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DISCUSSION PAPER

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Are Exporters More Environmentally Friendly? A Re-Appraisal that Uses China's Micro-Data

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Are exporters more environmentally friendly? A re-appraisal that uses China's micro-data

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Abstract: Is a firm's ability to export an important determinant of environmental performance? To answer this question, we construct a unique micro dataset that merged two rich firm-level datasets for China for 2007. When combining this new dataset with well-received empirical specifications, we found that both export status and export intensity are associated with lower sulfur dioxide (SO_2) emissions intensity. In addition to the traditional OLS estimation, we verified this association by using the propensity score matching method. Our findings show that the baseline result still holds. In short, exporters are more environmentally friendly than non-exporters, which is in line with previous evidence reported for developed economies. We further discuss mechanisms that explain the observed pattern and show that exporters realize higher abatement efforts compared to non-exporters. This study complements the literature in terms of providing China's micro evidence on SO_2 abatement efforts. It also serves as a first step toward a better understanding of the impact of trade on the environment, especially in developing countries.

JEL codes: F18; Q53; Q56

Keywords: Exporters and the environment; firm heterogeneity; SO_2 emissions; abatement

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1. Introduction

Along with the expansion of production across countries, due to ever declining trade costs and progress in information and communications technology, growth in trade exceeded that of gross domestic product over the last two decades (Constantinescu *et al.*, 2014). Meanwhile, as "pollution is a by-product of regular economic activities" (Leontief, 1970, p. 262), environmental degradation increased at an unprecedented rate in recent decades. China is a prominent example as it has become the largest sulfur dioxide (SO_2) emitter and the largest trading nation in recent years (Klimont *et al.*, 2013; and Trade Profiles in the World Trade Organization[1]). These well-perceived facts have intensified the long-time debate on whether trade is good or bad for the environment.

Grossman and Krueger (1991) were among the first to address the effects of trade on the environment. In their research, they disentangled pollution into three distinct elements that originate from trade; these are the scale effect, the composition effect, and the technology effect. Empirical findings on the impact of these effects are mixed in nature. Studies mainly center around the composition effect, examining whether different environmental regulations or different factor endowments would affect comparative advantage; thus, leading to two alternative hypotheses, namely, the "pollution haven hypothesis" and the "factor endowment hypothesis" (Copeland and Taylor, 1994; Antweiler *et al.*, 2001; Cole and Elliott, 2003).[2] The policy implications of these alternative hypotheses are different. For instance, if the empirical evidence were to not support the "pollution haven hypothesis", then the potential gains from trade would be largely underestimated. In other words, a deeper study that uses firm-level data may reveal new facts regarding the relationship between trade and the

1 China has ranked first in terms of merchandise exports in recent years, amounting to 2.48 trillion USD in 2018 (increasing from 1.22 trillion USD in 2007), see for example https://www.wto.org/english/res_e/publications_e/trade_profiles18_e.htm. As foreign exports are serve foreign demand, this can also be used as an indicator of international market exposure. Hence, in absolute terms of exports, China is subject to high exposure to international markets.

2 According to Copeland and Taylor (2004), the effects of trade liberalization on environmental quality depend on, among other factors, differences in pollution policy (more stringent environmental policy may drive away production, i.e., *the pollution haven hypothesis*) and differences in factor endowments (the capital-abundant country produces pollution-intensive goods that will increase pollution due to production expansion, i.e., *the factor endowment hypothesis*). In theory, it is not clear which hypothesis dominates in the real world; thus, empirical tests are called for (see also Temurshoev, 2006).

environment (as pursued in Cherniwchan *et al.*, 2017). In this paper, our claim is more focused as we test for Chinese data whether a firm's export intensity (respectively, export status) is associated with a lower environmental impact. Specifically, we focus on sulfur dioxide (SO_2) emissions, one of the main local pollutants with severe negative effects for the environment and human health (HEI, 2016).

Discussions on environmental policy issues have been growing in China (Xu, 2011), and trade policies are often adopted to address such issues (Eisenbarth, 2017). Furthermore, international events such as the 2008 Olympic Games in Beijing also tightened environmental constraints (He *et al.*, 2016). These developments have mixed effects on both exporters and non-exporters. In theory, there is a positive association among productivity, exporting decisions, and environmental performance (see Cui *et al.*, 2012 and Forslid *et al.*, 2018, for a related discussion). Typically, productive firms are more likely to export and also to adopt environmentally friendly technology. Hence, exporters are expected to have better environmental performance than non-exporters. However, studies that used Chinese data found paradoxical results on the relationship between exports and productivity; in particular, they found that exporting firms are less productive than non-exporting firms (Lu, 2010).[3] Thus, it is far from clear whether exporters are environmentally friendlier than non-exporters (Holladay, 2016).

The availability of micro-level data allows for a better understanding of firms' heterogeneity in 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. There are

3 In contrast, Dai *et al.* (2016) found that the exporters in China exhibited higher productivity than non-exporters, after removing the firms that perform processing trade.

two main reasons for the relatively small amount of literature for developing countries. First, data availability and quality are one of the main constraints; second, empirical techniques may not be readily available to address certain issues in the data.

This paper builds on previous research as it employs a unique dataset to investigate the relationship between export intensity (respectively, export status) and SO_2 emissions intensity at the firm level. Besides performing benchmark regressions, the propensity score matching – or PSM – is also adopted to the dataset. To that end, we combined two rich firm-level datasets for China, namely the National Bureau of Statistics' annual survey of industrial production (ASIP), which shows firm-level production information, and the environmental statistics database obtained from the Ministry of Ecology and Environment, both for the year 2007. Next we merged the two datasets in which the official enterprise name serves as a bridge to link the two datasets. A total of 37,446 observations were successfully matched.

Our findings can be summarized as follows. First, a negative effect of export intensity on the emissions intensity is observed. Specifically, a one percent increase in export intensity leads to a 0.167 percent decrease in SO_2 emissions intensity (other things being held constant). Next, as a robustness check, the PSM is adopted and the baseline results still hold. In short, exporters are more environmentally friendly than non-exporters, which is in line with previous evidence reported for developed economies.

We also discuss several potential mechanisms that explain the observed pattern. On one hand, there is an "internal" channel where governmental regulations, either targeted on the emissions of all polluters or on the pollution intensity of exports, incentivize pro-environmental behavior. On the other hand, supply-chain pressure from customers abroad, i.e., an "external" channel, induces exporting firms to reduce their pollution levels. Both channels imply that exporters abate more emissions and this is confirmed by our data. This result adds an additional rationale for coordinating environmental policy with trade policy in developing countries; thus, serving as a first step toward better understanding the role of trade on the environment.

Our study contributes to the existing literature in three ways: first, we merged two rich firm-level datasets for China, which adds to the literature on Chinese empirical evidence; second, besides exporting status, export intensity is used to better capture the relationship between exports and SO_2 emissions; and third, we propose to use the PSM method because it complements the traditional OLS approach.

The rest of this paper proceeds as follows. Section 2 provides a brief review of the related research. Section 3 describes our data base and presents some stylized facts on our unique dataset. Section 4 formally introduces the econometric models and conducts the empirical investigation on exports and SO_2 emissions. Section 5 discusses some potential explanations for the observed pattern. Section 6 concludes.

2. Related literature: A selected review

Our study relates to an active research area that uses macro models (e.g., the input-output model) to estimate emissions responsibility through the so-called production-based accounting method versus its consumption-based accounting counterpart (Peters *et al.*, 2011; Hertwich and Peters, 2009). It is common practice in this line of research to rely on the homogenous technology assumption to study emissions embodied in trade. Given the theoretical prediction that exporters have higher productivity levels and lower emissions intensity, if confirmed by the empirical evidence, to date this line of research has overstated the role of international trade in overall growth in emissions. In other words, the potential gains from trade are underestimated as the negative environmental consequences due to trade are overstated.

Importantly, Dietzenbacher *et al*. (2012) explicitly addressed heterogeneous technology for the processing trade; thereby distinguishing normal trade from production for domestic use by extending China's normal input-output table to distinguish processing exports from normal exports. They found that the usual estimation method would overstate the contribution of exports to carbon dioxide emissions by as much as 60 percent. From an accounting point of view, by implicitly assuming that the input structure determines the emissions intensity, they separately estimated the emissions intensities and found that processing exports are cleaner than normal exports, whereas the latter are cleaner than those that produce purely domestic production goods. The production structure was found to be the single most important factor in the observed pattern. This study clearly improves our understanding about exporters and environmental performance, and provides micro evidence that supports the differentiated treatments concerning exporting and non-exporting activities.

In a broader sense, the interactions between international trade and the environment have long been studied and discussed. As previously noted, Grossman and Krueger (1991) decoupled the three effects of trade on the environment: the scale effect (leading to more pollution as output expands); the composition effect (which may or may not contribute to more pollution, depending on the relative growth of clean industries and dirty ones); and the technology effect (which drives down pollution). Evidently, the impact of trade on the environment depends on the combined effect of these three distinct factors. Subsequently, Copeland and Taylor (1994) developed a North-South trade model that shows the interaction between trade and the environment, assuming a pollution tax as the main driving force behind trade and its environmental impact. They note that while high-income (developed) countries choose higher pollution taxes, which ultimately have a positive impact on the environmental quality in the North, there is a negative effect in the South.

More recent studies relax certain assumptions and incorporate imperfect competition (e.g., Beladi and Oladi, 2010) and heterogeneous trade theory (e.g., Kreickemeier *et al.*, 2014).[4] By and large, no clear consensus has been reached concerning the environmental effects of trade liberalization (also taking into account the two alternative hypotheses, namely the “factor endowment effect” and the “pollution haven hypothesis”). Therefore, there is a need to further empirically examine the impact of trade on the environment (see a recent review by Cherniwchan *et al.,* 2017).

Numerous empirical studies have tested the above-mentioned hypotheses. For

4 In a related study, Baldwin and Ravetti (2014) build an emission-augmented Melitz model, and provide the case that trade liberalization can unambiguously lower emissions if coupled with transfers of green technology, despite compound factors (such as the size, productivity, and emissions profile of the trading partner) are at play.

example, Antweiler *et al.* (2001) extended the Grossman and Krueger (1991) model by including a pollution demand-supply specification and empirically estimating both the signs and the magnitudes of the three effects, respectively. They found a relatively small composition effect, and since the technology effect is much larger than the scale effect, trade seems to have a positive effect on the environment (maybe partly due to the fact that trade can affect both output and income simultaneously).

As stated above, as China is the world's largest trading nation and SO_2 emitter, it has received considerable attention. For instance, Dean (2002) proxied environmental quality by using chemical oxygen demand (COD) and developed a testable model that is based on the factor endowment theory. She shows that the direct impact of trade on the environment is unfavorable; however, it is beneficial to the indirect effect (via increasing income) of environmental quality as it leads to a net positive effect in that trade is conducive to the improvement of environmental quality. Dean and Lovely (2010) further considered the effects of trade liberalization on the environment and find that both the composition effect and the technology effect can partly explain the observed pattern. Moreover, they point out the heterogeneous performance of different firms, an important aspect that will be further considered in our study.

One of the most related studies to our work is that of Forslid *et al.* (2018), who developed a model of trade and carbon dioxide (CO_2) emissions and heterogeneous firms, where firms make abatement investments and thereby have an impact on their emissions (see also Cui *et al.*, 2012). The model shows that investments in abatements are positively related to firms' productivity and exports. Emissions intensity, however, is negatively related to firms' productivity and exports. Forslid *et al.* (2018) show that the overall effect of trade is to reduce emissions, and they find empirical support by applying Swedish firm-level data to the model.

An endogeneity problem might arise when empirically examining the impact of trade on the environment; 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. For example, Frankel and Rose (2005) tackled the endogeneity issue of trade and income, focusing on the causal effects of trade on environmental quality (see also Löschel *et al.*, 2013; Managi *et al.*, 2009). Gamper-Rabindran (2006) used the difference-in-differences approach (DID) to address the endogeneity problem (see also Baghdadi *et al.*, 2013). These studies found a positive impact of trade on environmental quality.

In contrast, another strand of research argues that international trade is not conducive to improvements in environmental quality or at best the effect is ambiguous. For example, Cole *et al.* (2006) used energy consumption as the main dependent variable (rather than various pollutants) and found a positive correlation between the degree of trade openness and per capita energy consumption. Cole and Elliott (2003) focused on the determinants of the composition effect, basing their study on Antweiler *et al.* (2001). They show that the composition effects of trade on the environment can be distinguished into two channels that affect the product structure: i) through the comparative advantage that stems from different environmental regulations; and ii) through different factor endowments of countries (on the premise that pollution-intensive products are capital-intensive in nature). Their results show that the trade-induced composition effect is less than the scale effect, the technology effect, and the direct composition effect; further, the net effect of trade on environmental quality varies with the choices of pollutants and the dependent variables.

3. The data

Two rich datasets were combined to arrive at the final sample in this study; they are the annual survey of industrial production (i.e., ASIP) conducted by National Bureau of Statistics and the Ministry of Ecology and Environment's environmental statistics database; both datasets are for the year 2007 (see Wang *et al.*, 2018, who used a similar dataset to test COD-related regulations on manufacturers' productivity). The ASIP database records 336,768 industrial enterprises in China, accounting for about 95 percent of the total output value and covering most of the manufacturing sector and several service sectors. This dataset provides detailed production-related information, such as firm size, sales, capital flow, and export status; in addition, it provides a qualitative description of the enterprises' identity, and industry information and location, among others.

A total of 104,058 enterprises were surveyed in the environmental statistics database for 2007, which reports most of the environmentally related information on business enterprises: the name of the enterprise, the administrative area code, the date the firm opened, the total output value, the consumption of water, coal, oil, and gas; these firms' waste water discharge, chemical oxygen demand, and emissions of ammonia and nitrogen, sulfur dioxide, smoke and dust, and NO_x. Enterprises that discharged more than 85 percent of emissions in all regions (districts and counties as the basic units) are listed as the key enterprises to use in this investigation. In accordance with the national economic industry classification (GB/T4754-2002), these enterprises are listed in three broad industries: mining, manufacturing, and the production and supply of electricity, gas and water.

Next, we briefly discuss the matching procedure and data processing. First, all the firms' names in the ASIP and environmental statistics databases were checked, and invalid and/or duplicate records were deleted. By matching the firms' names, a total of 37,915 effective matching observations were obtained. Second, for the remaining unmatched sample, we further matched them by using firms' previously-registered names in the environmental statistics database and firms' current names in the ASIP database; thereby obtaining 507 additional effective observations for a total of 38,422. Third, enterprises with zero total output and/or no employees were omitted. Moreover, export intensity was defined as the ratio of the export delivery value in 1,000RMB +1 to the total industrial output value in 1,000RMB. By definition, the export intensity should be in the range of [0, 1]; thus, we omitted firms with export intensities larger than one. We also dropped observations with unreliable data on firm age, and missing or negative data on value added and capital stock and/or employment figures, and firms with fewer than 10 employees, where it was possible that data were missing due to a possible lack of reliable accounting methods (see e.g. Zhang *et al.*, 2018; Brandt *et al.*, 2012). Also, observations that violate basic accounting principles were dropped, such as when the total value of liquid assets, fixed assets, or net fixed assets was larger than the value of total assets and/or when the value of current depreciation was larger than the value of cumulative depreciation. Finally, 37,446 effective observations were used in this study.

To check for representativeness, the two main variables—SO_2 emissions and total output—are reported in Table 1.

Table 1: **Merged dataset using ASIP and environmental statistics**

	Number of firms	SO_2 emissions (in 1,000t)	Total output (in 1,000 mRMB)
ASIP (1)	336,768	n.a	405,142.93
Environmental statistics (2)	104,058	8,572.9	172,817.55
Matched (3)	37,446	3,957.28	106,954.57
(3)/(1) in %	11.12	n.a	26.40
(3)/(2) in %	35.99	46.16	61.89

In terms of the matches, 11.12 percent of firms in the ASIP database and 35.99 percent of firms in the environmental statistics database were successfully matched. If total output and SO_2 emissions are used as the metric, firms in the sample account for 46.16 percent of the total SO_2 emissions in the environmental statistics database and 26.4 percent of the total industrial output value in the ASIP database, respectively.[5]

To answer our research question, we chose to use SO_2 emissions intensity as the main dependent variable and export intensity as the main explanatory variable, all taking the natural logarithmic form. Additionally, we included control variables on firm characteristics, such as total output, total number of employees, labor productivity, and age. Information on location, industry type, and registration type were included as dummy variables. The names and definitions of all of the variables used in this paper are provided in Table 2.

5 Note that the share of total output in the ASIP database is roughly 95 percent of the total industrial output value for China as a whole; and SO_2 emissions in the environmental statistics database account for roughly 85 percent of China's total SO_2 emissions. This means we can obtain the representativeness of the total output value and total SO_2 emissions by multiplying the ratio of the total output from the matched sample by 95 percent (i.e., 0.264*0.95=0.251) and the ratio of the SO_2 emissions from the merged data by 85 percent (i.e., 0.4616*0.85=0.392). That is, our sample accounts for one quarter of the total output value and nearly 40 percent of China's total SO_2 emissions in 2007.

Table 2: Variable definition

Variables	Description
SO_2 emissions	Total sulfur dioxide emissions in t by enterprises
SO_2 emissions intensity	The ratio of sulfur dioxide emissions +1 in t to total industrial output value in mRMB
export	Export delivery value in mRMB
export intensity	The ratio of export delivery value +1 in mRMB to total industrial output value in mRMB
total output	Total industrial output value in mRMB by enterprises
total employees	Average number of employees
labor productivity	The ratio of value added in 1,000RMB to total employees
region	Origin of the firm: either *east*, *middle*, *west*, or *northeast*
industry	Industry classification: Either *mining* (mining industry), *manufacturing* (manufacture industry) or *power generation* (production and supply of electricity, gas and water)
ownership	Ownership structure: either *SOE* (State-owned enterprises. Included are state-owned enterprises, state-funded corporations, and state-owned joint-operation enterprises, where all assets are owned by the state); *other domestic* (with collectively owned enterprises, equity cooperative enterprises, collective joint-operation enterprises, state-collective joint-operation enterprises, other limited liability corporations, share-holding corporations ltd., private enterprises, and other domestic enterprises); *HMT* (with funds from Hong Kong, Macao, and Chinese Taipei); or *foreign* (with funds from foreign countries)
age	The total survival year of enterprises from the year of establishment to 2007
SO_2 removal ratio	The ratio of (SO_2 removal value +1) to total SO_2 production (SO_2 emissions + SO_2 removal value)

4. Statistical analysis

4.1 Descriptive statistics

Table 3 summarizes the differences between exporters and non-exporters across several variables. Columns (1) to (3) report the sample means for the total sample, the exporters and the non-exporters. Column (4) reports the differences between the sample means of the non-exporters and exporters, together with the level of statistical significance.

Given a simple distinction between exporters and non-exporters, where 10,117 exporting and 27,329 non-exporting enterprises can be distinguished, rich information can already be detected. For instance, exporters are characterized by their larger scale (total output) and lower SO_2 emissions intensity. Furthermore, exporters are more likely to be located in China's eastern region and to be funded by foreign capital.

As shown, exporters had higher mean SO_2 emissions than non-exporters; however, since the SO_2 emissions were heavily skewed to the right, the median would be a more appropriate measure for the center (see Tables A1-A3 in Appendix A for the summary statistics). On one hand, it was found that the median SO_2 emissions for exporters was 1.444 tSO_2 and statistically significantly lower than non-exporters' emissions of 8.1 tSO_2 (MWU test, p-value < 0.001). On the other hand, the relative difference in the unconditional mean for the SO_2 emissions intensity for exporters *vs.* non-exporters was quite large and statistically significant (t-test, p-value < 0.01). Precisely, we observed a mean SO_2 emissions intensity of 0.305 for exporters and 1.629 for non-exporters, meaning that exporters' SO_2 emissions intensity was about 81 percent lower than that of non-exporters.

Table 3: Comparison between exporting firms and non-exporting firms

Variable	(1) All	(2) Export	(3) No export	(4) Diff
total output	285.623	596.960	170.369	426.590***
	(1,588.950)	(2,757.434)	(771.824)	
total employees	462.986	892.840	303.857	588.983***
	(1,415.818)	(2,432.185)	(680.558)	
SO_2 emissions	105.680	144.395	91.347	53.047***
	(999.064)	(1,735.680)	(501.711)	
SO_2 emissions intensity	1.271	0.305	1.629	-1.324***
	(11.302)	(1.177)	(13.192)	
labor productivity	165.426	164.700	165.695	-0.995***
	(442.367)	(630.317)	(347.943)	
east	0.567	0.781	0.488	0.293***
	(0.496)	(0.414)	(0.500)	
middle	0.167	0.082	0.199	-0.117***
	(0.373)	(0.275)	(0.399)	
west	0.192	0.081	0.233	-0.152***
	(0.394)	(0.272)	(0.423)	
northeast	0.074	0.057	0.081	-0.024***
	(0.262)	(0.231)	(0.272)	
mining	0.056	0.005	0.075	-0.07***
	(0.230)	(0.073)	(0.263)	
manufacture	0.937	0.994	0.916	0.078***
	(0.242)	(0.076)	(0.277)	
power	0.007	0.000	0.009	-0.009***
	(0.080)	(0.020)	(0.093)	
SOE	0.052	0.048	0.054	-0.006***
	(0.222)	(0.214)	(0.225)	
HMT	0.098	0.213	0.056	0.157***
	(0.298)	(0.409)	(0.230)	
foreign	0.106	0.242	0.055	0.187***
	(0.307)	(0.428)	(0.228)	
other domestic	0.744	0.497	0.835	-0.338***
	(0.436)	(0.500)	(0.371)	
age	11.488	13.238	10.840	2.398***
	(12.410)	(13.704)	(11.830)	
n	37,446	10,117	27,329	

Note: Column (1) describes sample means and standard deviations (in parentheses) for the full data set, columns (2) and (3) summarize exporting firms and non-exporters, respectively. Column (4) gives the difference in unconditional means between exporters and non-exporters for selected variables. The units of each variable are listed in Table 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values are obtained by two-sample t-test for quantitative variables and by two-sample proportion test for binary variables.

4.2 Regression analysis

To answer our research question of whether a firm's ability to export is an important determinant for better environmental performance, the following regression was estimated (whose theoretical foundation can be found in Forslid *et al.*, 2018; Cui *et al.*, 2012):

$$\log \text{SO2 emissions intensity} = \alpha + \beta \log \text{export intensity} + W\pi + \varepsilon \qquad (1)$$

where the SO_2 emissions intensity is the ratio of (SO_2 emissions +1) to the total output, denoting the environmental impact; export intensity, the main explanatory variable, is defined as the ratio of (export value +1) to the total output, and β is the parameter of interest. W is a series of control variables, including the total output, the total number of employees, labor productivity (all in natural logarithmic form), the industry to which the firm belongs, the region where it is located, and the enterprise's property ownership. ε is the stochastic error term. Table 4 reports the OLS estimates for equation (1).

Column (1) estimates equation (1) with only the export intensity included. In this specification, the estimated coefficient for export intensity is negative and statistically significant, a result that supports the hypothesis that the ability to export (representing international market exposure) is important for a lower environmental burden.

Next, we controlled for firm characteristics, such as firm size (i.e., total output in column (2), total employment in column (3), and labor productivity in column (4)). The effect of export intensity remained negative and statistically significant. We also controlled for other determinants of emissions intensity that, if omitted, may bias the estimated importance of export propensity for improved environmental performance. Column (5) shows the "full" model with the complete set of control variables; it also shows that the association between export intensity and SO_2 emissions intensity was negative and statistically significant. Economically speaking, a one percent increase in export intensity leads to a 0.167 percent decrease in SO_2 emissions intensity if all else is held constant (*c.p.*).[6,7]

Table 4: The effects of export intensity on SO_2 emissions intensity

Log SO_2 emissions intensity	(1)	(2)	(3)	(4)	(5)
Log export intensity	-0.218***	-0.214***	-0.236***	-0.239***	-0.167***
	(0.00560)	(0.00552)	(0.00561)	(0.00564)	(0.00596)
Log total output		-0.573***	-0.908***	-0.759***	-0.770***
		(0.0165)	(0.0241)	(0.0464)	(0.0467)
Log total employees			0.591***	0.446***	0.560***
			(0.0311)	(0.0497)	(0.0502)
Log labor productivity				-0.164***	-0.0580
				(0.0436)	(0.0435)
east					-1.300***
					(0.0922)
middle					0.260**
					(0.104)
west					0.241**
					(0.102)
mining					-6.441***
					(0.309)
manufacture					-2.498***
					(0.294)
SOE					-0.819***
					(0.110)
HMT					-1.316***
					(0.0837)
foreign					-1.805***
					(0.0825)
cons	-6.080***	0.288	0.674***	0.511***	3.859***
	(0.0526)	(0.190)	(0.190)	(0.195)	(0.353)
n	37,446	37,446	37,446	37,446	37,446
R^2	0.039	0.069	0.078	0.078	0.144

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

The heterogeneous impact of firm characteristics, location, and registration type is also of interest. Specifically, it was found that larger firms tend to exhibit lower SO_2

6 In an alternative regression (see Table A4 in Appendix A) where the fixed effects for industry, province and registration type were introduced, the result was qualitatively the same (sign) but smaller in magnitude.

7 In Appendix B we present several robustness checks for the chosen specification of the intensities and the model. In all of the robustness checks, the effect of the export intensity on the SO_2 emissions intensity remains negative and statistically significant.

emissions intensities (a result in line with the large amount of literature on heterogeneous firms, e.g. Forslid *et al*., 2018), while higher employment in firms led to higher SO_2 emissions intensities. Firms located in the east tended to have a lower SO_2 emissions intensities (compared with the rest of China), an effect that may be related to the industrial distribution across regions.[8] The intensity of the SO_2 emissions of mining and manufacturing enterprises was lower than those in the electricity, gas and water industries. Lastly, foreign-invested enterprises had lower SO_2 emissions intensity than other types of firms.

The above estimation is conceptually distinct from studies that estimate a model to show that there is a negative relationship between whether or not a firm reports any exports and its environmental performance (e.g., Forslid *et al.*, 2018; Holladay, 2016). To reconcile with previous studies, we further discuss the effect of export status on the SO_2 emissions intensity. Essentially, as the core explanatory variable we switched to a dummy variable of whether or not a firm reported any exports, equaling 1 if the enterprise reported exports and 0 otherwise.

The regression results are shown in Table 5, column (5), which shows the set of control variables that serves as our main result. In line with previous studies on developed countries (e.g., Forslid *et al.*, 2018), the effect of export status remains negative and statistically significant when controlling for the alternative determinants of emissions intensity.

8 Using the share of value added of the tertiary industry to the total value added in each region as an indicator, it was found that the eastern region had a higher ratio (42 percent) than those of the other regions (37 percent) in China in 2007. Considering that the heterogeneity of industrial distribution across regions has direct impacts on environmental performance, such a distinction has also been made in relevant studies (see Wang *et al.*, 2018).

Table 5: The effects of export status on SO_2 emissions intensity

Log SO_2 emissions intensity	(1)	(2)	(3)	(4)	(5)
Dummy export	-2.514***	-2.149***	-2.358***	-2.377***	-1.663***
	(0.0553)	(0.0569)	(0.0578)	(0.0581)	(0.0609)
Log total output		-0.413***	-0.719***	-0.582***	-0.641***
		(0.0171)	(0.0239)	(0.0467)	(0.0466)
Log total employees			0.567***	0.435***	0.548***
			(0.0310)	(0.0497)	(0.0502)
Log labor productivity				-0.149***	-0.0501
				(0.0437)	(0.0435)
east					-1.310***
					(0.0922)
middle					0.268***
					(0.104)
west					0.248**
					(0.102)
mining					-6.432***
					(0.309)
manufacture					-2.475***
					(0.294)
SOE					-0.781***
					(0.110)
HMT					-1.340***
					(0.0837)
foreign					-1.858***
					(0.0822)
cons	-3.599***	0.877***	1.310***	1.167***	4.281***
	(0.0288)	(0.187)	(0.188)	(0.193)	(0.352)
n	37,446	37,446	37,446	37,446	37,446
R^2	0.052	0.067	0.075	0.075	0.143

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

The estimated relationship between export status and emissions intensity, in addition to being statistically significant, is also economically significant. According to the estimates of column (5), a back-of-the-envelope calculation suggests that SO_2 emissions intensity dropped by about 81 percent on average as a result of the export status switch from non-exporting to exporting.[9,10]

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 In the corresponding alternative regression (Table A7 in Appendix A), we can see that with the fixed effects for industry, province and registration type (last column), SO_2 emissions intensity drops

4.3 Propensity score matching

In order to use an alternative empirical method to investigate the causal effect of export status on SO_2 emissions intensity, a quasi-natural test was performed using the propensity score matching (PSM) method (proposed by Heckman *et al.*, 1997). This being said, the exporting enterprises were the treatment group, with the non-exporting enterprises as the control group. At the same time, we used a binary dummy variable for export D_i, an indicator variable that was equal to 1 if the enterprises were exporting firms and 0 if they were non-exporting firms. $\mathrm{y_i}$ indicates the log of the SO_2 emissions intensity, the PSM is the outcome variable. The two statuses depend on whether or not the enterprises were exporters:

$$\mathrm{y_i} = \begin{cases} \mathrm{y_{1i}}, \mathrm{D_i} = 1 \\ \mathrm{y_{0i}}, \mathrm{D_i} = 0 \end{cases}$$

Specifically, $\mathrm{y_{0i}}$ is the log of the SO_2 emissions intensity of non-exporting enterprises, and $\mathrm{y_{1i}}$ is the log of the SO_2 emissions intensity exhibited by exporting enterprises. The causal impact of the enterprises' participation in exports on the log of the SO_2 emissions intensity can be expressed as the ATT (i.e., average treatment effect on the treated):

$$\text{ATT} \equiv \mathrm{E}(\mathrm{y_{1i}} - \mathrm{y_{0i}} | \mathrm{D_i} = 1) \tag{2}$$

The ATT is the expected value of the log of the SO_2 emissions intensity of the exporting enterprises when they were not involved in exporting, a condition that is unobservable in the real world. The purpose of the PSM is to construct a counterfactual in order to be able to calculate the ATT (Gangl, 2015).

by about 50 percent on average as a result of the switch in status from non-exporting to exporting.

Table 6: Logit regression results

	Logit
Dummy export	
East	0.730***
	(0.0564)
middle	-0.428***
	(0.0674)
west	-0.545***
	(0.0668)
mining	0.886
	(0.564)
manufacture	3.105***
	(0.545)
SOE	-0.197***
	(0.0679)
HMT	1.407***
	(0.0404)
foreign	1.623***
	(0.0416)
Log total output	0.118***
	(0.0258)
Log total employees	0.537***
	(0.0290)
Log labor productivity	-0.170***
	(0.0239)
age	0.0119***
	(0.00113)
cons	-8.403***
	(0.558)
n	37,446
Pseudo-R^2	0.2376

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

Before determining the PSM, an accurate binary model must be developed in order to estimate the propensity score (Imbens, 2015). The propensity score is the conditional probability of individuals entering into the treatment group given their characteristics X_i. Rosenbaum and Rubin (1983) suggest using a flexible logit model to calculate the propensity score: i.e., $p(X_i) \equiv P(D_i = 1|X = X_i)$. According to the coefficients that are estimated by the logit model, the probability of whether an enterprise participates in export activities can be further predicted as the propensity score value. The logit regression results are shown in Table 6. Thereby we tried to include variables known to be related both to treatment assignment and the outcome (Stuart, 2010). These variables are the same as those used in the OLS model for equation (1), except for the variable age (see Table A6 for the accuracy rate of this model).

Many matching methods can be used to obtain the ATT results (e.g., k-nearest neighbor matching; caliper matching; kernel matching; among others). Consequently, the ATT can be calculated as the difference in the means of the log of the SO_2 emissions intensity between the treatment and control groups.

Next, five methods were adopted to find a control group for the treated, i.e. exporting enterprises so as to obtain the ATT. The results are shown in Table 7. The ATT value of the log of the SO_2 emissions intensity is negative and statistically significant, indicating that the exporting firms were more environmentally friendly than the non-exporting firms. Among the five matching methods, the ATT estimates for the log of the SO_2 emissions intensity are very close.

The ATT values estimated in Table 7 are very close to the coefficient estimated using the OLS regression with the dummy for export status (see Table 5).[11] Based on the ATT values, we can show that the SO_2 emissions intensity drops by about 81 percent, on average, as a result of switching from non-exporters to exporters.[12] Overall, the matching estimates provide further evidence that exporting status is an important determinant of SO_2 emissions intensity.

11 Due to the separation of both groups we have a 0-1 division. The difference to the OLS approach is that with PSM we do not compare all treated with all untreated firms but only the subset of matched firms.

12 The calculation follows footnote 9, where $\hat{\beta} = \text{ATT}$ (Gangl, 2015) and the nearest neighbor matching result is used (one-to-one matching, ATT = -1.657).

Table 7: ATT results of different matching methods

	Matching Methods	ATT
1	k-nearest neighbor matching (k=1, one-to-one matching)	-1.657***
		(0.101)
2	k-nearest-neighbor matching within caliper (k=4, one-to-four matching)	-1.606***
		(0.083)
3	radius matching	-1.620***
		(0.074)
4	kernel matching	-1.610***
		(0.075)
5	local linear regression matching	-1.539***
		(0.101)

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In order to evaluate the quality of the matching, the matching balance test was executed (see Table A5). To further verify the effectiveness of the PSM method, Figure A1 compares the density functions of the propensity score values of the treatment and control groups before and after matching. Figure A2 compares the difference between the standardized percent bias across covariates before and after matching. From the above results, it can be concluded that the quality of the matching is sufficient, in particular, that of the covariate balance of the matched groups.

The PSM was used as a complementary method to the traditional OLS model. There are two main advantages to using the PSM as a quasi-natural experiment method. First, it avoids the specification of a fully parametric model for outcomes but it estimates the treatment effects non-parametrically from the comparison of the outcome distributions across the matched samples. Second, this method uses transparent criteria to divide the observations into a control group and a treatment group and it ensures that the two sets of observations are as similar as possible, with the exception of the treatment variable. The use of both methods in combination, as an idea of “double robustness”, is recommended in the literature on observational studies (see, e.g., Stuart 2010). Furthermore, the use of multiple matching methods in this paper increases the credibility of our OLS estimation results.

5. Mechanisms test: Why are exporting firms cleaner?

We propose two channels to explain the observed pattern. First, emissions abatement is caused by governmental regulations that partly set different abatement incentives for exporters and non-exporters; second, customers abroad may trigger emissions abatement via supply chains. Both channels cause exporters' emissions abatement being higher compared to that of non-exporters.

As noted above, China is the world's largest SO_2 emitter. At the time of this study, it was also suffering from air pollution and its associated health problems, such as premature deaths (HEI, 2016). To address these environmental problems, intensive policies have been launched in recent years. For instance, in President Xi Jinping's "Report to the 19th National Congress of the Communist Party of China in 2017", the environment was named one of the key components to achieving sustainable development.

China's environmental efforts date back to its 11th Five-Year Plan (2006 through 2010), which set a goal of reducing SO_2 emissions by 10 percent (i.e., the total SO_2 emissions in 2010 would be 10 percent less than that in 2005) to demonstrate the top leaders' serious commitment to environmental protection (Xu, 2011).[13,14] This plan also marked the first time China explicitly linked local governments' environmental performance with the promotion or removal of local leaders. Here, three criteria were used (State Council, 2007), namely (1) a quantitative target and a target for general environmental quality; (2) the establishment and operation of environmental institutions; and (3) mitigation measures. The final evaluation will be based on a checklist for all of the above-listed criteria, and if any government fails to meet all of the criteria, the overall goal attainment will be judged a failure (State Council, 2007). Consequently, the Chinese government's commitment to this goal has led to the

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13 However, this goal was not reached. China's SO_2 emissions rose from 25,555 kt in 2005 to 27,893 kt in 2010 (9 percent higher than 2005) and 30,235 kt in 2012 (18 percent higher than 2005). See EC-ERC (2016).

14 Hering and Poncet (2014) studied the impact of environmental regulations on China's export trade in the so-called Two Control Zones (TCZ), which had more strict standards for SO_2 from 1997 to 2003. They found a relative reallocation of export activities away from pollution intensive sectors in the TCZ. While they evaluated the TCZ policy as effective they also stated that the relative decline of pollution-intense activities may reflect a relocation away from TCZ cities.

implementation of policies for the operation of SO_2 scrubbers. In short, SO_2 mitigation efforts are mandated to a large extent but they can vary across regions and industries (Shi and Xu, 2018). However, China's environmental policy suffers from severe enforcement problems, in particular due to local authorities' weak powers of enforcement, corruption, and the questionable deterrent effects of pollution levies (see, e.g., Eisenbarth, 2017). There is also evidence that state ownership appears to mitigate the impact of environmental policy (see, e.g., Hering and Poncet, 2014).

Regarding the question of how environmental regulation affects the business sector, He *et al.* (2002) found that small enterprises that use inefficient production technology exit the market because they cannot meet environmental regulations. Therefore, tightened environmental regulations raise the market share of large, clean, efficient enterprises. If environmental regulations cause some enterprises with low efficiency levels and serious pollution to exit the market, then the surviving exporting and non-exporting enterprises will be those that are relatively clean and relatively large in scale and, thus, able to bear the higher costs of pollution control. For example, Sheng and Zhang (2019) studied the impact of environmental policies on firm productivity in China's Two Control Zones (TCZ) and found that inefficient enterprises located in the two control zones had higher propensities to exit the market.[15] At the same time, subject to the abatement measures' increasing returns to scale (Andreoni and Levinson, 2001), large enterprises tended to take effective measures to reduce pollution (this is also captured in our control variables for firm characteristics). However, the reason why exporters are more sensitive to environmental regulations remains a puzzle.

Forslid *et al.* (2018) explained a mechanism through which firms' export intensity or export status affects their pollution-reduction ratios during their production processes and ultimately their emissions intensity, which may explain the negative relationship between emissions intensity and export intensity, respectively, their export status. As Forslid *et al.* (2018) show, exporters that are more productive

15 It is noted that our data are for above-scale firms, so this effect may be small. Still, the overall direction is towards environmentally friendly production. Thus, we may expect that even within the above-scale firms, the larger ones may respond better and acquire higher market shares.

(measured by total factor productivity) and have a larger market share are more likely to bear the costs of investing in fixed capital in the form of abatement equipment when this is enforced by governmental regulations, thus echoing to the economies-of-scale nature of abatement, as in Andreoni and Levinson (2001). As a consequence, firms' emissions intensities are negatively related to the level of export activity (see also Cui *et al.*, 2012, for a similar model). Similar results were found by Holladay (2016) who shows that US exporters are less pollution intensive. Holladay also assumed that exporting firms' higher productivity was the driving force behind their lower emissions intensity.

Generally speaking, under the compound influence of higher pollution control costs and eliminating inferior enterprises, export enterprises show a stronger reaction to emissions regulation than non-export enterprises, as they are able to bear the higher costs of pollution control, adopt the use of cleaner energy, which is also higher cost, increase their use of pollution control equipment, and upgrade and transform high-pollution production lines, among other measures. Therefore, export enterprises are better able to cope with the pollution regulations than non-export enterprises. Cao *et al.* (2016) found that more-productive firms invest more (less) in abatement technology if investment and productivity are complements (substitutes). They also found that in response to tightened environmental regulations, more-productive firms raise their respective investments in abatement technology, whereas less-productive firms do the opposite.

In our data set, we were only able to control for output size and not for firms' productivity levels. Hence, in order to use the above described productivity hypothesis to explain our empirical results, we had to assume that Chinese export enterprises have higher productivity levels than non-export enterprises. Under this condition, exporters can bear the cost of emissions reduction more easily than non-exporters; thus, these firms' higher investment in abatement facilities reduces their pollution emissions.

Besides the general domestic SO_2 mitigation policy, other regulations potentially cause Chinese exporters to use pollution abatement measures more than non-exporters.

In fact, domestic policies that target exporting firms, such as VAT rebates, may be used to address environmental concerns.[16] VAT rebates for exporters are used in order to ensure these producers do not face double taxation since these are taxed both in the country of origin and in the export destination country. Eisenbarth (2017) found that VAT rebates in China are set in such a way that they may discourage the exports of SO_2- and energy-intensive products. She also shows that, given the problems inherent in enforcing a first-best pollution regulation, VAT rebates may serve as a second best option to reduce pollution. In this sense, the design of the VAT rebate policy may be the cause of the different levels of environmental performance between exporting and non-exporting enterprises; that is, exporting enterprises' stronger incentives to reduce their pollutant emissions may be due to preferential tax policies. To sum up, there is evidence that several regulations push exporters toward being relatively more environmentally friendly.

The second channel we point to for explaining our results is based on the idea that export intensity may have a crucial effect on the implementation of green supply-chain management (GSCM) practices in Chinese companies. According to Srivastana (2007, p. 54), GSCM is defined as "[i]ntegrating environmental thinking into supply-chain management, including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers as well as end-of-life management of the product after its useful life" (see also de Oliveiria, 2018, for a recent survey).

Given that in developed countries environmental regulations are stronger, on average, and also there is possibly higher awareness of environmental protection (see, e.g., Franzen and Meyer, 2010), companies that sell products in developed countries may pressure their suppliers and sub-contractors to reduce their environmental burden, such as in those products' SO_2 emissions in developing countries. Additionally, importers could select firms from developing countries according to criteria that also

16 According to China's National Development and Reform Commission, the VAT rebate adjustments aim to control "exports of energy-intensive, pollution-intensive and resource-intensive products, so as to formulate an import and export structure that is favorable to promoting a cleaner and more optimal energy mix" (NDRC, 2007, p. 31; in Chinese).

take into account the environmental performance of suppliers and sub-contractors.[17] There could be several motives for such behavior but one of them is certainly the reputational risk of being accused of excessive environmental pollution in countries with lower environmental standards.

The GSCM literature supports the potentially positive effect of export behavior on environmental performance in China. Zhu and Sarkis (2006), based on a survey of local managers of exporting firms, investigated the drivers of GSCM in China. They confirmed that globalization and China's entry into the World Trade Organization helped promote GSCM practices among exporting manufacturing enterprises. In a similar study, Kuei *et al.* (2015) reported that external factors, such as customer pressure and regulatory pressure, were the most important factors in influencing the adoption of green practices among Chinese companies. Hall (2000) also noted that firms meet customer pressure that goes beyond legal environmental responsibilities and many suppliers are often under considerable pressure from their customers. For example, many Chinese companies acquired certification for ISO14001, the international standard for environmental management systems, in order to meet the environmental requirements of their foreign customers (Zhu and Geng, 2001). Clearly, these studies are suggestive and deserve further in-depth investigation, but this channel also implies that exporters should have higher abatement levels than non-exporters.

In order to quantitatively assess the proposition that exporters abate pollution more than non-exporters do, we ran a regression of the SO_2 removal ratio (see Table 2) by export intensity or status,[18] as follows:

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17 Such criteria need not directly to be related to environmental indicators (e.g., lower pollution) but can also be related to social criteria (e.g., higher wages, better working conditions), or resource efficiency (e.g., lower resource input). In this case, it is sufficient to assume that the criteria are associated with environmental indicators.

18 Several indicators can be used to capture abatement effort, such as investment in abatement (e.g., Cao *et al.*, 2016) and the emissions removal ratio. The reason we chose to use the pollution removal ratio rather than abatement investment is that firms may invest in abatement facilities (in terms of value, or units) but the usage ratio may vary. Suppose in an extreme case, firm A purchases more abatement facilities than firm B, but A never uses them whereas B operates the facilities full-time, meaning that the abatement investment is also subject to other confounding factors. Simply put, the abatement investment reflects a firm's effort but it does not necessarily lead to an abatement result. In contrast, the removal ratio is an output indicator as it captures the results of the actual abatement effort.

$$\log \mathrm{SO2\ removal\ ratio} \;=\; \alpha + \beta \log \mathrm{export\ intensity} \;+ \mathrm{W}\pi + \varepsilon \qquad (3a)$$

or

$$\log \mathrm{SO2\ removal\ ratio} = \alpha + \beta\ \mathrm{dummy\ export} + \mathrm{W}\pi + \varepsilon \qquad (3b)$$

Table 8 reflects the effect of export intensity or export status on the SO_2 removal ratio. Columns (1) and (3) are the dependent and explanatory variables, and columns (2) and (4) are the coefficients that are estimated by using OLS. The estimated coefficient of the log of the export intensity is 0.0517 and is significantly positive at the 1% level. This means that the higher the export intensity, the higher the SO_2 removal ratio; more precisely, the SO_2 removal ratio increases *c.p.* by 0.517 percent for every 10 percent increase in export intensity.

Taking a further look at column (4), it is found that exporting firms are associated with higher SO_2 removal ratios than non-exporting firms. The coefficient of the export status was estimated to be 0.524 and was significantly positive at the 1% level, implying that the SO_2 removal ratio *c.p.* increased by 68 percent, on average, as a result of switching from non-exporters to exporters (see footnote 9 for the calculation details).

Next, a look at the estimated coefficients for other control variables shows that interesting heterogeneous effects were found across regions, sectors, and (less for) firm types. In line with the argument made in Shi and Xu (2018), in general, the eastern region (compared with the northeastern region) is shown to have been more devoted to making an effort to deploy SO_2 scrubbers during the review year (2017) and, thus, shows a higher SO_2 removal ratio, while for the western region the opposite effect is noted (less effort was made than in the northeast region). That being said, coal-fired power plants are the main contributors to SO_2 emissions and account for most of the SO_2 scrubber installations. As a result, compared with the power-generating sector, mining and manufacturing industries did not perform as well.

Table 8: The effect of export intensity (export status) on SO_2 removal ratio

(1)	(2)	(3)	(4)
Log SO_2 removal ratio		Log SO_2 removal ratio	
Log export intensity	0.0517***	Dummy export	0.524***
	(0.00679)		(0.0696)
Log total output	0.126**	Log total output	0.0834
	(0.0512)		(0.0511)
Log total employment	-0.0275	Log total employment	-0.0248
	(0.0554)		(0.0554)
Log labor productivity	0.00117	Log labor productivity	-0.000288
	(0.0471)		(0.0471)
East	0.913***	east	0.914***
	(0.0958)		(0.0958)
middle	0.142	middle	0.141
	(0.106)		(0.106)
west	-0.399***	west	-0.400***
	(0.104)		(0.104)
SOE	0.970***	SOE	0.962***
	(0.121)		(0.121)
HMT	0.540***	HMT	0.545***
	(0.0998)		(0.0997)
Foreign	0.419***	Foreign	0.431***
	(0.0980)		(0.0978)
mining	-1.127***	mining	-1.133***
	(0.325)		(0.325)
manufacture	-1.179***	manufacture	-1.186***
	(0.298)		(0.298)
cons	-7.454***	cons	-7.555***
	(0.366)		(0.364)
n	25,924	n	25,924
R^2	0.032	R^2	0.032

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

6. Concluding remarks

This paper poses the classic question of whether exporting firms are, in general, cleaner than their non-exporting counterparts. After careful study, we found that a firm's ability to export is associated with better environmental performance. Specifically, the OLS estimates suggest there is a statistically negative association between export intensity (respectively, export status) and SO_2 emissions intensity.

This relationship is shown to be consistent and stable over various specifications and different sets of control variables. As an alternative to the OLS method, the PSM method was used. Interestingly, the estimated coefficients are quite similar to the corresponding OLS specifications.

In order to explain this observed pattern, two possible explanations are provided. First, in the “internal” channel—wherein government regulations provided incentives to reduce emissions intensity—exporters complied better with regulations through emissions abatement. Here, two different regulations can be distinguished: direct emissions regulation for all firms, which suffered from enforcement problems; and incentives for emissions abatement set by VAT export rebates, which differed according to pollution intensity. Second, in the “external” channel, customers abroad forced exporters to be more environmentally friendly, via the supply chain. A formal test confirmed our expectation that exporters tend to abate more than non-exporters, and heterogeneous effects were also found across regions and sectors.

This study clearly adds to the literature on micro evidence on SO_2 abatement among developing countries and serves as a starting point from which to coordinate trade policy and environmental policy. In a broader sense, our study also contributes to a large amount of literature that uses input-output tables to measure emissions; here, our paper provides micro guidance for distinguishing heterogeneous production technologies used in export products and other types of production. Future research could focus on the explanatory power of the identified channels. This could be done, for instance, by linking the emissions data with information on trading partners; this would allow researchers to formally test the hypothesis on green supply-chain management, which is beyond the scope of this study.

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Appendix A

Table A1: Summary statistics for the whole sample

variables	mean	sd	median	iqr	min	Max
total output (mRMB)	285.623	1,588.95	55.604	137.23	0.01	72,000
total employees (average)	462.986	1,415.818	180	312	10	108,525
SO_2 emissions (t)	105.68	999.064	6.045	38.4	0	99,000
SO_2 emissions intensity (t/mRMB)	1.271	11.302	0.09	0.647	0	1,600.1
labor productivity (1,000RMB)	0.165	0.442	0.081	0.127	0	51.908
export (mRMB)	52.112	599	0	1.779	0	45,000
export intensity	0.128	0.283	0	0.018	0	1
export status	0.27	0.444	0	1	0	1
east	0.567	0.496	1	1	0	1
west	0.192	0.394	0	0	0	1
middle	0.167	0.373	0	0	0	1
northeast	0.074	0.262	0	0	0	1
mining	0.056	0.23	0	0	0	1
manufacture	0.937	0.242	1	0	0	1
power	0.007	0.080	0	0	0	1
SOE	0.052	0.222	0	0	0	1
HMT	0.098	0.297	0	0	0	1
foreign	0.106	0.307	0	0	0	1
other domestic	0.744	0.436	1	1	0	1
age	11.488	12.410	7	9	0	179

Note: n = 37,446.

Table A2: Summary statistics for exporters

variables	mean	sd	median	Iqr
total output (mRMB)	596.96	2,757.434	109.59	279.924
total employees (average)	892.84	2,432.185	339	644
SO_2 emissions (t)	144.395	1,735.68	1.444	22.9
SO_2 emissions intensity (t/mRMB)	0.305	1.177	0.011	0.19
labor productivity (1,000RMB)	0.165	0.63	0.076	0.116
export (mRMB)	192.883	1,140.6	32.997	91.711
export intensity	0.474	0.364	0.424	0.742
east	0.781	0.414	1	0
west	0.081	0.272	0	0
middle	0.082	0.275	0	0
northeast	0.057	0.231	0	0
mining	0.005	0.073	0	0
manufacture	0.994	0.076	1	0
power	0.000	0.020	0	0
SOE	0.048	0.214	0	0
HMT	0.213	0.409	0	0
foreign	0.242	0.428	0	0
other domestic	0.497	0.500	0	1
age	13.238	13.704	9	9

Note: n = 10,117.

Table A3: Summary statistics for non-exporters

variables	mean	sd	median	Iqr
total output (mRMB)	170.369	771.824	44.843	98.511
total employees (average)	303.857	680.558	149	222
SO_2 emissions (t)	91.347	501.711	8.1	44.3
SO_2 emissions intensity (t/mRMB)	1.629	13.192	0.156	0.936
labor productivity (1,000RMB)	0.166	0.348	0.083	0.131
east	0.488	0.5	0	1
west	0.233	0.423	0	0
middle	0.199	0.399	0	0
northeast	0.081	0.272	0	0
mining	0.075	0.263	0	0
manufacture	0.916	0.277	1	0
power	0.009	0.093	0	0
SOE	0.054	0.225	0	0
HMT	0.056	0.230	0	0
foreign	0.055	0.228	0	0
other domestic	0.835	0.371	1	0
age	10.840	11.830	7	9

Note: n = 27,329.

Table A4: Alternative regression results

Log SO_2 emissions intensity	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log export intensity	-0.0849***	-0.143***	-0.162***	-0.0828***	-0.0729***	-0.138***	-0.0710***
	(0.0234)	(0.0234)	(0.0115)	(0.0118)	(0.0133)	(0.0124)	(0.00887)
Log total output	-0.825***	-0.764***	-0.773***	-0.828***	-0.814***	-0.757***	-0.810***
	(0.129)	(0.0850)	(0.104)	(0.0845)	(0.0709)	(0.0643)	(0.0555)
Log total employment	0.743***	0.466***	0.599***	0.765***	0.669***	0.501***	0.687***
	(0.189)	(0.117)	(0.149)	(0.115)	(0.0858)	(0.0829)	(0.0658)
Log labor productivity	-0.0866	-0.0842	-0.0577	-0.0863	-0.0826	-0.0885	-0.0867*
	(0.0695)	(0.0718)	(0.0936)	(0.0562)	(0.0541)	(0.0644)	(0.0451)
east	-1.237***		-1.274***	-1.219***			
	(0.310)		(0.116)	(0.152)			
middle	-0.138		0.292**	-0.113			
	(0.263)		(0.129)	(0.138)			
west	-0.156		0.283	-0.127			
	(0.384)		(0.167)	(0.173)			
SOE	-0.123	-0.762***			-0.111		
	(0.194)	(0.162)			(0.134)		
HMT	-0.987***	-1.086***			-0.818***		
	(0.261)	(0.127)			(0.163)		
foreign	-1.312***	-1.769***			-1.304***		
	(0.190)	(0.140)			(0.116)		
mining		-6.461***	-6.573***			-6.591***	
		(0.640)	(0.594)			(0.540)	
manufacture		-2.194***	-2.575***			-2.264***	
		(0.611)	(0.369)			(0.505)	
cons	-1.147*	1.361	2.886***	-1.484**	-3.582***	0.378	-3.958***
	(0.638)	(0.897)	(0.472)	(0.604)	(0.624)	(0.588)	(0.462)
Industry fixed	Yes	No	No	Yes	Yes	No	Yes
Region fixed	No	Yes	No	No	Yes	Yes	Yes
Registration type fixed	No	No	Yes	Yes	No	Yes	Yes
n	37,446	37,446	37,446	37,446	37,446	37,446	37,446
R^2	0.282	0.173	0.148	0.284	0.298	0.177	0.300

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The fixed effects are included to control for potential omitted industry-, region-, and/or registration type-specific variables. Industry (region, registration type) fixed includes 39 (30, 23) different categories. In general, if the fixed effects were not controlled for, the estimated effects would be overstated.

Table A5: Matching balance test

Variable	Before/After Matching	Mean Treat	Mean Control	Bias (%)	%reduction |bias|	t	p>|t|
east	Before	0.781	0.488	63.8	99.7	52.63	0.000
	After	0.780	0.780	-0.2		-0.14	0.892
middle	Before	0.082	0.199	-34.0	98.4	-27.10	0.000
	After	0.083	0.085	-0.6		-0.48	0.629
west	Before	0.081	0.233	-42.8	99.4	-33.73	0.000
	After	0.081	0.08	0.3		0.23	0.816
mining	Before	0.005	0.075	-36.0	99.9	-26.20	0.000
	After	0.005	0.005	0.1		0.10	0.923
manufacture	Before	0.994	0.916	38.4	100.0	27.92	0.000
	After	0.994	0.994	0.0		0.00	1.000
SOE	Before	0.048	0.054	-2.5	92.9	-2.16	0.030
	After	0.048	0.048	0.2		0.13	0.895
HMT	Before	0.213	0.056	47.3	99.2	46.64	0.000
	After	0.213	0.212	0.4		0.22	0.823
foreign	Before	0.242	0.055	54.4	96.1	54.20	0.000
	After	0.240	0.247	-2.1		-1.20	0.231
Log total output	Before	11.707	10.825	59.6	96.9	53.11	0.000
	After	11.691	11.718	-1.8		-1.24	0.216
Log total employee	Before	5.916	5.073	74.0	98.7	66.10	0.000
	After	5.901	5.891	0.9		0.65	0.516
Log labor productivity	Before	4.401	4.469	-6.3	47.4	-5.36	0.000
	After	4.401	4.437	-3.3		-2.29	0.022
age	Before	13.238	10.84	18.7	94.5	16.66	0.000
	After	13.238	13.105	1.0		0.67	0.502

Sample	Ps R2	LR chi2	p>chi2	Mean bias	Med bias
Unmatched	0.237	10,362.61	0.000	39.8	40.6
Matched	0.000	8.90	0.711	0.9	0.5

Note: Results for the nearest neighbor (one-to-one) matching. As can be seen from the above table, the standardized bias of all variables after matching is less than 5%, which is a threshold used in the literature (Gangl, 2015). The t-test results do not reject the null hypothesis that there is no difference of the mean between the treatment group and the control group, except for the log labor productivity.

To further verify the effectiveness of the PSM method, Figure A1 compares the density functions of the propensity score values of the treatment group and the control group before and after matching (results for the nearest neighbor one-to-one matching).

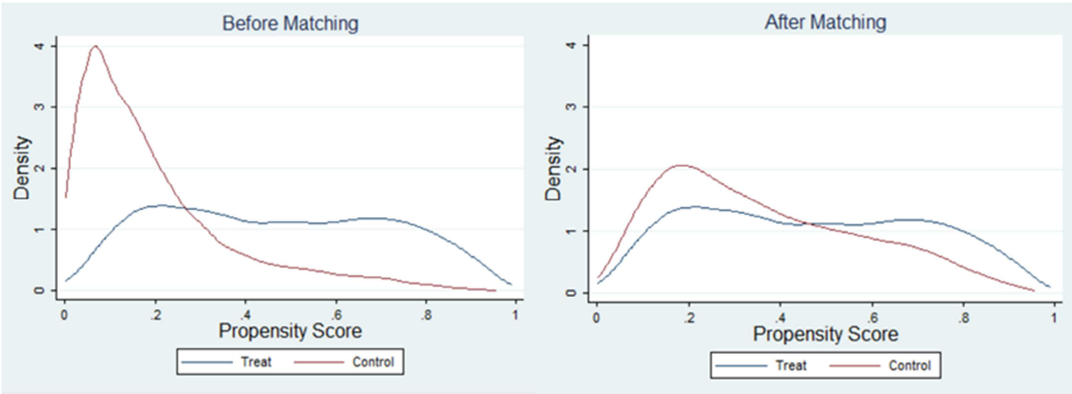

Figure A1：Comparison of propensity score density between treatment and control groups

As shown in Figure A1 above, the probability distributions of the two groups of samples before the match are quite different. This is due to the differences in the characteristics of the control group sample and the treatment group sample. In contrast, after matching, the probability distributions of the propensity score values of the two groups are relatively similar, indicating that the characteristics of the two groups are relatively close and the matching is considered effective. Next, Figure A2 is presented to visualize the difference between the standardized percent bias across covariates before and after matching; Again, this confirms the effectiveness of the matching (the results for the nearest neighbor one-to-one matching).

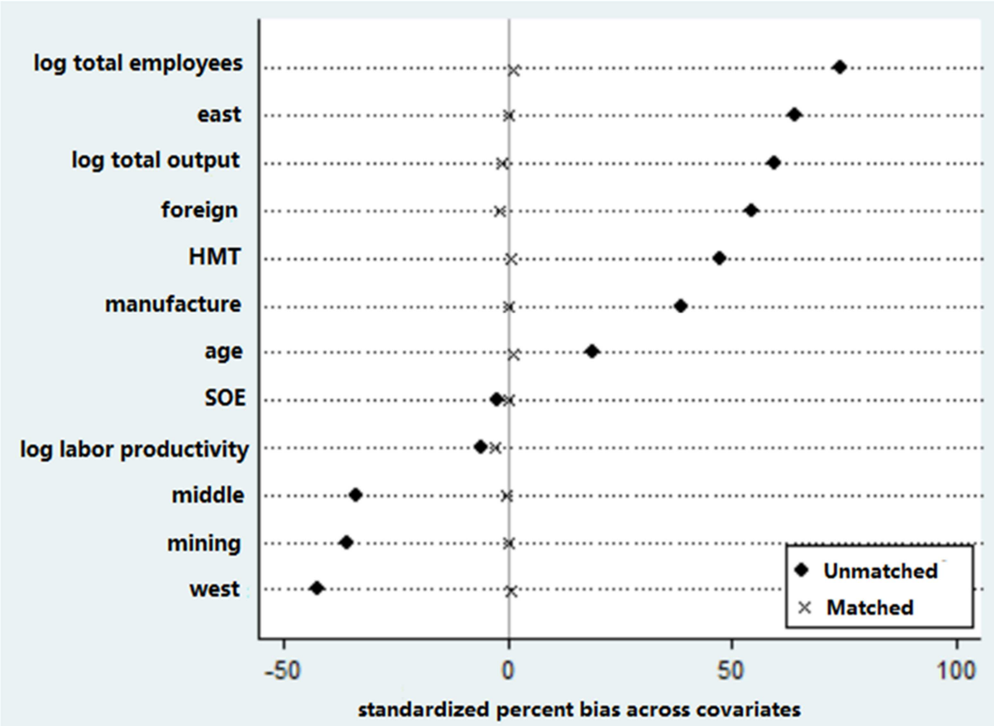

Figure A2: standardized percent bias across covariates before and after matching

Table A6: classification table and accuracy rate for logit model

	True		
classified	D	~D	Total
+	4,647	2,255	6,902
_	5,470	25,074	30,544
Total	10,117	27,329	37,446

Note: classified + if predicted Pr (D) >= 0.5. True D defined as dummy export ! = 0

Sensitivity	Pr (+|D)	45.93%
Specificity	Pr (-|~D)	91.75%
Positive predictive value	Pr (D|+)	67.33%
Negative predictive value	Pr (~D|-)	82.09%
False + rate for true ~D	Pr (+|~D)	8.25%
False - rate for true D	Pr (-|D)	54.07%
False + rate for classified +	Pr (~D|+)	32.67%
False - rate for classified -	Pr (D|-)	17.91%
Correctly classified		79.37%

Note: The table above reports various summary statistics, including the classification table. The overall rate of correct classification is estimated to be 79.37%, with 91.75% of the non-exporting group correctly classified (specificity) and only 45.93% of the exporting group correctly classified (sensitivity). Classification is sensitive to the relative sizes of each component group, and always favors classification into the larger group. This phenomenon is evident here.

Table A7: Alternative regression results for dummy variable export

Log SO_2 emissions intensity	(1)	(2)	(3)	(4)	(5)	(6)	(7)
dummy export	-0.833***	-1.411***	-1.613***	-0.813***	-0.712***	-1.360***	-0.692***
	(0.240)	(0.235)	(0.118)	(0.118)	(0.135)	(0.125)	(0.0890)
Log total output	-0.761***	-0.655***	-0.649***	-0.766***	-0.760***	-0.653***	-0.757***
	(0.119)	(0.0914)	(0.0986)	(0.0820)	(0.0725)	(0.0643)	(0.0559)
Log total employment	0.738***	0.455***	0.587***	0.759***	0.665***	0.491***	0.683***
	(0.188)	(0.120)	(0.152)	(0.115)	(0.0858)	(0.0835)	(0.0657)
Log labor productivity	-0.0831	-0.0769	-0.0491	-0.0824	-0.0792	-0.0809	-0.0831*
	(0.0693)	(0.0729)	(0.0919)	(0.0561)	(0.0540)	(0.0647)	(0.0451)
east	-1.239***		-1.283***	-1.221***			
	(0.311)		(0.117)	(0.152)			
middle	-0.133		0.298**	-0.108			
	(0.262)		(0.129)	(0.138)			
west	-0.152		0.287	-0.124			
	(0.383)		(0.166)	(0.172)			
SOE	-0.106	-0.730***			-0.0958		
	(0.195)	(0.163)			(0.135)		
HMT	-0.998***	-1.102***			-0.827***		
	(0.262)	(0.125)			(0.163)		
foreign	-1.340***	-1.814***			-1.328***		
	(0.191)	(0.140)			(0.116)		
mining		-6.449***	-6.556***			-6.574***	
		(0.638)	(0.598)			(0.539)	
manufacture		-2.171***	-2.549***			-2.240***	
		(0.610)	(0.371)			(0.505)	
cons	-0.920	1.754**	3.344***	-1.237**	-3.365***	0.797	-3.726***
	(0.628)	(0.828)	(0.510)	(0.602)	(0.616)	(0.573)	(0.457)
Industry fixed	Yes	No	No	Yes	Yes	No	Yes
Region fixed	No	Yes	No	No	Yes	Yes	Yes
Registration type fixed	No	No	Yes	Yes	No	Yes	Yes
n	37,446	37,446	37,446	37,446	37,446	37,446	37,446
R^2	0.281	0.172	0.147	0.283	0.297	0.176	0.299

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The fixed effects are included to control for potential omitted industry-, region-, and/or registration type-specific variables. Industry (region, registration type) fixed includes 39 (30, 23) different categories. In general, if the fixed effects were not controlled for, the estimated effects would be overstated.

Appendix B

In this appendix to the paper we present robustness checks w.r.t. the OLS estimates in Section 4.2 of the paper.

Robustness check 1: pollution intensity

According to the *First National Pollution Source Census Program* issued by the State Council, we divide the industry into pollution-intensive industry and non-pollution-intensive industry. The pollution-intensive industries includes the key pollution industries and key monitoring industries, while the non-pollution-intensive industry includes all other industries (State Council, 2007, see Table B1).

To allow for variation between the pollution-intensive industries and non-pollution-intensive industries, we re-estimate equation (1) in Section 4.2 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 B2.

Table B1: Classification of 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)	mining of other ores (11)
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) production and distribution of gas (45)
production and supply of electric power and heat power (44)	production and distribution of water (46)	manufacture of rubber (29)
	mining and washing of coal (06)	
	extraction of petroleum and natural gas (07)	
	mining of ferrous metal ores (08)	
	mining of non-ferrous metal ores (09)	
	mining and processing of nonmetal ores (10)	

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 B2: Effects of export intensity in pollution-intensive *vs.* non-pollution intensive industries

Dependent variable: Log SO_2 emissions intensity		
	Pollution-intensive industries	Non-pollution-intensive industries
Log export intensity	-0.138^{***}	-0.110^{***}
	(0.00644)	(0.0172)
East	-1.049^{***}	-2.160^{***}
	(0.0977)	(0.299)
Middle	0.138	-1.152^{***}
	(0.109)	(0.374)
West	0.137	-1.436^{***}
	(0.107)	(0.386)
Log total output	-0.440^{***}	-0.640^{***}
	(0.0488)	(0.146)
Log total employees	0.232^{***}	0.419^{***}
	(0.0525)	(0.160)
Log labor productivity	-0.409^{***}	0.113
	(0.0453)	(0.141)
SOE	-0.914^{***}	-0.332
	(0.117)	(0.328)
HMT	-1.103^{***}	-1.201^{***}
	(0.0918)	(0.213)
Foreign	-1.730^{***}	-1.294^{***}
	(0.0895)	(0.223)
_cons	1.145^{***}	-1.098^{*}
	(0.220)	(0.637)
n	33,870	3,576
R^2	0.102	0.084

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

In both sub-samples, the effect of an increase of the export intensity on the SO_2 emissions intensity is negative and statistically significant. In fact, the effects are stronger if the firm belongs to pollution-intensive industries, as can be seen from the different magnitudes, i.e. every 10 percent increase in export intensity is associated with 1.38 percent decrease of SO_2 emission intensity for firms belong to pollution-intensive industry while 1.1 percent decrease of SO_2 emission intensity for others.

Robustness check 2: The construction of intensities

In order to test the robustness of our results w.r.t. the construction of the export intensity and the SO_2 emissions intensity in the paper (see Table 5), in particular for those with zero values in either variable, we use an alternative method for the calculation:

$$export\ intensity = \frac{export}{total\ output} + 1$$

$$SO2\ emissions\ intensity = \frac{SO2}{total\ output} + 1$$

Table B3: Alternative construction of intensities

	Log SO_2 emissions intensity
Log export intensity	-0.434***
	(0.0169)
Log total output	-0.169***
	(0.00626)
Log total employees	0.132***
	(0.00671)
Log labor productivity	-0.00259
	(0.00601)
East	-0.0238**
	(0.0120)
Middle	0.154***
	(0.0135)
West	0.256***
	(0.0132)
Mining	-1.540***
	(0.0402)
Manufacture	-1.126***
	(0.0383)
SOE	-0.105***
	(0.0144)
HMT	-0.0898***
	(0.0110)
Foreign	-0.0804***
	(0.0108)
_cons	2.719***
	(0.0455)
n	37,446
R^2	0.180

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

From Table B3, we can see that the effect of the export intensity with alternative construction methods on the SO_2 emission intensity remains negative, and statistically significant at 1% level.

Robustness check 3: Sub-samples for positive SO_2 emissions and/or positive exports

By construction, if exports and SO_2 emissions are simultaneously zero in the raw data, we would end up with perfect linear association, which would bias the estimation. In order to tackle this issue, we proceed with the following treatment, delete i) enterprises with export value of 0; ii) firms with zero SO_2 emissions; and iii) enterprises with both zero values for export and SO_2 emissions; each in turn, and then re-run the regressions. The regression results for the three sub-samples are given in Table B4 below.

Table B4: Export and SO_2 emissions for sub-samples

Log SO_2 emissions intensity	Export>0	SO_2emissions>0	Export>0&SO_2emissions>0
Log export intensity	-0.248***	-0.0707***	-0.0827***
	(0.0323)	(0.00313)	(0.0173)
Log total output	-0.235**	-0.794***	-0.430***
	(0.0951)	(0.0236)	(0.0539)
Log total employees	-0.0954	0.459***	0.0558
	(0.101)	(0.0256)	(0.0574)
Log labor productivity	-0.144	-0.0543**	-0.183***
	(0.0916)	(0.0217)	(0.0510)
East	-2.458***	0.254***	-0.459***
	(0.207)	(0.0442)	(0.101)
Middle	-0.555**	0.520***	0.0620
	(0.259)	(0.0491)	(0.126)
West	-0.777***	0.653***	0.155
	(0.261)	(0.0482)	(0.127)
Mining	-6.756***	-3.267***	-1.581
	(2.457)	(0.150)	(1.075)
Manufacture	-5.805**	-2.188***	-2.721***
	(2.372)	(0.137)	(1.007)
SOE	-0.762***	-0.340***	-0.450***
	(0.235)	(0.0560)	(0.122)
HMT	-0.938***	-0.284***	-0.211***
	(0.126)	(0.0461)	(0.0721)
Foreign	-1.655***	-0.718***	-0.783***
	(0.121)	(0.0452)	(0.0684)
_cons	5.958**	6.632***	6.424***
	(2.409)	(0.169)	(1.032)
n	10,117	25,925	5,902
R^2	0.076	0.245	0.161

Note: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

From the results shown in Table B4 above, it is clear that the effect of the export intensity on the SO_2 emissions intensity is negative (and comparable in magnitude) and statistically significant at 1% level, in all three sub-samples. It further confirms the conclusion of benchmark regression in the paper.

Robustness check 4: Heterogeneous effects of regional structure and ownership

Do the effects vary across regions?

There may be reasons to suspect that the effects of the export intensity 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 analogues treatment in Wang *et al.*, 2018).

To check if the effects of the export intensity vary across regions, we re-estimate the model. First we test the effects of export intensity on SO_2 emission intensity in eastern and non-eastern sub-samples respectively. The results are reported in Table B5.1. In order to further verify the effects of export intensity on SO_2 emission intensity in eastern and non-eastern, we add interaction terms of the export intensity and the regional dummies for the eastern and the other (i.e. central, western and northeastern) regions. The results are reported in Table B5.2. Both coefficients for the two regions are negative, and are statistically significant. Overall, the findings are consistent with those reported earlier in our paper. That is to say, the higher the export intensity is, the lower the SO_2 emission intensity is. Irrespective where the enterprise is located, it will have qualitatively the same effect.

Table B5.1: Heterogeneous effects for the subsets of eastern and other regions

Log SO_2 emissions intensity	Eastern	Other regions
	(1)	(2)
Log export intensity	-0.184***	-0.111***
	(0.00740)	(0.0105)
Log total output	-0.634***	-1.014***
	(0.0641)	(0.0674)
Log total employees	0.400***	0.831***
	(0.0690)	(0.0721)
Log labor productivity	0.0393	-0.0917
	(0.0617)	(0.0604)
Mining	-5.171***	-6.923***
	(0.506)	(0.387)
Manufacture	-2.105***	-2.756***
	(0.451)	(0.376)
SOE	-0.994***	-0.899***
	(0.184)	(0.134)
HMT	-1.228***	-1.324***
	(0.0976)	(0.182)
Foreign	-1.848***	-1.784***
	(0.102)	(0.144)
_cons	0.935*	6.287***
	(0.515)	(0.454)
n	21,225	16,221
R^2	0.096	0.143

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

Table B5.2: Regressions with dummy variables for eastern and other regions

Log SO_2 emissions intensity	(1)	(2)
Log export intensity*Eastern	-0.193***	
	(0.00686)	
Eastern	-3.292***	
	(0.0733)	
Log total output	-0.751***	-0.696***
	(0.0466)	(0.0471)
Log total employees	0.553***	0.431***
	(0.0501)	(0.0504)
Log labor productivity	-0.0400	-0.0126
	(0.0435)	(0.0439)
Mining	-6.358***	-6.516***
	(0.309)	(0.312)
Manufacture	-2.546***	-2.725***
	(0.294)	(0.297)
SOE	-0.886***	-0.749***
	(0.110)	(0.112)
HMT	-1.307***	-1.803***
	(0.0838)	(0.0826)
Foreign	-1.882***	-2.354***
	(0.0818)	(0.0809)
Log export intensity*other regions		-0.0743***
		(0.0110)
Other regions		1.079***
		(0.116)
_cons	5.466***	3.802***
	(0.341)	(0.346)
n	37,446	37,446
R^2	0.144	0.127

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The column (1) ((2)) shows: in the total sample, according to whether the enterprise is located in the eastern region (other regions), we generate a dummy variable “east” (“other regions”), if the enterprise is located in the eastern region (other regions) to take the value of 1, otherwise take 0. From column (1) ((2)), we can see if the enterprise is located in the eastern region (other regions), when the export intensity increases by 10 percent, the SO_2 emission intensity c.p. decreases by 1.93 percent (0.743 percent).

Do the effects vary by ownership?

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 less bargaining power 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.

Table B6 presents estimates of the effect of the export intensity on SO_2 emissions intensity by ownership type. The results suggest that the export intensity had statistically significantly negative effect on SO_2 emissions intensity for all ownership type.

Table B6: Regressions with dummies for ownership

Log SO_2 emissions intensity	(1)	(2)	(3)	(4)
Log export intensity * SOE	-0.153***			
	(0.0260)			
Log export intensity * Other domestic		-0.169***		
		(0.00752)		
Log export intensity * HMT			-0.155***	
			(0.0146)	
Log export intensity * Foreign				-0.113***
				(0.0139)
SOE	-1.648***			
	(0.260)			
Other domestic		0.361***		
		(0.0869)		
HMT			-2.204***	
			(0.113)	
Foreign				-2.649***
				(0.108)
Log total output	-0.708***	-0.772***	-0.733***	-0.658***
	(0.0478)	(0.0469)	(0.0475)	(0.0473)
Log total employees	0.284***	0.549***	0.341***	0.314***
	(0.0511)	(0.0503)	(0.0506)	(0.0503)
Log labor productivity	-0.0515	-0.0467	-0.0544	-0.0260
	(0.0446)	(0.0437)	(0.0444)	(0.0442)
East	-1.664***	-1.401***	-1.501***	-1.622***
	(0.0940)	(0.0924)	(0.0938)	(0.0931)
Middle	0.579***	0.321***	0.557***	0.406***
	(0.106)	(0.104)	(0.105)	(0.105)
West	0.564***	0.303***	0.525***	0.400***
	(0.104)	(0.102)	(0.103)	(0.103)
Mining	-6.290***	-6.906***	-6.229***	-6.268***
	(0.317)	(0.309)	(0.313)	(0.312)
Manufacture	-2.696***	-3.112***	-2.584***	-2.586***
	(0.302)	(0.293)	(0.297)	(0.295)
_cons	5.909***	4.139***	5.826***	5.228***
	(0.358)	(0.354)	(0.354)	(0.353)
n	37,446	37,446	37,446	37,446
R^2	0.099	0.134	0.108	0.116

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The column (1) ((2), (3), (4)) shows: in the total sample, according to whether the enterprise belongs to SOE (Other domestic, HMT, Foreign), we generate a dummy variable “SOE” (“Other domestic”, “HMT”, “Foreign”), if the enterprise belongs to SOE (Other domestic, HMT, Foreign) take the value of 1, otherwise take 0. From column (1) ((2), (3), (4)), we can see if the enterprise belongs to SOE (Other domestic, HMT, Foreign), when the export intensity increases by 10 percent, the SO_2 emission intensity c.p. decreases by 1.53 percent (1.69 percent, 1.55 percent, 1.13 percent).

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