but the DID method requires that the differences are constant, i.e. the treatment group and the control group exhibit the same development trend before the implementation of the policy (or external shock).

intensity relative to firms engaged in processing trade in the years before China's WTO entry.

However, due to data availability, only two data points are available before the policy shock. In this sense, our result is only suggestive evidence for a parallel trend assumption. After China's accession to the WTO, the SO_2 emission intensity of the treatment group and the control group exhibited different dynamics. The DID specification examines the differential effects of China's accession to WTO on the SO_2 emission intensity of firms engaging in the two different trade modes.

3.2.3 Empirical results based on DID specification

Table 6 shows differences in mean value of natural logarithm of SO_2 emission intensity between treatment (i.e., normal exporters) and control groups (i.e., processing exporters) before and after China's WTO entry.

Table 6: Differences in mean value of natural logarithm of SO_2 emission intensity between treatment (i.e., normal exporters) and control groups (i.e., processing exporters) before and after China's WTO entry

	Before		After		Difference		DID
	Control (1)	Treated (2)	Control (3)	Treated (4)	(5)=(2)-(1)	(6)=(4)-(3)	(7)=(6)-(5)
Whole Sample	0.278	0.442	0.215	0.327	0.165*** (0.025)	0.113*** (0.012)	-0.052* (0.028)

Note: Before refers to the period before China's accession to the WTO; After refers to the period after China's accession to the WTO; Control refers to processing exporters; Treated refers to normal exporters; Difference refers to the difference of mean value of natural logarithm of SO_2 emission intensity between normal exporters and processing exporters after China's accession to the WTO compared with the difference between the SO_2 emission intensity before China's accession to the WTO. Standard errors in parentheses. All of the values in the last row are logarithms of SO_2 emission intensity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

There are three general observations: first, processing exporters have lower SO_2 emission intensity in the whole study period (a micro evidence supporting the differential treatment for processing trade and normal trade in studies using macro framework, e.g. Dietzenbacher et al., 2012); second, both types of exporters saw emission intensity decline after China's WTO entry (in line with the general trend of

China's SO_2 emission intensity declining, from 1.12t/mRMB in 2000 to 0.506t/mRMB in 2007 in all industries); third, normal exporters were affected more than processing exporters (echoing previous studies for other outcome variables such as TFP, see e.g. Yu, 2015). In particular, it is observed that China's WTO entry contributed to less SO_2 emission intensity for normal traders (statistically significant at the level of 10%, see column (7)).

Table 7: DID empirical results

Log (SO_2 emission intensity)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$\boldsymbol{Normal_i \times Post2002_t}$	-0.055**	-0.066**	-0.055**	-0.048*	-0.062**
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
$\mathrm{TFP(ACF)}_{ijt}$		-0.227***	-0.316***	-0.179***	-0.323***
		(0.039)	(0.071)	(0.037)	(0.073)
$\mathrm{Log\ (employment)}_{ijt}$		-0.075***			-0.100***
		(0.029)			(0.030)
$\mathrm{Log\ (intermediate\ ratio)}_{ijt}$			-0.096*		-0.092***
			(0.051)		(0.051)
$\mathrm{Log\ (wage\ ratio)}_{ijt}$				0.066***	0.072***
				(0.013)	(0.013)
Constant	0.008	0.481**	0.082	0.439***	1.046***
	(0.143)	(0.203)	(0.143)	(0.160)	(0.239)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
n	13,641	13,641	13,641	13,641	13,641
$\boldsymbol{R^2}$	0.0006	0.0002	0.0002	0.0013	0.0013

Note: Standard errors in parentheses, clustered at firm level if not otherwise stated. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 210 different categories.

In order to partial out the effects of covariates, Table 7 highlights the results of DID estimation of relative SO_2 emission intensity change of normal exporters after China's WTO entry, where fixed effects for firms and industry*year are always included. It is found that the coefficient of $\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t}$ is negative and statistically significant.[8]

We start with the specification with only the interaction term included (column (1)), the coefficient -0.055 means that compared with the processing exporters that are not directly affected by the WTO entry, SO_2 emission intensity of normal exporters were reduced by 5.39 percent after China's accession to WTO.[9] This difference is also economically significant (noting that, during the same period, the annual average SO_2 emission intensity in China's manufacturing sector declined by 10.7 percent from 2000 till 2007).

Next, acknowledging the important role of productivity, employment, wage ratio and intermediate input ratio (see e.g., Forslid et al., 2018; Liu et al., 2016; Holladay, 2016; Wang et al., 2018; Kee and Tang, 2016), these control variables were each included in the regression. The results still hold (see column (2)-(5)). Column (5) is our preferred estimation. As expected, firms with higher productivity, larger employment and larger intermediate input ratio saw a decline in the emission intensity. Whereas, firms with higher wage ratio saw a rise in the emission intensity.

Essentially, in column (5) we have excluded potential confounding explanations stemming from scale (where we controlled for employment), technology (we controlled for TFP), outsourcing (intermediate input ratio), as well as wage ratio and *c.p.* the WTO entry contributed to an extra 6% decline of SO_2 emission intensity for normal exporting firms.[10] The conclusion can be drawn with relative confidence that, compared with the processing exporters that are not directly affected by the trade shock (i.e., China's WTO entry), SO_2 emission intensity of normal exporters saw a

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[8] By adopting an alternative method to delineate trade modes (e.g., Lu et al., 2015), we also found that China's accession to the WTO contributed to statistically significant negative impact on the SO_2 emission intensity of normal exporters. These additional results are available upon request to the authors.

[9] Following Halvorsen and Palmquist (1980) and Kennedy (1981), the percentage is calculated as $\exp(\hat{\beta} - \frac{1}{2}\hat{V}(\hat{\beta})) - 1$, where $\hat{\beta}$ is the estimate of $\hat{\beta}$ and $\hat{V}(\hat{\beta})$ is the estimate of the variance of $\hat{\beta}$.

[10] We also run all the regressions with TFP estimated using OLS and OP methods, the results are essentially the same. In addition, taking advantage of the fact that there is information for the trade mode at firm level, we have re-run the estimation with clustering enterprises at the level of trade mode. The results are comparable, and for the sake of brevity are omitted from the text but available upon request.

reduction by as much as 6% (see column (5)) after the trade shock.

This result is in line with studies for developed economies (e.g. the US, see Cherniwchan, 2017); however, the underlying mechanism is different. Cherniwchan (2017) attributes the clean-up of US firms exposed more to the trade shocks via substitution of inputs by Mexican imported materials; while in our case, the declining of SO_2 emission intensity is mainly due to technology advancement (for more details see the following section). It is worth noting that, additional results (see Appendix A7) indicate that only in pollution-intensive manufacture industries samples, China's WTO entry contributed to less SO_2 emission intensity for normal traders, which is different from the findings in Forslid et al. (2018).[11]

Further, the pre-2002 trend indicates whether environmental performance of normal exporters followed the same trend before China's WTO entry. To investigate this issue, we estimate a more flexible version following Che and Zhang (2017).

$$\log(SO_2\ intensity)_{ijt} = \alpha_i + \gamma_{jt} + \sum_{t=2000}^{2007} \beta_t \times Normal_i \times yr_t + \varphi Control_{ijt} + \varepsilon_{ijt} \quad (2)$$

Table 8 reports estimates on the interactions between normal exporters and year dummies for equation (2), where we examine the timing of normal exporters' environmental performance to China's WTO entry. The absence of a pre-existing trend indicates that the relative changes post-2002 is likely due to the China's WTO entry. Estimates on the interactions for 2001 are not statistically significant, suggesting that relative to 2000, firms engaged in normal trade did not exhibit significantly lower SO_2 emission intensity relative to firms engaged in processing trade in the years before China's WTO entry.

Whereas in the years after 2002, the estimates on the interactions between normal exporters and year dummies are statistically significant. This finding supports our identification assumption that there is no systematic difference in SO_2 emission intensity before the China's WTO entry, i.e. it is unlikely that there would have been a post-2002 environmental performance difference were it not for the China's WTO

[11] In fact, they divide the sample into energy-intensive and non-energy-intensive industries, but found no effects in energy-intensive industries.

entry shock.

Table 8: Dynamic effects of China's WTO entry on normal exporters' environmental performance

Log (SO_2 emission intensity)	(1)	(2)	(3)	(4)	(5)
$Normal_i \times 2001$	-0.071	-0.065	-0.059	-0.057	-0.062
	(0.046)	(0.047)	(0.046)	(0.047)	(0.049)
$Normal_i \times 2002$	-0.092**	-0.099**	-0.086*	-0.082*	-0.095**
	(0.043)	(0.045)	(0.043)	(0.043)	(0.046)
$Normal_i \times 2003$	-0.118**	-0.122**	-0.111**	-0.104**	-0.121**
	(0.043)	(0.047)	(0.045)	(0.043)	(0.047)
$Normal_i \times 2004$	-0.127***	-0.136***	-0.117***	-0.108***	-0.128***
	(0.040)	(0.041)	(0.039)	(0.039)	(0.041)
$Normal_i \times 2005$	-0.080*	-0.091*	-0.069	-0.055	-0.079
	(0.047)	(0.049)	(0.046)	(0.046)	(0.050)
$Normal_i \times 2006$	-0.093**	-0.106**	-0.082*	-0.062	-0.090*
	(0.045)	(0.048)	(0.045)	(0.044)	(0.049)
$Normal_i \times 2007$	-0.168***	-0.195***	-0.158***	-0.152**	-0.196***
	(0.052)	(0.054)	(0.053)	(0.056)	(0.057)
TFP(ACF)_{ijt}		-0.226***	-0.315***	-0.178***	-0.321***
		(0.053)	(0.088)	(0.046)	(0.099)
$\text{Log (employment)}_{ijt}$		-0.076**			-0.100***
		(0.032)			(0.036)
$\text{Log (intermediate ratio)}_{ijt}$			-0.096*		-0.092
			(0.054)		(0.054)
$\text{Log (wage ratio)}_{ijt}$				0.067***	0.072***
				(0.018)	(0.020)
Constant	0.053	0.524**	0.118	0.474***	1.087***
	(0.078)	(0.218)	(0.079)	(0.115)	(0.311)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
n	13,641	13,641	13,641	13,641	13,641
$\boldsymbol{R^2}$	0.0008	0.0003	0.0001	0.0011	0.0010

Note: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 210 different categories.

4. Mechanism test

This section proposes a potential mechanism regarding why normal exporters saw lower emission intensity after China's entry into WTO. Our point of departure is the Melitz (2003) model with heterogeneous firms. Confounding policies are then identified and discussed. Lastly, we present a further mechanism test.

4.1 Productivity channel

Previous studies have confirmed that China's accession to the WTO has significant impact on enterprises engaged in normal trade, by increasing the total export volume and mark-up (Brandt et al., 2017) and productivity (Yu, 2015). An additional robust empirical finding is that processing exporters are less productive than normal exporters, and have inferior performance in many other aspects such as profitability, wage, R&D and skill intensity (Dai et al., 2016). Given reasonable conditions, production volumes increase with firm productivity and, as a consequence, firms' emission intensity is negatively related to firm productivity (Forslid et al., 2018). In addition, trade openness increases local competition, implying that the least productive, and usually also the most polluting, firms are forced to close down (or are forced to scale down their production volume), thus losing market share. The Forslid et al. (2018) model has the property that i) more productive firms are cleaner since they find it profitable to make larger fixed investments in clean technology; ii) exporters are cleaner for a given productivity level, since exporting implies a larger scale of production which motivates a larger fixed investment in clean technology.

In this section, we show that these properties are largely consistent with Chinese manufacturing survey data. As stated, the dataset contains rich information at the firm level for a large number of variables relating to production. In line with previous sections, the firms' productivity is measured by TFP, and is calculated based on Ackerberg et al. (2015).

Table 9 shows how firm-level SO_2 emissions per unit of output vary with productivity and with being a normal exporter. To account for sectoral differences in emissions, we include industry dummies (two-digit industries for 28 categories); and the year dummies are included to control for time trends. In addition, we also include firm-level fixed effects (see also Wang et al., 2018).

Column (1) only includes the interaction term, which is interpreted as follows: for normal exporters (compared with processing exporters), higher productivity contributes to greater reduction of SO_2 emission intensity. It is suggestive that our proposed mechanism that China's WTO entry contributes to normal exporting firms' productivity (confirming previous findings, see e.g. Yu, 2015), and higher productivity resulting in the observed lower emission intensity. Next, we explicitly add different control variables in the regressions, and the result remains significantly negative.[12] Overall, we show that more productive normal exporters are cleaner (with lower SO_2 emission per unit of output).

Table 9: Empirical results, clustered at industry and year

Log (SO_2 emission intensity)	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{Normal_i \times TFP_{ijt}}$	-0.205***	-0.229***	-0.290***	-0.184***	-0.286***
	(0.038)	(0.040)	(0.056)	(0.037)	(0.058)
Log $(\text{employment})_{ijt}$		-0.071***			-0.093***
		(0.022)			(0.023)
Log (intermediate ratio)			-0.071**		-0.061**
			(0.029)		(0.027)
Log (wage ratio)				0.067***	0.075***
				(0.011)	(0.012)
Constant	0.043	0.431**	0.065	0.428***	1.000***
	(0.122)	(0.177)	(0.122)	(0.135)	(0.222)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
Cluster	Industry & Year				
N	13,641	13,641	13,641	13,641	13,641
$\boldsymbol{R^2}$	0.0000	0.0003	0.0000	0.0011	0.0007

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed

[12] Similar results are found when errors are clustered at the sector and trade mode level (available upon request). Further, in the Appendix, we extend the analysis to i) conduct falsification test via deliberately incorrectly define hybrid exporters as normal counterparts (Table A2); ii) align the analysis taking into account the environmental policy regarding pollution-intensive versus non-pollution-intensive firms (Table A4); and iii) examine potential heterogeneous effects across regions and firm ownership (Table A5) as well as ruling out trade intermediaries (Table A6).

effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 210 different categories.

4.2 Ruling out confounding policies

If other policies issued before and after China's accession to the WTO that may have different impacts on our treatment and control groups, then the effect of these policy reforms may also be reflected in the estimates of DID.

In that case, the regression result from Eq. (1) will not be the pure effect of China's accession to WTO. In fact, two important reforms have taken place at the beginning of the 2000s: the reform of state-owned enterprises (SOEs) and the relaxation of regulations on the entry of foreign invested enterprises (FIEs).[13] However, in order to control the possible confounding effects of these two policy reforms, we add two additional control variables in our DID estimation following Liu et al. (2016): $\mathrm{SOEratio}_{jt}$ (the ratio of SOEs number to the total domestic firms number) and $\mathrm{Log\,(FIE\,number)}_{jt}$ (the logarithm of the number of foreign invested enterprises).

The results of Table 10 show that China's accession to the WTO still has a significantly negative impact on the SO_2 emissions intensity. Our main conclusion is still present. Firms in industries with a higher share of state-owned enterprises often have lower SO_2 emissions intensity (not statistically significant), which may be because state-owned enterprises have a major responsibility for environmental protection and should maintain their reputation. However, an increasing share of

[13] These reforms were on-going reforms that had started in the 1980s and 1990s, respectively, and accelerated after the WTO accession. The SOE reform resulted in a large-scale privatization, close-down of small SOEs, and an improvement in the efficiency of surviving (large) SOEs. The new FDI regulations relaxed the entry requirements for foreign investors and reduced the range of industries restricted to foreign investment. These reforms may not have differentiated effects on the treatment and control groups.

foreign firms has *c.p.* no effect on the emissions intensity.

Table 10: Ruling out confounding policies

Log (SO_2 emission intensity)	(1)	(2)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t}$	-0.037**	-0.038**
	(0.002)	(0.001)
TFP(ACF)_{ijt}	-0.319*	-0.319*
	(0.034)	(0.032)
$\text{Log (employment)}_{ijt}$	-0.095*	-0.096*
	(0.013)	(0.013)
$\text{Log (intermediate ratio)}_{ijt}$	-0.087	-0.086
	(0.027)	(0.026)
$\text{Log (wage ratio)}_{ijt}$	0.076**	0.076**
	(0.005)	(0.006)
SOE ratio_{jt}		-0.209
		(0.039)
$\text{Log (FIE number)}_{it}$		-0.002
		(0.012)
Constant	1.319**	1.414***
	(0.096)	(0.008)
Year fixed	Yes	Yes
Firm fixed	Yes	Yes
n	13,641	13,641
$\boldsymbol{R^2}$	0.0205	0.0220

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible.

4.3 Further mechanism check

To further investigate the impact of the productivity change of normal exporters on their environmental performance after China's accession to WTO, we have generated a triple interaction term $\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t} \times \boldsymbol{TFP_{ijt}}$ added to Eq. (1), to examine whether there is a differential effect that increases with TFP.

Table 11: Empirical results, clustered at industry and year

Log (SO_2 emission intensity)	(1)	(2)	(3)	(4)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t} \times \boldsymbol{TFP_{ijt}}$	-0.144***	-0.143***	-0.117***	-0.122***
	(0.032)	(0.040)	(0.031)	(0.040)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t}$	-0.010	-0.001	-0.004	-0.013
	(0.030)	(0.031)	(0.031)	(0.032)
Log (employment)$_{ijt}$	-0.065***			-0.084***
	(0.021)			(0.022)
Log (intermediate ratio)		-0.009		0.006
		(0.017)		(0.017)
Log (wage ratio)			0.069***	0.079***
			(0.011)	(0.013)
Constant	0.365	0.010	0.409***	0.931***
	(0.177)	(0.127)	(0.138)	(0.215)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes
n	13,641	13,641	13,641	13,641
$\boldsymbol{R^2}$	0.0006	0.0001	0.0008	0.0003

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 210 different categories.

Table 11 presents estimates of the effects of China's WTO entry on normal exporters' environmental performance when their productivity increase. The results suggest that China's WTO entry contributed to less SO_2 emission intensity for normal exporters, especially those enterprises with high productivity. These results are consistent with our previous mechanism test (i.e., Table 9).

5. Concluding remarks

This paper contributes to a long-standing debate over the environmental consequences of trade liberalization. To date, research has primarily focused on the relationship between trade and aggregate pollution levels. While these studies find that trade is not necessarily bad for the environment, they often appeal to the unobserved responses of individual polluters to explain the mechanisms underlying their findings. Yet, there has been little evidence of how trade liberalization affects the pollution from individual manufacturing plants especially in developing countries.

This paper provides additional evidence and extends the literature in several dimensions: First, we merged three rich firm-level datasets for China, which adds to the empirical evidence for China, one of the most important countries in the environment-trade debate; second, we examined the impact of trade liberalization on China's manufacturing firms' environmental performances with this unique dataset at the plant level, thereby taking advantage of China's dual trade regime (processing *vs.* normal trade) and China's WTO entry in 2001 by using a DID estimation strategy. Third, we investigated why normal exporters saw lower emission intensity after China's entry into WTO pointing at the role of productive firms, echoing the channel proposed in Melitz (2003).

Our results suggest that WTO entry played an important role in the observed clean-up of the Chinese normal exporters in the manufacturing sector. We find that trade liberalization following China's accession into WTO decreased emission intensity of sulfur dioxide from affected plants. Altogether, our estimates suggest that, compared with the processing exporters that are not directly affected by the WTO entry, SO_2 emission intensity of normal exporters were reduced by roughly 6% due to the trade shock. In short, China's WTO entry contributed to less SO_2 emission intensity for normal traders, which is in line with previous evidence reported for developed economies.

We also discuss one important mechanism that explains the observed pattern, which is the productivity channel (motivated by Melitz, 2003 and Forslid et al., 2018). Indeed, our results show that more productive normal exporters are cleaner (have lower SO_2 emissions per output) following China's accession to the WTO; and this effect is more pronounced for emission-intensive industries. Future research may focus on the explanatory power of the identified channel.

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Appendix

A1. ***Matching and merging the datasets***

Following previous research for matching and merging China's micro data, we first match the ASIP and the CESD. The matching and merging process is roughly divided into two main steps (see Pei et al., 2019 for a related discussion regarding the year 2007).

Step 1: First, the ASIP and CESD databases are matched for the same year according to enterprise name (note, duplication records are dealt with beforehand). Second given the fact that the CESD also discloses the name an enterprise used in previous years, the enterprise name in the remaining ASIP data sample that were not matched in the previous step are matched with the remaining sample of CESD by using the previously used name. Successfully matched observations are supplemented in the original matched sample.

Step 2: Some enterprises have the same name in the ASIP database, however the corporate code, administrative division code, telephone number, postal code and other enterprise information may be different. Therefore, third, samples which have the same enterprise name but different other information were screened. Likewise, there are samples with the same enterprise name but different enterprise information in the CESD. Based on this observation, we use the combination of enterprise name and administration code to generate a new combination variable, and then match the corresponding combination variable in the environmental statistics. Fourth, the remaining ASIP database sample without being matched in the previous steps are matched again using the combination variable generated by the name and administration code with the environmental statistics database. Successfully matched observations are also supplemented to samples previously obtained. Now we have the final merged sample with both production information and environmental performance indicators.

However, challenges remain when matching and merging the aforementioned dataset with customs data. One typical issue is that ASIP data and customs data have their own company identification numbers, and the two datasets belong to different authorities. Consequently, one cannot merge these databases directly using enterprise code. Following Yu and Tian (2012), we merge the two databases in two steps. First, we merge companies with the same company name (for each year); second, we then also merge companies with the same postal code and the same last seven digits of the phone number. It is worth noting that, during the matching and merging process, companies with invalid postal codes and phone numbers were excluded, i.e. 1) postal code or phone number is lost; 2) postal code is invalid (e.g., postal code value is less than 100000); and 3) phone number is invalid (that is, the number is less than 1000000).

Finally, our dataset is an unbalanced panel from 2000 to 2007 with 13,641 observations (plus 10,412 observations for hybrid firms; and for identification consideration, the 13,641 observations of pure processing and normal exporters are used in subsequent analysis, if not otherwise stated). To get a sense of the dataset, we present three sets of information, namely the frequency distribution of survival years and corresponding number of enterprises (given in Table A1a), the fraction of observations matched to previous year's firms (see Table A1b), and the dynamics of the firms (see Table A1c).

According to the statistics, there are 7,822 (resp. 6,004) enterprises included in the unbalanced panel (resp. hybrid firms) in the period of 2000-2007.

Table A1a: Survival years and the number of firms

Survival Years	Number of enterprises (pure normal & processing exporters)	Number of enterprises (Hybrid)
1	4,543	3,974
2	1,776	965
3	880	513
4	344	275
5	170	135
6	83	84
7	26	44
8	0	14
Total	7,822	6,004
Observations	13,641	10,142

Source: Authors' own calculation based on the matched dataset.

Further, unique firms' IDs enable us to link firms over time.[14] In our context, it is important to be able to link subsequent observations of the same firm even when the firm ID changed. In this way, it is possible to understand the dynamics of entry and exit of firms. Table A1b reports the percentage of firms that are matched each year on the basis of firm ID and those matched using other information. The total proportion of successfully matched enterprises, for example, in 2000-2001 is 27.28%, and 25.49% in 2006-2007. Overall, the proportion of matched firms is rather stable over time.

[14] Firms occasionally receive a new ID if they encounter restructuring, merger and/or acquisition. Following Brandt et al. (2012), we linked and also tracked firms as their boundaries or ownership structure changed, where possible, using information such as firm name, industry, phone number, post, etc. Many incumbents were restructured or privatized and we want to make sure not to lump these with exiting firms or classify them as *de novo* entrants under their new firm ID.

Table A1b: Fraction of observations matched to previous year's firms

Year	Total number	Matched by firm ID (%)	Match by other information (%)	Total percent（%）
2001	1,477	399/1477=27.01	4/1477=0.27	403/1477=27.28
2002	1,515	610/1515=40.26	4/1515=0.26	614/1515=40.52
2003	1,645	652/1645=39.64	1/1645=0.061	653/1645=39.701
2004	2,301	616/2301=26.77	3/2301=0.13	619/2301=26.9
2005	2,173	1002/2173=46.11	3/2173=0.14	1005/2173=46.25
2006	2,542	1026/2542=40.36	2/2542=0.079	1028/2542=40.439
2007	816	203/816=24.88	5/816=0.61	208/816=25.49

Source: Authors' own calculation based on the matched dataset.

Finally, Table A1c shows the dynamics of firms in our unbalanced panel, and provides the frequency distribution of the years of survival and the corresponding number of enterprises. For instance, from 2000 to 2001, the total number of enterprises increased from 1,172 to 1,477, with a total increase of 305 enterprises. Compared with 2000, the total number of new entrants in 2001 was 1,074, while during the same period 863 enterprises exit market.

Table A1c: The dynamics of firms

	Effective number of enterprises	Final		Initial	
Year	Total Number	Survival	Exit	Incumbent	Entry
2000	1,172	403	769		
2001	1,477	614	863	403	1,074
2002	1,515	653	862	614	901
2003	1,645	619	1,026	653	992
2004	2,301	1005	1,296	619	1,682
2005	2,173	1028	1,145	1,005	1,168
2006	2,542	208	2,334	1,028	1,514
2007	816			208	608

Source: Authors' own calculation based on the matched dataset.

Robustness check 1: Replacing normal trade with hybrid trade

As explained previously, there are enterprises engaged in both normal trade and processing trade, and we termed these enterprises as hybrid firms. In theory, if we have a ranking for the firms that are directly affected by trade shocks, it is reasonable to consider that the normal exporting firms would be the most affected by China's accession to the WTO, and the processing exporters would be the least, while the hybrid firms lie in between (i.e., ambiguous or insignificant effects are expected).

Table A2: DID Results: falsification test

Log (SO_2 emission intensity)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$\boldsymbol{hybrid_i \times Post2002_t}$	-0.011	-0.012	-0.011	-0.010	-0.010
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
TFP(ACF)_{ijt}		-0.079**	-0.213***	-0.055*	-0.225***
		(0.031)	(0.064)	(0.030)	(0.068)
$\text{Log (employment)}_{ijt}$		-0.033***			-0.049***
		(0.012)			(0.013)
$\text{Log (intermediate ratio)}_{ijt}$			-0.121***		-0.125***
			(0.044)		(0.046)
$\text{Log (wage ratio)}_{ijt}$				0.036***	0.035***
				(0.011)	(0.011)
Constant	0.322	0.556**	0.366*	0.513***	0.810***
	(0.200)	(0.229)	(0.202)	(0.187)	(0.195)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
N	11,908	11,908	11,908	11,908	11,908
$\boldsymbol{R^2}$	0.0021	0.0033	0.0041	0.0034	0.0055

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 204 different categories.

Empirically, we deliberately replace the normal exporters using the hybrid firms and re-run the regression (similar to a falsification test). The results are shown in Table A2.

We observe that China's accession to the WTO also contributed to lower SO_2 emission intensity for hybrid firms, however, the result is not statistically significant.

Robustness check 2: pollution intensity

According to the *First National Pollution Source Census Program* issued by the State Council, we divide the manufacturing industry into pollution-intensive industry and non-pollution-intensive industry. The pollution-intensive industries include the key pollution industries and key monitoring industries, while the non-pollution-intensive industry includes all other industries (State Council, 2007, see Table A3).

To allow for variation between the pollution-intensive industries and non-pollution-intensive industries, we re-estimate equation (1) in Section 3.2 of the paper by splitting the sample into pollution-intensive industries and non-pollution-intensive industries. The results are reported for both groups of industries in Table A4.

Table A3: Classification of manufacture industries

Pollution-intensive industries		Non-pollution-intensive industries
Heavy Pollution Industries	**Key Monitoring Industries**	
processing of food from agricultural products (13)	manufacture of textile wearing apparel, footwear, and caps (18)	manufacture of furniture (21)
manufacture of food (14)	processing of timbers, manufacture of wood, bamboo, rattan products (20)	manufacture of articles for culture, education and sport act (24)
manufacture of textile (17)	manufacture of general purpose machinery (35)	manufacture of plastic (30)
manufacture of leather, fur, feather and its products (19)	manufacture of special purpose machinery (36)	
manufacture of paper and paper products (22)	manufacture of transport equipment (37)	manufacture of tobacco (16)
processing of petroleum, coking, processing of nucleus fuel (25)	manufacture of communication equipment, computer and other electronic equipment (40)	printing reproduction of recording media (23)
manufacture of chemical raw material and chemical products (26)	manufacture of beverage (15)	manufacture of electrical machinery and equipment (39)
manufacture of non-metallic mineral products (31)	manufacture of metal products (34)	manufacture of measuring instrument and machinery for culture and office (41)
manufacture and processing of ferrous metal (32)	manufacture of medicines (27)	manufacture of artwork, other manufacture (42)
manufacture and processing of non-ferrous metals (33)	manufacture of chemical fiber (28)	recycling and disposal of waste (43) manufacture of rubber (29)

Note: The figures in parentheses are the large-size industry codes of industries, corresponding to the national industry classification issued by the National Bureau of Statistics of China (GB/T 4754-2002).

Table A4: Effects of export status in pollution-intensive *vs.* non-pollution intensive manufacture industries

Part A: Pollution intensive manufacture industries

Log (SO_2 emission intensity)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$\boldsymbol{Normal_i \times Post2002_t}$	-0.064*	-0.075**	-0.072**	-0.059*	-0.065*
	(0.031)	(0.032)	(0.032)	(0.034)	(0.035)
$\mathrm{TFP(ACF)}_{ijt}$		-0.294***	-0.458***	-0.242***	-0.474***
		(0.055)	(0.090)	(0.052)	(0.099)
$\mathrm{Log\ (employment)}_{ijt}$		-0.086**			-0.121***
		(0.036)			(0.035)
$\mathrm{Log\ (intermediate\ ratio)}_{ijt}$			-0.168**		-0.166**
			(0.075)		(0.070)
$\mathrm{Log\ (wage\ ratio)}_{ijt}$				0.077***	0.083***
				(0.021)	(0.022)
Constant	0.250***	0.786***	0.359***	0.749***	1.456***
	(0.062)	(0.229)	(0.057)	(0.106)	(0.300)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
N	9455	9455	9455	9455	9455
$\boldsymbol{R^2}$	0.0030	0.0029	0.0125	0.0172	0.0100

Note: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 121 different categories.

Part B: Non-pollution intensive manufacture industries					
Log (SO_2 emission intensity)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t}$	-0.027	-0.028	-0.026	-0.025	-0.029
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
TFP(ACF)_{ijt}		-0.022	-0.010	-0.006	0.010
		(0.033)	(0.046)	(0.036)	(0.049)
$\text{Log (employment)}_{ijt}$		-0.007			-0.013
		(0.020)			(0.021)
$\text{Log (intermediate ratio)}_{ijt}$			0.007		0.016
			(0.014)		(0.013)
$\text{Log (wage ratio)}_{ijt}$				0.033***	0.035
				(0.009)	(0.010)
Constant	0.145***	0.195	0.143***	0.244***	0.333*
	(0.018)	(0.132)	(0.018)	(0.034)	(0.154)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
N	4186	4186	4186	4186	4186
$\boldsymbol{R^2}$	0.0023	0.0029	0.0024	0.0083	0.0095

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 91 different categories.

The results indicate that only in pollution-intensive manufacture industries samples, China's WTO entry contributed to less SO_2 emission intensity for normal traders, which is different from the findings in Forslid et al. (2018).[15]

[15] In fact, they divide the sample into energy-intensive and non-energy-intensive industries, but found no effects in energy-intensive industries.

Robustness check 2: Heterogeneous effects of regional structure and ownership

Do the effects vary across regions?

There may be reasons to suspect that the effects of China's WTO entry on normal exporters' environmental performance vary across regions. Because of the different level of economic development in different regions, they have different degrees of environmental protection, coupled with region-specific characteristics. According to the classification of the central government, the address codes in our sample can be divided into four regions: eastern, central, western and northeastern. The sub-samples of the eastern region are larger than those of other regions, so we merge the samples of three regions except the eastern region into one sample (other regions) for analysis (see analogous treatment in Wang et al., 2018).

Do the effects vary by ownership?

One important feature of the Chinese economy is that state owned enterprises (SOEs), other domestic enterprises, Hong Kong, Macao, Taiwan (HMT) invested enterprises and foreign invested enterprises (FIEs) may face different incentives and constraints, which may lead to different responses during China's entry to WTO. Ownership may also affect an enterprise's response to environmental regulations. Pargal and Wheeler (1996) find that the marginal abatement cost of state-owned enterprises is higher than that of private firms. By comparing the environmental performance of enterprises with different ownership types, some studies have also found that multinational enterprises are more inclined to have clean technology than other types of enterprises. Developed countries usually have higher environmental standards than developing countries, so this is more conducive to the innovation and development of environment-friendly technologies in developed countries (Lanjouw and Mody, 1996).

Therefore, even where standards are relatively weak, foreign-invested enterprises often adopt newer and cleaner technologies. Domestic enterprises in many developing countries do not have enough funds to acquire environmental technologies to cope with new entrants and foreign competition (Christmann and Taylor, 2001). Multinational corporations usually face greater environmental protection pressures. The institutional pressure of environmental self-regulation of multinational corporations stems from a complex legal environment, including supranational institutional pressure (Kostova and Zaheer, 1999).

Customers and the public may be much less tolerant of foreign companies' misconduct than domestic companies, and in terms of bargaining power, foreign companies may be weaker than domestic companies (Lin et al., 2014). Companies with different ownership structures have different bargaining power in enforcing environmental regulations, such as pollution charges and fines (Wang and Wheeler, 2003). Foreign companies are often the target of regulatory enforcement as they are not familiar with the local political background.

In sum, to check whether the effects of China's WTO entry on normal exporters' environmental performance vary across ownership in different regions, one reference is specified (i.e., other domestic firms). The results are reported in Table A5.

It is found that in Eastern regions, China's WTO entry contributed to lower SO_2 emissions intensity for normal exporters when the enterprise is state owned enterprise (statistically significant at 10% level); for foreign invested normal exporters, China's WTO entry contributed to higher SO_2 emissions intensity; while for HMT invested normal exporters, there is no statistical significance; all compared with domestic other firms. It is noted that, for China's 11th Five-Year-Plan starting from 2006 till 2010, the binding SO_2 reduction targets (nation-wide is 10% lower in 2010 compared with 2005) for eastern regions (e.g., Shanghai need to reduce 26%) are more ambitious than other regions (e.g., Inner Mongolia for less than 4%); this could be one of the reasons but should only play out after 2006. While in other regions, China's WTO entry contributed to higher SO_2 emission intensity for normal exporters, in particular, when the enterprise is state owned.

Table A5: Heterogeneous effects for different ownership in subsets of eastern and other regions

Part A: Eastern regions

Log (SO_2 emission intensity)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t}$	-0.059***	-0.064***	-0.060***	-0.050**	-0.058***
	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t} \times SOE$	-0.046	-0.050	-0.042	-0.048	-0.054
	(0.044)	(0.045)	(0.045)	(0.045)	(0.047)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t} \times HMT$	0.037	0.035	0.038	0.028	0.029
	(0.039)	(0.039)	(0.039)	(0.037)	(0.037)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t} \times Foreign$	0.054**	0.054**	0.053**	0.047**	0.051**
	(0.022)	(0.023)	(0.022)	(0.021)	(0.022)
TFP(ACF)_{ijt}		-0.187***	-0.285**	-0.153**	-0.272**
		(0.062)	(0.113)	(0.058)	(0.122)
$\text{Log (employment)}_{ijt}$		-0.040***			-0.065***
		(0.014)			(0.021)
$\text{Log (intermediate ratio)}_{ijt}$			-0.095		-0.082
			(0.063)		(0.062)
$\text{Log (wage ratio)}_{ijt}$				0.070***	0.073***
				(0.014)	(0.015)
Constant	0.124*	0.379***	0.189**	0.569***	0.953***
	(0.065)	(0.115)	(0.069)	(0.128)	(0.223)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
n	9934	9934	9934	9934	9934
$\boldsymbol{R^2}$	0.0014	0.0052	0.0059	0.0097	0.0149

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 210 different categories.

Part B: Other regions					
Log (SO_2 emission intensity)	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t}$	0.127	0.134	0.133	0.141	0.124
	(0.174)	(0.171)	(0.172)	(0.174)	(0.175)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t} \times SOE$	0.120**	0.111**	0.113**	0.111**	0.111**
	(0.049)	(0.048)	(0.050)	(0.051)	(0.049)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t} \times HMT$	0.070	0.087	0.061	0.056	0.068
	(0.132)	(0.127)	(0.130)	(0.134)	(0.134)
$\boldsymbol{Normal_i} \times \boldsymbol{Post2002_t} \times Foreign$	0.104	0.122*	0.097	0.092	0.113
	(0.084)	(0.070)	(0.083)	(0.087)	(0.078)
TFP(ACF)_{ijt}		-0.266**	-0.356***	-0.190*	-0.452**
		(0.116)	(0.108)	(0.109)	(0.166)
$\text{Log (employment)}_{ijt}$		-0.186			-0.207*
		(0.114)			(0.116)
$\text{Log (intermediate ratio)}_{ijt}$			-0.122**		-0.162**
			(0.052)		(0.062)
$\text{Log (wage ratio)}_{ijt}$				0.045	0.053
				(0.053)	(0.053)
Constant	0.534***	1.630**	0.640***	0.717**	2.075**
	(0.154)	(0.703)	(0.168)	(0.284)	(0.862)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
n	3707	3707	3707	3707	3707
$\boldsymbol{R^2}$	0.0001	0.0002	0.0006	0.0010	0.0001

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 195 different categories.

Robustness check 3: Delete intermediaries

There are some coordinator-firms, which we call intermediaries. Intermediaries just act as "Forwarders" of cross industry products and they do not do much production. In sum, in order to check the impact of China's WTO entry on pure normal exporters, we should delete these intermediaries from our sample and do robustness check. Following Ahn et al. (2011), we identify the set of intermediary firms based on Chinese characters that have the English-equivalent meaning of “importer”, “exporter”, and/or “trading” in the firm's name. Specifically, we search for Chinese characters that mean “trading” and “importer” and “exporter”. In Chinese *Pinyin*, these phrases are: “*jin chu kou*”, “*jing mao*”, “*mao yi*”, “*ke mao*” and “*wai jing*”. So we delete these firms according these Chinese characters. The results are reported in Table A6.

Table A6: Delete intermediary firms

Log (SO_2 emission intensity)	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{Normal_i \times Post2002_t}$	-0.055**	-0.067**	-0.055**	-0.049*	-0.063**
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
TFP(ACF)_{ijt}		-0.230***	-0.319***	-0.181***	-0.325***
		(0.039)	(0.071)	(0.037)	(0.073)
$\text{Log (employment)}_{ijt}$		-0.076***			-0.100***
		(0.029)			(0.030)
$\text{Log (intermediate ratio)}_{ijt}$			-0.097*		-0.092*
			(0.051)		(0.051)
$\text{Log (wage ratio)}_{ijt}$				0.066***	0.072***
				(0.013)	(0.013)
Constant	0.010	0.484**	0.084	0.440***	1.049***
	(0.143)	(0.203)	(0.143)	(0.160)	(0.240)
Industry fixed * Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
n	13,589	13,589	13,589	13,589	13,589
$\boldsymbol{R^2}$	0.0006	0.0002	0.0002	0.0014	0.0013

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effect is to exclude the influence of other unobservable factors that do not change with the enterprise; time fixed effect is to control the influence of other unobservable factors that do not change with the time, so as to exclude the influence of other policy factors as much as possible; industry fixed effect is to control the influence of other unobservable factors that do not change with the industry. The fixed effects are included to control for potential omitted industry-year-specific variables. We control for general macro-economic factors that affect all enterprises over time in different industries as well as enterprise-specific characteristics which are time invariant. Industry-year fixed includes 210 different categories.

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ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de