Exporting, Abatement, and Firm-Level Emissions: Evidence from China's Accession to the WTO*

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Abstract

This paper studies the complementarity between exporting and abatement and their joint impact on the environmental performance of Chinese manufacturers. For two common air pollutants (SO_2 and industrial dust) we document that (a) exporters are significantly less emissions-intensive relative to their non-exporting counterparts and (b) this difference cannot be explained by differential rates of abatement alone. We argue that the standard heterogeneous firms, trade and emissions model cannot simultaneously match these stylized facts and propose a model which allows for export-driven emission-complementarities (such as technological upgrading). Treating WTO-accession as a sharp reduction in trade barriers across countries, we quantify the impact of endogenous export and abatement decisions on firm-level emissions. We find that exporting *reduces* emissions by at least 36 percent across pollutants. Observable changes in product scope, capital-vintage, energy sourcing and R&D account for 75 percent of the empirical relationship between exporting and emissions. Abatement, in contrast, has a much smaller impact on emissions between 1999 and 2005. Using the structural model we quantify the implied emissions taxes and the impact of trade and environmental policy alternatives on the Chinese manufacturing sector.

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1 Introduction

China's accession to the WTO has driven a rapid rise in trade, manufacturing production and emissions. Indeed, sulfur dioxide emissions (SO_2), production and trade from the Chinese manufacturing sector increased by 40, 150 and 250 percent, respectively, over the 2000-2005 period (Rodrigue, Sheng and Tan, 2020). Despite the sharp rise in aggregate exports, production and emissions, little is known as to how WTO accession affected firm-level pollution among Chinese manufacturers, largely due to a lack of compelling data. This paper is among the very first to document the environmental performance of a wide set of individual Chinese manufacturers during the WTO-accession period and quantify the relationship between emissions, exporting and abatement across heterogeneous producers. We study a host of key, policy-relevant questions that cannot be addressed without directly examining the impact of trade liberalization on individual producers: how did WTO-induced exporting affect overall firm-level emissions? If emissions rose, did they do so because of growth in total output, an increase in the emission-intensity of production or both? Is there evidence that trade liberalization lead to changes in Chinese firm-level input demand, scale and technology? Do these, in turn, exacerbate or mitigate firm-level pollution?

On one hand, if trade liberalization induced Chinese producers to switch to cheap and dirty sources of energy, encouraged growth in less regulated locations, or reduced the incentive to introduce costly abatement technology, we might expect that the growth in Chinese emissions is particularly severe during the WTO-accesion period. On the other hand, to the extent that WTO-accession allowed producers to invest in cleaner production, it is plausible that just the opposite occurred. In a companion paper, Rodrigue, Sheng and Tan (2020), we demonstrate that within-firm technological improvement significantly mitigated the aggregate, trade-induced, emissions growth by as much as 14 percent during China's accession to the WTO. While our associated research focussed on linking aggregate movements to within-firm changes, this paper studies the underlying determinants of differential firm-level behavior. Characterizing the determinants of environmental and economic responses are of particular interest in this context since there is little existing evidence of significant Chinese environmental regulation over the WTO-accession period (Jia, 2012; Wu et al, 2013).

Using detailed firm-level emissions data, annual manufacturing surveys, and customs records over the 1999-2005 period, we document three striking facts:

1. Chinese exporters are significantly less emissions-intensive relative to their non-exporting counterparts. Moreover, these differences *grew* over the WTO-accession period as Chinese exporters expanded into world markets.

2. The differences in emissions-intensity across export status cannot be explained by differential rates of abatement alone. Rather, endogenous abatement investment contributes relatively little to the observed emissions-intensity declines.

3. Although dirty producers grew relatively quickly after WTO-accession, emissions-intensities among initially dirty producers fell relatively rapidly.

To help us understand how these facts can co-exist, we extend the workhorse model of international trade, heterogeneous firms and emissions to highlight how WTO-accession may have simultaneously affected Chinese firm-level exports, abatement, and pollution as posited in Shapiro and Walker (2018) and Forslid et al. (2018).[1] As in the preceding literature we allow exporting to directly affect emissions through its impact on endogenous abatement decisions, but we also allow exporting to indirectly affect emissions through firm growth. This is not to say, however, that the firm is unaware of the impact of its growth on emissions. Rather, there are a host of changes which are complementary to exporting and firm growth, such as the investment in new technology, which plausibly affect firm pollution even if the act itself (investment) is not primarily driven by a desire to reduce the firm's environmental impact. Thus, we provide a structure which rationalizes changes in firm-level emissions and emissions-intensity even if there is minimal enforcement of environmental regulation.[2]

We proceed to identify the causal impact of exporting and abatement on Chinese firm-level emissions-intensity over the WTO-accession period. In particular, we exploit exogenous variation in Chinese tariffs (driven by WTO accession) and exogenous variation in the dispersion of air pollution (driven by geographic attributes) to disentangle the individual impact of each margin. In this sense we contribute to the literature which broadly documents that exporters tend to be more environmentally efficient producers,[3] but directly address the underlying mechanisms through which emissions decline. We find that starting to export is predicted to reduce SO_2 emissions-intensity by 36 percent for the average exporter, while abatement is only predicted to reduce emissions by 4 percent. The relatively small estimate on abatement is not due to a small marginal impact; rather, it is reflective of the small average investment made in abatement among Chinese manufacturers over the 1999-2005 period. Investigating how exporters reduce emissions despite small investments in direct abatement, we find that observable changes in product scope, capital-vintage, R&D activities and energy sourcing account for 75 perecent of the empirical relationship between exporting and emissions.

Our reduced-form estimates jointly identify key structural parameters common to modern quantitative models used to evaluate the policy impact of trade and environmental outcomes (See Shapiro (2016), Forslid (2018), or Shapiro and Walker (2018) for examples). Using our structural estimates we compute the implied emissions taxes faced by Chinese producers. We document that, consistent with the institutional background, existing environmental policy is broadly characterized by a wide degree of variability across firms, but did systematically become more stringent over time. Using the implied taxes we counterfactually examine the impact of uniform emissions taxation on endogenous firm-level export and emissions responses. In this sense, our work also complements research which quantifies the impact of domestic environmental regulation on Chinese emissions.[4]

We find that existing regulation, as measured by implied emissions taxes, was highly dis-

[1] Our framework is also related to models to heterogeneous firms and abatement as posited in Bajona et al (2010), Krickemeier and Richter (2014), Rodrigue and Soumonni (2014) and Barrows and Ollivier (2018).

[2] In this sense, our results also complement those in Harrison et al (2016) which finds that increases in the price of coal were more effective at mitigating emissions in India than poorly enforced environmental regulation.

[3] See Galdeano-Gómez (2010), Cui et al (2016), Holladay (2016) for example. Batrakova and Davies (2012) similarly use propensity score matching combined with a differences-in-differences approach to evalute the impact of exporting on energy consumption among Irish producers.

[4] See Nam et al 2013, 2014; Qi et al 2014; Zhang et al 2013, 2014, 2016a, 2016b, Springmann et al 2015, Kishimoto et al 2017, Wong et al 2017, Cao and Karplus, 2014 and Karplus and Zhang, 2017 for examples. Likewise, Cao and Karplus (2014) study the drivers of energy, electricity and carbon intensity among a sample of 800 Chinese firms between 2005 and 2009. Although we observe similar trends, the Cao and Karplus (2014) study differs from ours in the outcome variables under consideration, the mechanisms evaluated in the paper, the sample of firms, and the stringency of environmental regulation during the observed time period.

tortionary: assigning each firm the current average emissions tax rate would have induced much greater output and increased emissions by 27 percent during the WTO accession period. Nonetheless, the removal of the distortionary nature of emissions taxation leaves significant room for policy improvement. Using our structural model we find that modest increases in uniform emissions taxes could have held aggregate manufacturing constant at their pre-WTO levels *and* maintained total output and exports by encouraging the growth of clean producers into world markets.

We also use our model to quantify the impact of increased trade costs, as driven by increasing post-WTO trade tensions, on the emissions outcomes in the Chinese manufacturing sector. We find modest emissions reductions due to the decline of large, pollution-intensive exporters which respond to trade costs by lowering total production. Indeed, our counterfactuals indicate that a 20 percent across the board increase in trade costs would reduce aggregate Chinese manufacturing emissions by 13 percent.

This paper is most closely tied to studies which examine firm-level pollution responses to trade liberalization, in particular those which characterize the impact of trade liberalization on exporting, abatement and pollution. Cherniwchan (2017) demonstrates that the North American Free Trade Agreement caused pollution-intensity to fall in affected manufacturing plants and accounts for nearly two-thirds of the aggregate manufacturing declines in the emissions of SO_2 and PM_{10} over the 1994-1998 period. Levinson (2009) and Shapiro and Walker (2018) similarly document declines in emissions-intensity among US manufacturers over the 1990s and early 2000s. We complement these cases by documenting similar patterns in China during the WTO-accession period where there was relatively little enforcement of environmental regulation.

Although we are not aware of another paper which characterizes the impact of exporting and abatement on firm-level emissions in China, there are numerous existing studies at the intersection of trade, growth, and pollution in the Chinese context. For instance, Yan and Yang (2010) apply input-output methods to study the embodied carbon dioxide in China's foreign trade, while Dean (2002), Ebenstein et al. (2015), de Sousa et al. (2015), and Bombardini and Li (2020) use (often trade-driven) variation in exposure to economic growth to quantify the impact of expansions on regional emissions and consequent outcomes across provinces.[5] We extend this literature by providing a first look at the degree to which trade simultaneously affected Chinese firm-level production, exporting, abatement and emissions.

More broadly, our work contributes to the rich literature examining the role of international trade in determining global environmental outcomes.[6] Existing work by Copeland and Taylor (1994, 1995), Ederington et al. (2005), and Levinson and Taylor (2008) suggests that trade liberalization may increase pollution in countries that have a comparative advantage in pollution-intensive industries. Given the lack of environmental regulation and enforcment, we empirically extend this analysis to examine whether WTO accession led to significant differences in trade driven pollution-intensity at the firm, rather than country, level. We find that China's exports grew faster among emissions-intensive firms, but exporters were able to mitigate these environmental externalities through changes in production technology. In this sense, our empirical results document effects of trade on environmental quality similar to those em-

[5]See Hao et al (2007), Cropper (2012), Chen et al (2013), Lin et al (2014), Tanaka (2015), or He (2016) for studies of the impact of Chinese industrial pollution on air quality and/or measures of health outcomes.

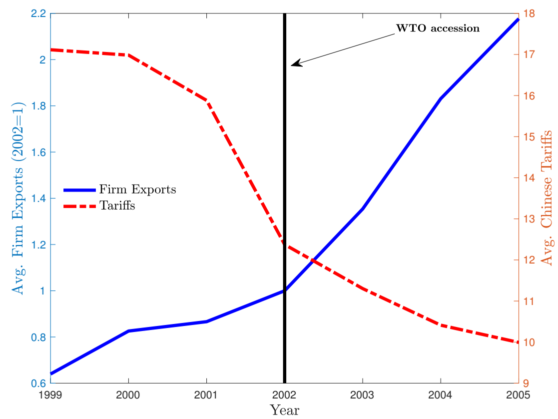
[6]See Copeland and Taylor (2004) and Cherniwchan et al (2017) for reviews of the literature studying trade, growth and the environment.

phasized in Grossman and Krueger (1995), Antweiler et al. (2001), and Frankel and Rose (2005), but manifest at the firm-level rather than the country-level.

The next section documents the institutional background during our period of study, particularly as it pertains to environmental and trade policy. Section 3 documents key patterns in our data, while section 4 presents the simple model that guides our empirics. Sections 5 and 6 discuss our empirical methodology, describe our identification strategy, and present our empirical results. Section 7 describes our counterfactual policy experiments and section 8 concludes.

2 Institutional Background

Among the most striking features of China's accession to the WTO in December 2001 is the rapid, export-lead expansion of the domestic manufacturing industry. In our sample of Chinese manufacturing exporters, this phenomenon is clear; as documented in Figure 1, average firm-level export sales more than doubled in the three years after WTO accession.



Notes: Figure 1 plots average firm-level manufacturing exports. For each year, this value is computed using all active exporters in the matched data set. Average tariff rates are computed by weighting MFN tariffs by initial import shares in 1999.

Figure 1: Exporting and Tariffs

WTO-induced tariff changes represent a key determinant of future exporting and an important source of productivity growth among Chinese firms during the WTO-accession period. However, the rapid rise of manufacturing exports simultaneously produced significant social, environmental, and health concerns among domestic policymakers (see CCINED 2003, 2004 for examples).

While Chinese environmental air quality legislation was first implemented in the 1970s, and strengthened a decade later, there is little evidence of significant policy enforcement.[7] During our sample period the Chinese environmental agency, *The Ministry of Ecology and the Environment (MEE)*, was responsible for setting pollution standards and regulation across the country.[8]

[7]The first legislative document penalizing firms for excessive emissions, was implemented in 1989 (Jin et al, 2016) and was later revised in 1995, with specific emphasis on sulfur dioxide emissions.

[8]In 2018 *The Ministry of Environmental Protection (MEP)* was renamed *The Ministry of Ecology and Environment (MEE)*.

It also mandated the collection of regional and establishment-specific pollution information, and is the primary source of firm-level data for this study.

While national state agencies mandated policy, implementation, verification and enforcment of environmental policy was outsourced to a disaggregated set of local *Environmental Protection Bureaus (EPBs)*. There were approximately 3060 EPBs across China charged with the enforcement of enviromental standards and the administration of penalties for policy violations. Between 1999 and 2005 local EPBs issued permits to limit the quantity and concentration of pollutants for every establishment in their jurisdiction.

The EPBs directly report to the local township, district or prefecture government rather than higher state ministries.[9] The difference in jurisdiction created an inherent conflict across governmental objectives: career concerns caused local administrators to prioritize *local* economic development (Jia, 2012; Wu et al, 2013) at the expense of enforcing national environmental policy. Firms which were responsible for substantial local employment or fiscal revenues were often given preferential treatment from the local EPB (OECD, 2009).

Despite the apparent conflict of interest, EPBs nonetheless had the power to substantially influence firm-level pollution. Once a firm was found to be non-compliant with existing legislation, the local EPB would usually issue warning letters and, if necessary, impose fines on the establishment. If that did not bring the firm into compliance, EPBs were further empowered to fine the manager directly and/or withdraw the firm's operating permit altogether. During our sample period, fines were the most common form of non-compliance penalty. In aggregate, EPBs imposed sanctions in roughly 80,000 cases per year with total monetary penalties of 460 million RMB (56 million US dollars).

3 Data

This study focuses on two firm-specific measures of air pollution, sulfur dioxide and industrial dust, over the 1999-2005 period:[10]

- **Sulfur Dioxide (SO_2)**: The total weight of SO_2 emitted by a firm over the course of a calendar year;
- **Industrial Dust (Dust)**: The total weight of solid particles, with a diameter of 10 micrometers or smaller, emitted by a firm over the course of a calendar year.

Although MEE collects pollution emissions at for individual plants, it reports pollution at the *firm-level*. If a firm has multiple plants, the survey data aggregates total pollution across plants in the same firm. The pollution survey also documents a limited number of firm characteristics including the location of each firm (city/province), domestic revenues, export revenues, and energy consumption by energy type (coal, natural gas, diesel fuel, heavy oil). MEE also computes the amount of pollution *generated* by each firm. Following a methodology pioneered by the US EPA, the computation of emission generation is based on the firm's input consumption and the emission factor assigned to each input by the EPA. Variation in pollution generation

[9]On occasion, the EPB may also be administered at the provincial level.

[10]A detailed description of emission measurement is provided in the appendix. A detailed discussion of data quality can also be found in the appendix, while a longer discussion is presented in Rodrigue, Sheng and Tan (2020).

and emissions further allow us to measure differences in abatement-intensity across the distribution of heterogeneous firms.

The MEE data set does not record key production variables for our analysis, such as employment, capital use, or intermediate material purchases. It also does not provide any measure of firm-efficiency and does not distinguish between domestic, state or foreign-owned firms. These excluded co-variates are particularly significant, given that firm-level environmental performance has long been associated with differences in production technology and economic scale. Likewise, access to export markets and the incentive to escape environmental regulation varied significantly with firm-ownership and location in China.

We proceed to match the firm-level pollution data with annual manufacturing surveys. While the manufacturing surveys fill in these missing dimensions of our data set, it also restricts attention the manufacturing sector (which was arguably most affected by WTO accession). We match roughly half of the firms in the manufacturing survey to corresponding data in the pollution survey despite the fact that the manufacturing surveys only cover firms with revenues of at least 5 million RMB and not all large manufacturing firms are necessarily large polluters.[11]

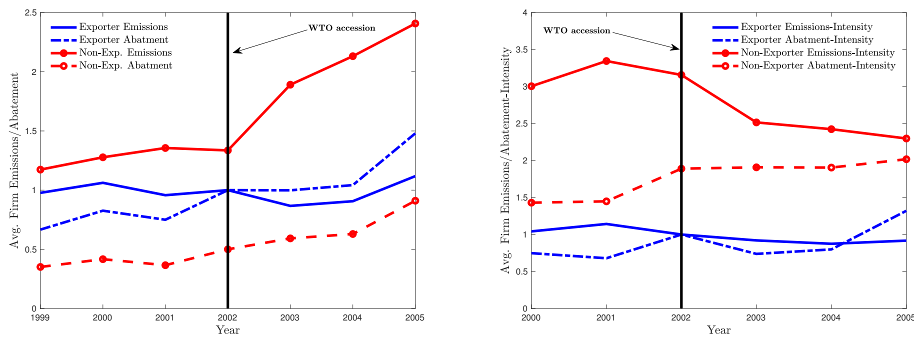
3.1 Exporting, Emissions & Abatement

Panel (a) of Figure 2 documents average firm-level SO_2 emissions and abatement among Chinese exporters and non-exporters over the 1999-2005 period, normalized by their 2002 values. It is apparent that exporters emitted significantly less emissions, on average, than non-exporters. In 1999, for example, the average exporter emitted 17 percent less SO_2 relative to the average non-exporter. More surprisingly, firm-level emissions among exporters grew substantially slower than those among non-exporting firms. By 2005 the difference between exporting and non-exporting firms grew to 54 percent.

Corresponding differences in abatement form a natural explanation for the observed differences emissions rates across export status. We indeed observe that the average exporter abates significantly more than the average non-exporter, but rather than growing over time, these differences shrunk. For instance, the average exporter abated 90 percent more SO_2 emissions than the average non-exporter in 1999. In 2005 the same calculation reveals a 63 percent difference in average firm-level SO_2 abatement between exporters and non-exporters.

An alternative explanation for the observed differences in firm-level emissions are that Chinese exporters are relatively clean producers. We proxy environmental efficiency by emissions-intensity, measured as the ratio of firm-level emissions to (deflated) firm-level revenue, as typically measured in this literature. In Figure 2(b) we observe that exporters also have significantly lower emissions intensities. Even though the gap between average exporter and non-exporter emissions-intensities declines over time, the average emissions-intensity among exporters remains 60 percent smaller than that of non-exporters in 2005. This is surprising for a number of reasons: China had a comparative advantage in energy-intensive products, exporters generally produce much more output than non-exporters, exporters grew faster than non-exporters

[11] A comparison of firm characteristics in the environmental survey, the manufacturing survey and the matched data set can be found in the appendix. Likewise, we separately plot differences in the distribution of emissions-intensity across export status for foreign, domestic and state-owned firms. In each case, we observe significant differences in the distribution of emissions-intensity across export status.



(a) SO_2 Emissions/Abatement

(b) SO_2 Emissions/Abatement-Intensity

Notes: The solid blue line and the dashed blue line respectively plot the average firm-level SO_2 emissions and abatement among exporting firms. The solid red line with circles and the dashed red line with circles respectively plot the average firm-level SO_2 emissions and abatement among non-exporting firms. Emissions/abatement values are normalized by the average exporter in 2002.

Figure 2: Exporters, Emissions & Abatement

over the WTO-accession period[12] and exporters tend to abate a smaller share of their generated emissions.

Specifically, we develop a consumption-based measure of abatement-intensity defined as the ratio of emissions removal to generation, for both exporters and non-exporters alike. Surprisingly, average abatement-intensity is roughly constant over time among Chinese exporters. Non-exporters, in contrast, display continuously increasing rates of abatement. Could the change in abatement fully explain the difference between total emissions and emissions-intensity? At a very rudimentary level, this appears unlikely.

Instead, we propose two complementary explanations. First, as in previous work, exporting is complementary to abatement. Endogenous changes in the size distribution of exporters, particularly with the advent of WTO-accession may potentially explain the increasing differences between exporting and non-exporting firms. Likewise, the post-2002 tariff driven reductions in input costs may encourage abatement and emissions. Second, we also propose that much of the reduction in emissions-intensity among Chinese manufacturers may be driven by contemporaneous changes in firm structure and production associated with exporting, even if that was not the firm's original intention. Rapid growth into export markets can induce significant investment in capital upgrading (Rho and Rodrigue, 2016), investment in productivity-enhancing research and development (Aw et al., 2011; Bustos, 2011), or changes in the mix of products produced by individual firms (Mayer et al., 2016; Barrows and Ollivier, 2018). Each of these are potential sources of complementary environmental efficiency gains.

[12] For instance, average revenues among exporting firms were three times larger than revenues among non-exporting firms in 2002.

4 A Simple Model of Exporting and Abatement

We extend the workhorse model of trade, heterogeneous firms and the environment for salient features of the Chinese manufacturing sector. This framework helps sort out potential sources of efficiency gains and environmental consequences over the WTO accession period, guides our measurement and identification of each potential mechanism, and characterizes potential sources of bias. Our model follows the theoretical framework laid out in Shapiro and Walker (2018) and Forslid et al. (2018), but allows for (1) tariff changes to directly impact firm input costs and (2) endogenous complementarity or substituability between exporting and abatement.

Specifically, we consider an economy with two countries, Home and Foreign (*), which are endowed with non-depreciating stocks of labour ($\bar{l}$) and capital ($\bar{k}$) which households supply inelastically. Consumers in each country have CES preferences over a continuum of horizontally differentiated manufactured goods indexed by i: $U = (\int_{i \in \Omega} x_i^{\frac{\sigma-1}{\sigma}} di)^{\frac{\sigma}{\sigma-1}}$ and σ is the elasticity of substitution across varieties. Consumer preferences generate a residual demand curve for variety i in both the home and foreign markets, respectively,

$$x_i = \Phi p_i^{-\sigma} \text{ and } x_i^* = \Phi^* p_i^{*-\sigma} \tag{1}$$

where $\Phi = RP^{1-\sigma}$ captures market size, R is the total manufacturing revenue, P is the manufacturing price index and p_i is the price chosen by an individual manufacturing producer.

4.1 Intermediate Production

There is a continuum of intermediate input producers that operate under perfectly competitive conditions in each country. Intermediate input producers combine capital and labour to produce a non-traded intermediate (N) or a country-specific traded intermediate (T) according to $\iota_j = k_j^{\gamma_j} l_j^{1-\gamma_j}$ where $j \in \{N, T\}$. Manufacturing firms purchase local non-traded inputs, domestic traded inputs and foreign traded inputs at prices w_N, w_T and $\tau_m w_T^*$, respectively, where τ_m is an iceberg trade cost capturing the current tariff on foreign-produced intermediates. Traded and non-traded intermediates are combined through a Cobb-Douglas aggregator to produce an aggregate intermediate input $m_i = \iota_{Ni}^{\mu_N} \iota_{Ti}^{\mu_T} \iota_{Ti}^{*\,\nu}$ where $\nu = 1 - \mu_N - \mu_T$ and a unit of m has price $\tau_m^{\nu} \omega = w_N^{\mu_N} w_T^{\mu_T} (\tau_m w_T^*)^{\nu} / (\mu_N^{\mu_N} \mu_T^{\mu_T} \nu^{\nu})$.[13]

4.2 Manufacturing Production and Pollution

Potential manufacturing producers incur sunk costs f_e to enter the market. Upon entry firm productivity, φ_i and the firm-level emissions tax, t_i, are drawn from the joint distribution $G(\varphi, t)$. We flexibly approximate the institutional context through a firm-specific tax since it allows for a parsimonious, but arbitrary allocation of emission taxes across firms which may vary across ownership, location or industry. Successful entrants purchase intermediate inputs

[13] We abstract from pollution arising from intermediate production since, in practice, intermediates are often produced in-house, sourced from other manufacturing firms (and are thus accounted for), or sourced from non-manufacturing firms (and are outside the scope of our study).

on competitive markets and produce output according the production function:

$$x_i = (1 - \theta_i)\varphi_i m_i. \tag{2}$$

As in Shapiro and Walker (2018) and Forslid et al. (2018) we model abatement activity through the parameter θ_i which captures the fraction of firm inputs which are redirected towards the reduction of firm-level emissions, e_i:

$$e_i = (1 - \theta_i)^{\frac{1}{\alpha}} (\varphi_i m_i)^{\beta} \tag{3}$$

The emission function parameters α and β are key to our analysis. The parameter α measures abatement efficiency. If $\alpha < 1$ ($\alpha > 1$) successive investments in abatement will induce larger (smaller) declines in emissions. In a similar sense, we argue that the parameter β captures systematic changes in the relationship between output and emissions across the firm size distribution.[14] In previous literature, β is assumed to be one. Under this restriction, any decline in emissions-intensity, e_i/x_i, can only be driven by greater abatement, θ_i. The parameter β, though a small addition to the workhorse model, allows us to capture environmental externalities associated economic growth in a parsimonious fashion. Moreover, allowing for multiple sources of emissions reductions is a first order issue: we observe emissions-intensity declines for many Chinese producers with minimal direct abatement and/or no observable change in abatement.

Combining equations (2) and (3) we write output directly as a function of emissions

$$x_i = e_i^{\alpha} (\varphi_i m_i)^{1-\alpha\beta}. \tag{4}$$

When $\beta < 1$ the augmented production function (4) exhibits increasing returns to scale. In this sense, firm expansion reduces per unit emissions costs through economies of scale; firm growth and abatement are substitutes in reducing firm emissions. We might expect this to be the case if rapid growth also lead to the adoption of efficient and clean production technology as in Forslid et al. (2018). In contrast, if $\beta > 1$ the augmented production function (4) has decreasing returns to scale and firm growth and abatement will prove to be complementary in the reduction of emissions. This alternative may hold if expansions cause firms to use increasing amounts of energy to produce marginal units of output as China grew into world markets.

This is not to suggest that emission reductions are free. Rather, we expect that costly investment associated with firm growth, such as that induced by trade liberalization, will be associated with changes in firm structure. Investment in new technology, for example, may have positive spillovers on environmental efficiency even if environmental concern was not the primary motivation for the investment itself. We interpret β broadly, but also fully intend that the fixed costs associated with firm production and exporting, as specified below, should also be interpreted as encompassing the full set of costs associated with firm expansion.

Given this structure, each firm solves its cost minimization problem

$$\min_{e_i, l_i} \quad t_i e_i + \omega \tau_m^{\nu} m_i \ \text{ subject to } \ e_i^{\alpha} (\varphi_i m_i)^{1-\alpha\beta} = \bar{x}_i \tag{5}$$

[14] Alternatively, one may similarly expect that β may capture systematic differences across industries, regions or ownership-types. We abstract from this difference for now, but investigate it further below.

where $\bar{x}_i$ is the target amount of total firm production. The solution to (5) yields conditional input and emission demand

$$m_i = \left(\bar{x}_i \varphi_i^{\alpha\beta-1} \left(\frac{(1-\alpha\beta)t_i}{\alpha \tau_m^{\nu} \omega} \right)^{\alpha} \right)^{\frac{1}{1-\alpha(\beta-1)}} \quad (6)$$

$$e_i = \left(\bar{x}_i \varphi_i^{\alpha\beta-1} \left(\frac{(1-\alpha\beta)t_i}{\alpha \tau_m^{\nu} \omega} \right)^{\alpha\beta-1} \right)^{\frac{1}{1-\alpha(\beta-1)}} \quad (7)$$

as a function of output, productivity, input costs, and the emissions tax faced by the firm.

Equation (7) implies that total firm-level emissions are increasing in total output as long as $\beta < 1/\alpha$, conditional on firm productivity and current emission taxes. At the same time, however, emissions intensity need not increase with firm production. Dividing both sides of equation (7) by firm output yields

$$\frac{e_i}{\bar{x}_i} = \left[\left(\frac{\alpha}{1-\alpha\beta} \right) \left(\frac{\tau_m^{\nu} \omega}{\varphi_i t_i} \right) \right]^{\frac{1-\alpha\beta}{1-\alpha(\beta-1)}} \bar{x}_i^{\frac{\alpha(\beta-1)}{1-\alpha(\beta-1)}} \quad (8)$$

If $\beta < 1$ emission intensity is strictly decreasing in total output, $\bar{x}_i$, conditional on firm characteristics and emission taxes. The impact of firm expansion on emissions-intensity through scale economies has important consequences for environmental policy. While the imposition of higher emission taxes may improve environmental outcomes by encouraging greater firm-level abatement, these efforts may be mitigated if they reduce the environmental benefits of firm-growth. Policies which induce firm growth, such as trade liberalization, are also likely to induce environmental spillovers which endogenously affect abatement choices. Alternatively, if $1 < \beta < 1/\alpha$ emissions-intensity is increasing in firm output and, despite greater investment in abatement, emissions per unit of production will increase as firms grow into export markets.

Equations (6) and (7) further imply that the firm's cost function is a non-linear function of total output

$$C_i(\bar{x}_i) = \left[\frac{1-\alpha(\beta-1)}{1-\alpha\beta} \right] \left[\left(\frac{1-\alpha\beta}{\alpha} \right)^{\alpha} \left(\frac{\omega \tau^{\nu}}{\varphi_i} \right)^{1-\alpha\beta} t_i^{\alpha} \bar{x}_i \right]^{\frac{1}{1-\alpha(\beta-1)}}.$$

where costs are always an increasing function of tariffs as long as $\beta < 1/\alpha$, the relevant case for our application.[15]

4.3 Profit Maximization

Each firm chooses whether to export and charges its optimal price in each market. Producing for either the domestic or export market requires paying a fixed entry costs, f and f^*, while exporters also incur iceberg transport costs, $\tau_x > 1$, on every unit shipped to the foreign mar-

[15]Moreover, if $\beta \neq 1$ emissions will evolve non-linearly with output and export driven firm growth will affect firm competitiveness both on domestic and export markets. Though we consider a general equilibrium setting here, this feature of production is similar to the partial equilibrium models presented in Riano (2011), Vannoorenberghe (2012), Rho and Rodrigue (2016), or Ahn and McQuoid (2017).

ket.[16] Because the cost function is a (potentially) non-linear function of total output we first solve for optimal profits conditional on the firm's export decision. Specifically, the firm's profit maximization problem, conditional on the decision to export, can be written

$$\max_{p_i,\, p_i^*} \pi_i(\varphi_i, \delta_i, t_i) = p_i x_i + \delta_i p_i^* x_i^* - C(\varphi_i, x_i + \delta_i \tau x_i^*, t_i) - (f + \delta_i f^*)$$

where the firm is subject to the inverse demand functions (1) and δ_i is a binary variable which takes the value of 1 if the firm exports and is zero otherwise. Solving the firm's profit maximization problem conditional on export status yields an optimal pricing equation at home

$$p_i = \left[\kappa \left(\frac{\omega \tau_m^{\nu}}{\varphi_i}\right)^{1-\alpha\beta} t_i^{\alpha} \left(\Phi(1 + \delta_i \phi \tau_x^{1-\sigma})\right)^{\alpha(\beta-1)}\right]^{\frac{1}{\lambda}} \tag{9}$$

where the exporter's optimal price in the export market is $p_i^* = \tau_x p_i$, $\phi = \Phi^*/\Phi$ measures relative size of the foreign market, $\lambda = 1 + (\sigma - 1)\alpha(\beta - 1)$ and κ collects model constants.[17] If $\beta \neq 1$ pricing is a non-linear function of the firm's export decision.[18] Unlike the standard framework, prices will decline (increase) with domestic and export market size if $\beta < 1$ (if $1 < \beta < 1/\alpha$). This non-linearity is an important feature the underlying economic problem. If firm-growth, induced by exporting or otherwise, is associated with within-firm changes that affect total firm-emissions (e.g. installation of new abatement technology), domestic and export prices will be linked through the emission production function (4).[19] The pricing rule implies that total quantity, $\bar{x}(\varphi_i, \delta_i, t_i)$, and profits, $\pi(\varphi_i, \delta_i, t_i)$, are a direct function of the firm's export decision and model primitives:

$$\bar{x}(\varphi_i, \delta_i, t_i) = \Phi(1 + \delta_i \phi \tau_x^{1-\sigma}) p_i^{-\sigma} \tag{10}$$

$$\pi(\varphi_i, \delta_i, t_i) = \frac{\lambda}{\sigma}\left(\kappa(\omega\tau_m^{\nu}/\varphi_i)^{1-\alpha\beta} t_i^{\alpha}\left(\Phi(1 + \delta_i \phi \tau_x^{1-\sigma})\right)^{\frac{1}{1-\sigma}}\right)^{\frac{1-\sigma}{\lambda}} - (f + \delta_i f^*). \tag{11}$$

4.4 Exporting

As common to this class of models, we characterize the decision to export by comparing the profits of an exporter to that of a non-exporter. Let ϕ^* denote the productivity of the marginal exporter for any given emissions tax, $t_i = t$, $\pi(\varphi^*, 1, t) = \pi(\varphi^*, 0, t)$:

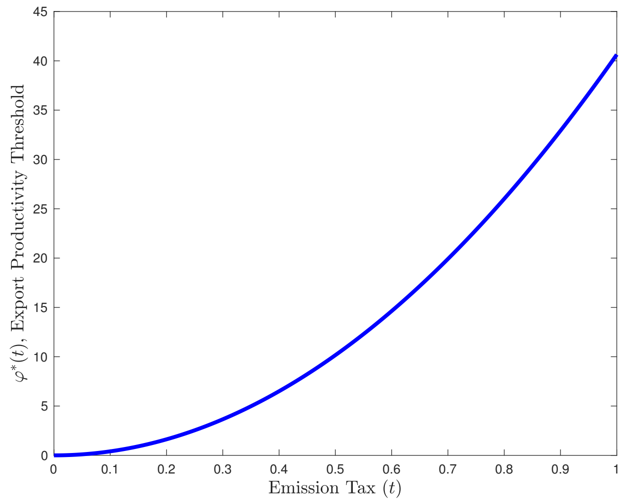
$$\varphi^*(t) = \omega \tau_m^{\nu} (\kappa t^{\alpha})^{\frac{1}{1-\alpha\beta}} \left(\frac{(f^*\sigma)/(\lambda \Phi^{1/\lambda})}{(1 + \phi \tau_x^{1-\sigma})^{\frac{1}{\lambda}} - 1}\right)^{\frac{1}{(\sigma-1)(1-\alpha\beta)}} \tag{12}$$

[16] For simplicity we assume that all fixed costs are paid in terms of the combined intermediate input, m_i.

[17] Specifically, $\kappa = \left[\frac{1}{\alpha^{\alpha}(1-\alpha\beta)^{1-\alpha\beta}}\right]\left[\frac{\sigma}{\sigma-1}\right]^{1-\alpha(\beta-1)}$.

[18] If $\beta < 1/\alpha$ prices will increase with costs (emission taxes and tariffs, in our case) and decrease with productivity, as in the standard heterogeneous firms framework, while the opposite is true otherwise. A sufficient condition for prices to decline with productivity is that $\sigma > 2$. If $\beta = 1$ we recover the standard CES markup over marginal cost pricing equation from Melitz (2003).

[19] Rodrigue, Sheng and Tan (2020) provides further estimates and discussion of the evolution of pricing, markups, output and emissions among Chinese manufacturers over the WTO accession period.



Notes: The above figure plots the relationship between the threshold export productivity and emissions taxes implied by the model.

Figure 3: Emission Taxes and Exporting

Given $t_i = t$, any firm with productivity above $\varphi_i > \varphi^*(t)$ will choose to export, while relatively unproductive firms, $\varphi_i < \varphi^*(t)$, will only serve the domestic market.

Not surprisingly, the export threshold is increasing in trade costs, τ and f^*, and decreasing in export market size, ϕ. The export threshold function (12) also captures the fact that expansions are particularly costly (beneficial) if they raise (lower) marginal costs and decrease (increase) domestic sales accordingly. What is new in our context is how exporting and emission taxes interact. Not only do higher emissions taxes imply higher export thresholds, but for every marginal increase in the emission tax t an increasingly large increase in the firm's underlying productivity is required to export. To the extent that emission taxes vary across firm ownership or geographic space in China, we would expect that export behavior will also systematically vary across these observable dimensions of firm heterogeneity.

4.5 Abatement

Using the production function (2) and the conditional input demand function (6) we can characterize the firm's optimal abatement choice as:

$$1 - \theta_i = \left[\left(\frac{\alpha}{1 - \alpha\beta} \right) \left(\frac{\tau_m^{\nu}\omega}{\varphi_i t_i} \right) \bar{x}_i^{1-\beta} \right]^{\frac{\alpha}{1-\alpha(\beta-1)}} \tag{13}$$

The relationship between exporting and abatement is governed by α and β. When $\beta < 1$, export-induced changes in firm scale are associated with reductions in abatement and, as such, exporting substitutes for direct investment in abatement. Alternatively, if $1 < \beta < 1/\alpha$, export driven expansions are associated with a rise in abatement. Regardless of the impact of exporting on emissions, a constant feature of this relationship is that it is offset by the firm's endogenous abatement response.

Whether abatement increases or decreases with productivity is less clear. On one hand, because productive firms efficiently turn inputs into output, it is particularly costly to devote resources to abatement. This in turn diminishes the incentive to abate. On the other hand, like exporting, productivity increases total output which encourages the firm to increase (decrease) abatement-intensity if $\beta < 1$ ($1 < \beta < 1/\alpha$).

In contrast, the fraction of resources devoted to abatement, θ_i, always increases monotonically in the emission tax, conditional on firm fundamentals. This will be a useful feature in our empirical work as we are able to measure abatement investment well, but have little direct information on *enforced* emission taxes.

4.6 Equilibrium

We focus on general equilibrium conditions between two symmetric countries. Since most conditions are standard, details are relegated to the Supplemental Appendix.

Intermediates
Capital and labor are devoted to producing intermediate inputs under perfectly competitive conditions. Factors are paid the value of their marginal product in all intermediate sectors so that aggregate demand for each type of intermediate across countries meets supply.

Manufactures
Among manufacturers, profits depend on both firm-specific productivity, φ_i, and the firm-specific regulatory conditions, t_i. We can summarize an individual firm's cost advantage by the profitability index, $\zeta_i \equiv (\varphi/(\omega\tau_m^{\nu}))^{1-\alpha\beta}(\kappa t^{\alpha})^{-1}$. Since all firms with the same profit index act identically, we omit the index i hereafter and write *total* non-exporting profits, π_n, and exporting profits, π_x, respectively as

$$\pi_n(\zeta) = (\lambda/\sigma)\zeta^{\frac{\sigma-1}{\lambda}}\Phi^{1/\lambda} - f \text{ and } \pi_x(\zeta) = (\lambda/\sigma)\left[\Phi(1+\phi\tau_x^{1-\sigma})\right]^{1/\lambda}\zeta^{\frac{\sigma-1}{\lambda}} - (f+f^*).$$

The profit functions in turn allow us to define unique profitability thresholds for production ($\underline{\zeta}$) and exporting ($\underline{\zeta}_x$):

$$\pi_n(\underline{\zeta}) = 0 \Rightarrow \underline{\zeta} = \left(\frac{f\sigma}{\lambda\Phi^{1/\lambda}}\right)^{\frac{\lambda}{\sigma-1}} \text{ and } \pi_x(\underline{\zeta}_x) - \pi_n(\underline{\zeta}_x) = 0 \Rightarrow \underline{\zeta}_x = \left(\frac{(f^*\sigma)/(\lambda\Phi^{1/\lambda})}{(1+\phi\tau_x^{1-\sigma})^{1/\lambda}-1}\right)^{\frac{\lambda}{\sigma-1}}$$

Letting $\tilde{G}(\zeta)$ represent the cumulative distribution function of ζ we write the potential entrant's probability of producing as, $1 - G(\underline{\zeta})$, the probability of being a non-exporter, $p_n = \frac{G(\underline{\zeta}_x)-G(\underline{\zeta})}{1-G(\underline{\zeta})}$, and the probability of exporting, $p_x = \frac{1-G(\underline{\zeta}_x)}{1-G(\underline{\zeta})}$, and the endogenous profitability index distribution as

$$\psi(\zeta) = \begin{cases} \frac{\tilde{g}(\zeta)}{1-\tilde{G}(\zeta)} & \text{if } \zeta \geq \underline{\zeta} \\ 0 & \text{otherwise.} \end{cases}$$

Further, the thresholds allow us to respectively define average profitability among non-exporting

($\tilde{\zeta}_n$) and exporting ($\tilde{\zeta}_s$) firms,

$$\tilde{\zeta}_n \equiv \frac{1}{p_n}\left[\int_{\underline{\zeta}}^{\underline{\zeta}_x} \zeta^{\frac{\sigma-1}{\lambda}}\psi(\zeta)d\zeta\right]^{\frac{\lambda}{\sigma-1}} \text{ and } \tilde{\zeta}_x \equiv \frac{1}{p_x}\left[\int_{\underline{\zeta}_x}^{\infty} \zeta^{\frac{\sigma-1}{\lambda}}\psi(\zeta)d\zeta\right]^{\frac{\lambda}{\sigma-1}}$$

along with average profits among non-exporters and exporters alike

$$\frac{1}{p_n}\int_{\underline{\zeta}}^{\underline{\zeta}_x} \pi_n(\zeta)\psi(\zeta)d\zeta = \pi_n(\tilde{\zeta}_n) \text{ and } \frac{1}{p_x}\int_{\underline{\zeta}_x}^{\infty} \pi_x(\zeta)\psi(\zeta)d\zeta = \pi_x(\tilde{\zeta}_x).$$

Average profits among incumbent producers, $\bar{\pi}$, is expressed as

$$\bar{\pi} = p_n\pi_n(\tilde{\zeta}_n) + p_x\pi_x(\tilde{\zeta}_x). \tag{ZCP}$$

Emissions Tax Revenues
We assume all emissions revenues are redistributed to consumers. The conditional emissions demand function (7) among non-exporters implies:

$$e_i = \alpha\left(\frac{\sigma-1}{\sigma}\right)\left(\Phi(1+\delta_i\phi\tau_x^{1-\sigma})\right)^{1/\lambda}\frac{\zeta_i^{\frac{\sigma-1}{\lambda}}}{t_i}$$

which depends on the emissions tax, t_i, directly and indirectly through the profitability index. It also implies that the firm's emissions tax bill $T_i = t_i e_i$ only depends on the emissions tax though the firms profitability index ζ. This, in turn, allows us to write the firm's emissions tax bill as function of the profitability index equilibrium parameters for both non-exporting (T_n) and exporting (T_x) firms

$$T_n(s) = \frac{\alpha(\sigma-1)}{\lambda}\left(\frac{\zeta}{\underline{\zeta}}\right)^{\frac{\sigma-1}{\lambda}} f \text{ and } T_x(\zeta) = T_n(\zeta) + \frac{\alpha(\sigma-1)}{\lambda}\left(\frac{\zeta}{\underline{\zeta}_x}\right)^{\frac{\sigma-1}{\lambda}} f^*.$$

where the average tax bill among each group of firms are likewise

$$\frac{1}{p_n}\int_{\underline{\zeta}}^{\underline{\zeta}_x} T_n(\zeta)\psi(\zeta)d\zeta = T_n(\tilde{\zeta}_n) \text{ and } \frac{1}{p_x}\int_{\underline{\zeta}_x}^{\infty} T_x(\zeta)\psi(\zeta)d\zeta = T_x(\tilde{\zeta}_x)$$

Average emissions tax revenues paid by an individual producer are then $\bar{T} = p_n T_n(\tilde{\zeta}_n) + p_x T_x(\tilde{\zeta}_x)$ and we can compute total emissions tax revenues as $T = \mathcal{M}\bar{T}$.

Free entry
Free entry implies that the expected value of a potential entrant is

$$V_e = (1-\tilde{G}(\underline{\zeta}))\bar{\pi} - f_e = 0 \Rightarrow \bar{\pi} = \frac{f_e}{1-\tilde{G}(\underline{\zeta})}). \tag{FE}$$

The free entry (FE) and zero cutoff profitability (ZCP) conditions intersect once, which pins down equilibrium profits, production and exports thresholds, and the mass of firms ($\mathcal{M}$):

$$\mathcal{M} = \frac{(r_l \bar{l} + r_k \bar{k})\lambda}{[\sigma - (\sigma-1)\alpha][\bar{\pi} + f + f^*]}.$$

5 Measurement, Identification and Estimation

Estimating equation (8) is our primary empirical objective. Consistent estimates of the reduced-form parameters return the causal impact of exporting and abatement on firm-level emissions-intensity and allow us to recover the underlying structural parameters of our model. There are, however, numerous hurdles associated with taking the theoretical emissions-intensity equation directly to the data. We address each of these in turn.

5.1 Emissions-Intensity

Our benchmark measures of emission-intensity follow the standard practice of dividing firm-level emissions by firm revenues. This is potentially misleading if firm-level pricing varies across firm size and export decisions. Our simple structure highlights this feature emphatically: for any firm, regardless of their productivity or export status, standard profit maximization implies that any difference in revenue-based emissions-intensity over time can be entirely attributed to changes in emission taxation:

$$\frac{t_{it} e_{it}}{\bar{r}_{it}} = \alpha \left(\frac{\sigma - 1}{\sigma} \right) \Rightarrow \Delta \ln t_{it} = -\Delta \ln \frac{e_{it}}{\bar{r}_{it}} \tag{14}$$

where $\bar{r}_{it}$ is firm i's total revenue.[20] A number of existing studies (a) use emissions-intensity as a dependent variable and (b) find significant correlation between productivity (and/or exporting) even after conditioning on precise measures of emissions taxes.[21] Nonetheless, equation (14) suggests that there should not exist meaningful correlation between revenue-based emissions-intensity and firm size/export status if the model is correctly specified.

Direct information on the emissions tax faced by individual firms would provide identifying variation for the abatement technology parameter, α, and the elasticity of substitution, σ, both of which are key model parameters. Unfortunately, our data does not provide a measure of t_{it}, the emissions tax enforced on firm i.[22] Instead, we employ the firm's optimal abatement choice, which we observe for each firm in our sample. Because $1 - \theta_{it}$ is a monotonic function of t_{it} we can invert equation (13) for t_{it} and write emissions directly as a function of observables:

$$\frac{e_{it}}{\bar{r}_{it}} = \left(\frac{\sigma - 1}{\sigma} \right) \left[\left(\frac{1 - \alpha\beta}{\omega_t} \right) \left(\frac{\varphi_{it}}{\tau^{\nu}_{m,t}} \right) \right]^{1+\sigma(\beta-1)} (1 - \theta_{it})^{\lambda/\alpha} \left[\Phi(1 + \delta_{it} \phi_t \tau^{1-\sigma}_{x,t}) \right]^{\beta-1}. \tag{15}$$

[20] Rodrigue, Sheng and Tan (2020) argue that this condition holds for a large number of demand systems. They do not, however, study the impact of exporting or abatement on emissions-intensity in China.

[21] For example, using a measure of deflated revenue as a proxy for output, Shapiro and Walker (2018) find that decline in US manufacturing emissions intensity are largely determined by increased regulation.

[22] In practice, measuring t_i would remain problematic in the sense that we would be implicitly assuming that *enforcement* of the existing environmental policy also did not change over our sample even though China witnessed significant increases in emissions after WTO accession.

This specification has three key advantages. First, we can directly measure revenue-based emissions-intensity. Second, the model structure suggests that conditional on other model co-variates, abatement-intensity is a sufficient, albeit endogenous, proxy for emissions-taxes. Third, the exponent on export market access, $\beta - 1$, identifies the impact of exporting on *physical* emissions-intensity even though we use a revenue-based outcome variable.[23]

5.2 Abatement

As specified by the model, we measure firm-level abatement-intensity, θ_{it}, as the fraction of generated pollution which is removed prior to emission. The variable which enters our empirical specifications, however, is the log fraction of inputs devoted to production activities, $\ln(1-\theta_{it})$. We employ a theoretically-consistent measure of abatement, $\tilde{\theta}_{it}$, instead

$$\tilde{\theta}_{it} \equiv -\ln(1-\theta_{it}) = \ln\left(\frac{\text{Pollution Generated}_{it}}{\text{Pollution Emitted}_{it}}\right)$$

so that the coefficient on the abatement variable is intuitive: greater abatement will be associated with lower emissions, ceteris paribus.

5.3 Productivity

To develop a model-consistent measure of firm-level productivity we follow the control-function literature pioneered by Olley and Pakes (1996), Levinson and Petrin (2003), Wooldridge (2009), De Loecker (2011) and Ackerberg, Caves and Frazer (2015), among others. Specifically, total firm-level revenues are

$$\bar{r}_{it} = \left[\Phi_t(1+\delta_{it}\phi_t\tau_{x,t}^{1-\sigma})\right]^{\frac{1}{\sigma}}\left[(1-\theta_{it})\varphi_{it}n_{it}^{\gamma_n}k_{it}^{\gamma_k}l_{it}^{\gamma_l}\right]^{\frac{\sigma-1}{\sigma}} \tag{16}$$

where we have incorporated the assumption that some fraction of inputs are produced in-house, while the remainder, n_{it}, are sourced from arms-length intermediate producers. Taking logs of equation (16) and inverting the materials demand function we write firm revenues as a series of year fixed effects and a control function of abatement, inputs (capital, labor, materials), exporting and input tariffs:

$$\ln\bar{r}_{it} = \Gamma_t^r + h(\theta_{it}, k_{it}, l_{it}, n_{it}, \delta_{it}, \tau_{m,t}) + \varepsilon_{it}^r \tag{17}$$

where ε_{it}^r is an *iid* error term. Estimating equation (17) by OLS we can recover predictable components of productivity as

$$\widehat{h}_{it} = \frac{\sigma-1}{\sigma}\left[\ln\varphi_{it} - \tilde{\theta}_{it} + \gamma_k\ln k_{it} + \gamma_l\ln l_{it} + \gamma_n\ln n_{it} + \frac{\delta_{it}\phi_t\tau_{x,t}^{1-\sigma}}{\sigma-1}\right] \tag{18}$$

Following the control function literature we assume that productivity follows a Markov process:

$$\ln\varphi_{it} \quad = \quad g(\varphi_{i,t-1}) + \varepsilon_{it}^{\varphi} = \rho_0 + \rho_\varphi\ln\varphi_{i,t-1} + \varepsilon_{it}^{\varphi} \tag{19}$$

[23]Equations (2) and (3) jointly imply that we can write physical emissions intensity as $\frac{e_i}{\bar{x}_i} = (1-\theta_i)^{\frac{1-\alpha\beta}{\alpha}}\bar{x}_i^{\beta-1}$.

where $\varepsilon_{it}^{\varphi}$ is an unexpected productivity shock. Combining equations (18) and (19) we write the estimating equation for the productivity process as a function of observables

$$\begin{aligned}\widehat{h}_{it} &= \eta_0+\eta_1\widehat{h}_{it-1}+\eta_2\tilde{\theta}_{it}+\eta_3\tilde{\theta}_{it-1}+\eta_4\ln k_{it}+\eta_5\ln k_{it-1}+\eta_6\ln l_{it}+\eta_7\ln l_{it-1}\\ &\quad +\eta_8\ln n_{it}+\eta_9\ln n_{it-1}+\boldsymbol{\eta}_t\delta_{it}+\boldsymbol{\eta}_{t-1}\delta_{it-1}+\xi_{it}\end{aligned} \tag{20}$$

where $\boldsymbol{\eta}_t$ is a vector of year-specific export terms to capture growing export market-access and ξ_{it} is an *iid* error term. Estimating equation (20) by OLS will potentially suffer from endogeneity bias since current firm-level abatement, export and input choices are functions of firm-level productivity. As such, we follow Ackerberg, Caves and Frazer (2015) and form 21 moment conditions to obtain our estimates of the productivity process. Specifically, we assume that $E[\xi_{it}|Z_{it}]=0$ where

$$\begin{aligned}Z_{it} &= [k_{it},k_{it}^2,k_{it}^3,k_{it-1},k_{it-1}^2,k_{it-1}^3,l_{it-1},l_{it-1}^2,l_{it-1}^3,n_{it-1},n_{it-1}^2,n_{it-1}^3,\\ &\quad \delta_{it-1},\delta_{it-1}^2,\delta_{it-1}^3,\widehat{h}_{it-1},\widehat{h}_{it-1}^2,\widehat{h}_{it-1}^3,\tau_{m,t-1},\tau_{m,t-1}^2,\tau_{m,t-1}^3].\end{aligned}$$

We estimate equation (20) by GMM and construct a model-consistent measure of *revenue-based* productivity as

$$\tilde{\varphi}_{it}=\frac{\sigma-1}{\sigma}\ln\varphi_{it}=\widehat{h}_{it}-\eta_2\tilde{\theta}_{it}-\eta_4\ln k_{it}-\eta_6\ln l_{it}-\eta_8\ln n_{it}-\eta_t\delta_{it}$$

We recognize that measured productivity $\tilde{\varphi}_{it}$ is a combination of both physical productivity φ_{it} and the markup. We account for the structural difference between physical and revenue productivity when we recover the structural parameters below from our reduced-form estimates.

5.4 Trade Costs

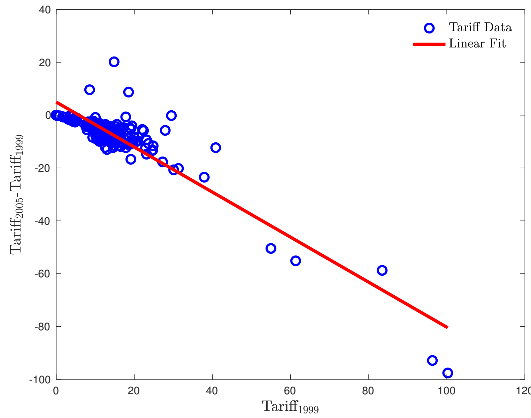
We consider two types of trade costs: (1) the trade costs which restrict export 'market access,' $\tau_{x,t}$, and those which reflect the trade costs on imports to China, $\tau_{m,t}$. To measure variation in import trade costs we use direct information on WTO-induced changes in Chinese import tariffs.[24] A key feature of China's accession to the WTO was that all tariffs were reduced to low and uniform levels. As such, an industry's exposure to the tariff change was predetermined by the pre-existing tariff schedule; as documented in Figure 4 industries which were protected by high tariffs in the pre-WTO period experienced the largest tariff declines thereafter. Following the preceding literature we construct an 'input-tariff' measure of exposure to the WTO-induced tariff changes. For each industry j in the base year (1999), $\tau_{m,99}^{j}$, represents the firm's exposure to WTO-induced tariff change:

$$\tau_{m,t}^{j}=\sum_{j'}s_{j',99}^{j}\tau_{j',t} \tag{21}$$

where $\tau_{j,t}$ is the tariff set on imports of j in year t by the Chinese government and $s_{j',99}^{j}$ is the share of industry j' inputs imported from firms in industry j in our base year, 1999.

The impact of exporting on output and emissions also depends on the export market access.

[24] WTO-induced tariff changes represent a key determinant of future exporting and have often been used as a source of exogenous policy change. See Bas and Strauss-Kahn (2015), Lu and Yu (2015), Feng, Li and Swenson (2016), or Fan, Li and Yeaple (2018) for examples.



Notes: The above figure plots initial 1999 tariffs against subsequent tariff changes over the 1999-2005 period.

Figure 4: Chinese Tariff Reduction and WTO accession

In our model this feature is captured by the foreign country size, ϕ, trade costs, τ_x, and the elasticity of substitution, σ, which governs the sensitivity of export flows to changes in trade costs. Although we do not have direct measures of WTO-induced changes in export market access tariffs, we use the data at hand to develop a model-consistent measure of the market access trade costs faced by Chinese exporters.

Specifically, we estimate the following linear regression of export-intensity, among exporting firms, on a series of time dummies

$$\ln \frac{\bar{r}_{it}}{r_{it}} \equiv \ln \left(\frac{p_{it}x_{it} + p^*_{it}x^*_{it}}{p_{it}x_{it}} \right) = \Gamma^x_t + \varepsilon^x_{it} \tag{22}$$

where ε^x_{it} is an *iid* error term and $\Gamma^x_t = \ln(1 + \tau^{1-\sigma}_{x,t})$ under the normalization $\phi = 1$.[25] Given an estimate of σ, the annual estimates of Γ^x_t allow us to recover a sequence of industry-specific, market access trade costs associated with WTO accession.

Estimating equation (22) by OLS will not produce unbiased estimates of Γ^x_t because only firms with sufficiently high export cost shocks will optimally choose to export. We use a standard selection correction (Heckman, 1979) in equation (22). We use a full set of firm-characteristics in the first-stage regression to capture the decision to export since the explanatory variables in equation (22) are only composed a series of time dummies.[26]

5.5 Structural Identification

Given our measures of abatement, productivity and trade costs, we reconsider the primary estimating equation (15). Taking logs and adding a time subscript we write its empirical coun-

[25] This normalization has no impact on the interpretation of our estimates since export market country size, ϕ, always multiplies trade costs, $\tau^{1-\sigma}_{x,t}$.

[26] In practice, we estimate the decision to export using a probit regression where the explanatory variables include measured productivity, capital-intensity, lagged abatement, input tariffs and a full set of industry, year and ownership fixed effects.

terpart as

$$\ln\left(\frac{e_{it}}{\bar{r}_{it}}\right) = \gamma_0 + \gamma_\theta \tilde{\theta}_{it} + \gamma_\delta \Gamma_t^x \delta_{it} + \gamma_\varphi \tilde{\varphi}_{it} + \gamma_\tau \tau_{m,ft} + \varepsilon_{it}^e \tag{23}$$

where ε_{it}^e is an *iid* error term and the structural interpretation of each reduced form parameter is collected in Table 1.

The estimate of γ_δ directly identifies the impact of exporting on *physical* emissions-intensity, β. With β in hand, the parameter γ_φ identifies σ while γ_θ pins down α. Similarly, conditional on γ_φ and σ, the estimate of γ_τ allows us to recover the share parameter on traded inputs. With an estimate of σ we can use Γ_t^x to recover estimates of market access trade costs in each year, τ_t.

Table 1: Reduced-Form and Structural Parameters

Parameter	Structural Interpretation	Identifies
γ_δ	$\beta - 1$	β, given Γ_t^x
γ_φ	$\frac{\sigma(1+\sigma(\beta-1))}{\sigma-1}$	σ, given β
γ_θ	$-\lambda/\alpha$	α, given β, σ
γ_τ	$-\nu(1+\sigma(\beta-1))$	ν, given β, σ
Γ_t^x	$1+\tau_{x,t}^{1-\sigma}$	$\tau_{x,t}$ given σ.

Notes: The first two columns of the above table document the structural interpretation of reduced form parameters in equation (23). The last columns documents which structural parameters are identified through the reduced-form estimates.

Last, we consider the error term ε_{it}^e. We assume that unobserved emissions-intensity may vary systematically across 4-digit industry codes, ownership-types (private, state, foreign), regions and years. We accordingly include industry, ownership, province and year fixed effects in all specifications. Likewise, although we do not have a precise measure of the firm's product mix, we condition our analysis on the firm's capital-labor ratio and the firm's initial emissions-intensity to capture systematic differences in unobserved variation in product scope.[27]

5.6 Endogeneity Bias

Because exporting and abatement are endogenous firm-level decisions, OLS estimates of equation (23) will likely suffer from endogeneity bias. We consider a two-stage least squares (2SLS) approach to identify the coefficients of equation (23), recover the stuctural parameters, and identify causal impact of exporting and abatement on Chinese emissions.

We leverage location-specific 'ventilation coefficients' as an instrument for abatement. Formally, the ventilation coefficient is the product of wind speed and mixing height. Using a Box model, Jacobson (2002) demonstrates that these two geographical features largely determine the rate at which air pollution disperses over space. Variation in ventilation coefficients over space and time capture the exogenous shifts in environmental concern and the implicit pressure on local officials to increase abatement incentives.[28]

[27] Schott (2003) demonstrates that the capital-labor ratio is a reasonable proxy for a Chinese firm's capacity to produce a particular range of products. Similarly, Boehm et al. (2019) argue that firms diversify into industries in which they have input-based comparative advantage. Our robustness checks further explore the nature of firm-level changes in product-scope on a subset of firms as in Rodrigue, Sheng and Tan (2020).

[28] Indeed, Shi and Xu (2018) use regional ventilation coefficients to predict variation in Chinese environmental policy across provinces in the years following our sample period.

Our second instrument interacts the ventilation coefficient with the firm's initial productivity. As depicted in Figure 3, we expect that the decision to export will vary with both the level of the emission tax and firm-level productivity. In a similar vein, we also include an interaction between firm-level productivity and initial input tariffs to capture systematic variation in exposure to tariff change across the productivity distribution. Using all three instruments also allows us to consider standard overidentification/misspecification tests in this setting.

The validity of this approach rests on two well-known assumptions. The first assumption is simply that the excluded instruments are correlated with the endogenous regressors, conditional on the remaining co-variates. We test this assumption in the first stage of our 2SLS regression using standard measures of weak instruments. Tables 11-13 confirm that the excluded instruments are strong predictors of the decision to export and abate, respectively. Moreover, the instruments maintain their predictive power across all of our robustness checks.

The second assumption requires that the instruments can be safely excluded from the second stage estimation of equation (23). Under the assumption that the workhorse model is correctly specified, our instruments should satisfy this condition as well. However, there may remain potential concern that the parameters reflect unmodeled, unobserved heterogeneous responses across firms. For instance, if the export parameter, $\gamma_{\delta} = \beta - 1$, fully reflects returns to scale in emissions then the 2SLS estimates are likely to be unbiased. However, should input tariff or emission tax changes induce innovative activity within the firm that reduces emissions-intensity, we would also expect that this would also potentially vary across the firm-size distribution. Our second and third instruments remain valid as long as initial productivity is sufficiently removed from the firm's current decisions. We check the robustness of our results to persistent unobserved heterogeneity, assumptions on the persistence of productivity shocks, and a host of alternative fixed effect structures on the error term. Moreover, for each regression we test for both over and underidentification. In each case, we find consistent point estimates and cannot conclude that there is significant evidence of either source of misspecification.[29]

5.7 Inference

Our benchmark *t*-statisics are constructed using heteroskedasticity-robust standard errors with clusters defined at the tariff-line level. However, we note that both measured productivity, $\tilde{\varphi}_{it}$, and trade costs, Γ_x are estimated variables. As such, our reported *t*-statisics may potentially be too small. We address this issue by bootstrapping the entire estimation procedure over firms. That is, for each bootstrap sample, we re-compute productivity and trade costs. We then repeat each regression exercise using the updated productivity and trade cost measures. We additionally report bootstrap 95% confidence intervals for each estimated coefficient. In every regression exercise and for every estimated coefficient, both measures of inference lead to very similar conclusions.

[29] As in numerous preceding studies of exporting, abatement and emissions, assigning a causal interpretation to the positive correlation between firm-level export status and emissions-intensity has been a signficant challenge in this literature (Galdeano-Gómez, 2010; Batrakova and Davies, 2012; Kreickemeier and Richter, 2013; Girma and Hanley, 2015; Cui et al., 2016; Holladay, 2016; Forslid et al., 2018). We have also conducted each experiment using OLS and the constructed IV approach in Lewbel (2012, 2018). The OLS results are consistently smaller than the 2SLS across across exercises. The constructed IV estimates uniformly lie between the 2SLS and OLS estimates. Given that the constructed IV approach requires stonger assumptions on the error terms, we emphasize the 2SLS findings in the main text. Each estimation methodolgy returns similar qualitative conclusions, though the size of the parameter estimates varies by estimation approach.

6 Results

Table 2 documents our benchmark results. The OLS estimates, in columns (1) and (3), indicate that exporting is negatively associated with emissions-intensity. Exporters report SO_2 and industrial dust emissions-intensities which are 11 and 14 percent smaller than those of comparable Chinese manufacturers. As in previous studies, we find that Chinese exporters tend to use cleaner production in the sense that exporting firms report lower measured emissions intensities even once we condition on relevant firm-level characterisitics such as abatement and productivity.

Abatement is also negatively associated with emissions-intensity. On average, a 10 percent increase in abatement is associated with 2-4 percent decline in emissions across pollutants. Over our sample period, SO_2 abatement increased by 63 percent for the average Chinese manufacturer accounting for a 25.9 percent reduction in observed emissions-intensity. In contrast, rising abatement only accounts for a one percent decline in industrial dust emissions-intensity. This difference in the importance of abatement across pollutants is consistent with the growing concern regarding SO_2 emissions and increased enforcement of SO_2 regulation.

We also find that more productive firms are less emissions-intensive. Similarly, firms facing input tariffs reductions, and the contemporaneous decline in firm-level marginal costs, are more likely to reduce emissions-intensity. While the coefficient on firm-level productivity is always precisely estimated, the coefficient on input tariffs is generally small and insignificantly different from zero. Capital-intensity is negatively associated with emissions-intensity, which could be viewed as surprising if capital-intensive firms are simultaneously energy-intensive. However, we also expect that capital-intensity may reflect differences in product mix,[30] the vintage of capital stock, directed technical change, or otherwise unaccounted differences in firm-size. We further explore these alternative interpretations in our robustness checks. Last, firms with higher initial rates of emissions-intensity continue to produce with significantly higher emissions-intensity over time. This suggests that there is meaningful persistence in firm-level emissions-intensity even if it is declining over our sample period.[31]

Columns (2) and (4) document our corresponding 2SLS estimates. In each case our 2SLS estimates perform well on standard tests of weak instruments, overidentifying restrictions, and underidentification. For both pollutants we find that addressing the endogeneity of the export and abatement decisions increases the absolute magnitude of the export coefficient significantly. Among firms induced to export through variation in tariffs and pollution dispersion, exporting is estimated to reduce $S0_2$ and industrial dust emissions-intensity by 36 and 51 percent, respectively. The coefficients on the firm's abatement decision are similar to those reported in the OLS regressions and again indicate that a significant percentage of the observed reduction in emissions-intensity can be attributed to direct abatement investment by individual manufacturers. Likewise, the coefficients on productivity, tariffs, capital-intensity and initial emissions-intensity are nearly identical to those reported in columns (1) and (3). A plausible interpretation for the difference in the estimated magnitude of the export coefficients across estimation methods is the presence of endogeneity bias in the OLS estimates. Alternatively, if

[30]Schott (2003) uses capital-intensity to proxy for differences in the capacity of Chinese manufacturers to produce a particular range of products, while Boehm et al. (2019) argue that firms diversify into industries in which they have input-based comparative advantage.

[31]To the extent that firm-level emissions reflect manufacturing technique we would expect emissions-intensity to be somewhat persistent.

Table 2: Exporting, Abatement and Emissions Intensity

Dep. Var	SO_2 Emissions-Intensity		Dust Emissions-Intensity	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Export_t	-0.114***	-0.452***	-0.138***	-0.717***
	(-12.78)	(-4.66)	(-13.67)	(-6.05)
	[-0.137, -0.103]	[-0.672, -0.240]	[-0.163, -0.123]	[-0.970, -0.505]
Abatement_t	-0.446***	-0.396***	-0.228***	-0.482**
	(-23.06)	(-4.65)	(-20.54)	(-2.04)
	[-0.480, -0.420]	[-0.603, -0.239]	[-0.246, -0.213]	[-0.644, -0.236]
Productivity_t	-0.223***	-0.313***	-0.279***	-0.329**
	(-4.00)	(-3.94)	(-3.59)	(-2.24)
	[-0.311, -0.118]	[-0.418, -0.078]	[-0.355, -0.109]	[-0.411, -0.104]
Tariff_t	0.234	0.147	0.173	0.035
	(1.60)	(1.06)	(1.05)	(0.21)
	[-0.027, 0.333]	[-0.156, 0.407]	[-0.017, 0.386]	[-0.285, 0.317]
$\ln(K/L)_{t-1}$	-0.140***	-0.112***	-0.159***	-0.095***
	(-15.33)	(-9.20)	(-15.69)	(-5.23)
	[-0.159, -0.127]	[-0.138,-0.083]	[-0.194, -0.156]	[-0.129, -0.067]
$\ln(e/\bar{r})_{\text{initial}}$	0.302***	0.300***	0.331***	0.326***
	(14.89)	(38.12)	(13.70)	(30.18)
	[0.294, 0.318]	[0.288, 0.324]	[0.315, 0.340]	[0.311, 0.348]
Province FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cragg-Donald F-statistic		104.92		25.58
Kleibergen-Paap LM-statistic		223.96		42.69
Hansen J-statistic		0.98		0.02
Adj. R^2	0.174	0.136	0.191	0.165
No. obs.	47984	46821	45157	44028

Notes: Standard errors are clustered at the industry (tariff) level. t-statistics are reported in parentheses where ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively. 95% bootstrap confidence intervals are reported in square brackets. We report the Cragg-Donald Wald F-statistic for weak instruments, Kleibergen-Paap rk LM statistic as an underidentification test, and the Hanson J-statistic of overidentifying restrictions.

the export treatment effect varies across Chinese manufacturers, we might expect that the differences across tables may reflect response heterogeneity. We investigate sources of potential heterogeneity in Sections 6.1 and 6.2.

6.1 Robustness

This section outlines a series of robustness checks for our benchmark results. In particular, we examine the consistency of our findings across firm-ownership, firm-location, pollution dispersion, initial export status, and various assumptions on the unobserved components of the error terms.

6.1.1 Ownership Differences

The enforcement of Chinese environmental policy is reported to have varied across firm ownership. While all of our benchmark regressions include fixed effects controlling for average differences across ownership-type, these regressions do not allow us to investigate the degree to which firm-level responses differ across foreign-owned, state-owned and private firms. For instance, we expect that foreign-owned firms may receive particularly special treatment should they be viewed as an important source of local revenue or employment and are likely to change locations should they be subject to stringent environmental policy.

Table 3 reports 2SLS findings separately for state-owned firms, foreign-owned firms, and privately held domestic firms. The export coefficients are consistently negative and significantly different from zero among foreign and state-owned producers, but insignificant for private firms. This result is in line with the narrative that state-owned had access to relatively cheap sources of finance to improve environmental performance, while foreign-owned were the most efficient producers. In each case, the coefficient for foreign-producers is always largest in absolute magnitude, which suggests that technological differences may play an important role in explaining the sources of export-led emissions performance.

Similarly, the abatement point estimate is always negative and precisely estimated among state-owned enterprises. In contrast, the point estimates among private firms are always negative, but smaller and marginally significant. The estimates from the sample of foreign producers are insignificantly different from zero. The pattern of abatement estimates is consistent with the notion that the firms which are least able escape local environmental regulation are likely to have the strongest abatement response to greater taxation.

6.1.2 Regional Differences

It is well known that there were significant differences in access to export markets across Chinese provinces and these differences were particularly pronounced prior to WTO accession. While coastal provinces were already well-integrated in global export markets, the impact of trade liberalization was arguably smaller among less exposed, inland provinces (Wu et al, 2016). Likewise, the health and environmental consequences of pollution vary significantly across Chinese locations (Kahn et al., 2015; Bombardini and Li, 2020). To investigate response heterogeneity across geographic space we split our sample into two groups, coastal and non-coastal provinces, and repeat our benchmark exercises separately for each region.[32]

Table 4 documents the differences across coastal and non-coastal regions. The export and abatement coefficients among the firms located along the coast are always negative, large and statistically significant. For inland firms, in contrast, the 2SLS estimates are small and only marginally significant for SO_2. This pattern is further reinforced by the coefficients on firm-productivity. The estimated impact of productivity growth on emissions-intensity is always greater among coastal firms rather than non-coastal firms. In this sense, the estimated differences across regions are consistent with much larger firm-level changes among producers which were most exposed to WTO accession.

The differential responses across regions may also reflect heterogeneity in the degree to which emissions from coastal and non-coastal firms disperse across geographic space. For example, we expect that the incentive to invest in emissions-reducing abatement is significantly smaller in provinces where air pollution disperses rapidly. To investigate this hypothesis we split our sample into provinces characterized by high and low ventilation coefficients and re-

[32]Coastal provinces include Liaoning, Hebei, Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan.

Table 3: Exporting, Abatement and Emissions Intensity Across Ownership (2SLS)

Dep. Var	SO_2 Emissions-Intensity			Dust Emissions-Intensity		
	SOE	Private	Foreign	SOE	Private	Foreign
	(1)	(2)	(3)	(4)	(5)	(6)
Export_t	-0.326***	0.197	-0.988**	-0.587***	-1.065	-1.410**
	(-3.45)	(0.37)	(-2.48)	(-4.75)	(-0.94)	(-2.47)
	[-0.527, -0.087]	[-0.701, 1.095]	[-1.805, -0.173]	[-0.894, -0.266]	[-2.065, 0.351]	[-2.668, -0.111]
Abatement_t	-0.483***	-0.356*	-0.126	-0.777**	-1.517	0.050
	(-4.80)	(-1.85)	(-0.59)	(-1.97)	(-1.50)	(0.15)
	[-0.761, -0.273]	[-0.761, 0.102]	[-0.628, 0.418]	[-1.914, 0.358]	[-2.919, -0.368]	[-1.436, 1.088]
Productivity_t	-0.238**	-0.142	-0.298**	-0.060	0.101	-0.393**
	(-2.26)	(-0.80)	(-2.32)	(-0.24)	(0.027)	(-2.29)
	[-0.473, -0.137]	[-0.741, 0.493]	[-0.647, 0.079]	[-0.358, 0.210]	[-1.483, 1.607]	[-0.846, 0.027]
Tariff_t	0.163	0.091	0.378	0.394*	-0.217	-0.202
	(0.99)	(0.29)	(0.91)	(1.82)	(-0.44)	(-0.48)
	[-0.106, 0.453]	[-0.545, 0.551]	[-1.183, 1.768]	[0.009, 0.707]	[-1.126, 0.691]	[-1.302, -0.897]
$\ln(K/L)_{t-1}$	-0.096***	-0.127***	-0.156***	-0.043	-0.071	-0.151***
	(-5.50)	(-6.01)	(-4.23)	(-0.85)	(-1.57)	(-3.67)
	[-0.139, -0.060]	[-0.155, -0.081]	[-0.293, -0.008]	[-0.140, 0.055]	[-0.146, -0.016]	[-0.229, -0.072]
$\ln(e/\bar{r})_{\text{initial}}$	0.324***	0.182***	0.307***	0.338***	0.217***	0.286***
	(33.72)	(8.20)	(17.38)	(28.47)	(6.61)	(7.56)
	[0.312, 0.354]	[0.160, 0.211]	[0.234, 0.378]	[0.322, 0.374]	[0.177, 0.284]	[0.183, 0.416]
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F-statistic	100.25	15.34	13.43	16.98	12.41	13.83
Kleibergen-Paap LM-statistic	101.42	12.83	11.45	21.39	7.39	10.30
Hansen J-statistic	1.47	0.34	2.43	2.22	0.55	1.83
Adj. R^2	0.187	0.041	0.047	0.085	0.040	0.207
No. obs.	29089	10901	6748	27453	10288	6213

Notes: Standard errors are clustered at the industry (tariff) level. t-statistics are reported in parentheses where ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively. 95% bootstrap confidence intervals are reported in square brackets. We report the Cragg-Donald Wald F-statistic for weak instruments, Kleibergen-Paap rk LM statistic as an underidentification test, and the Hanson J-statistic of overidentifying restrictions.

Table 4: Exporting, Abatement and Emissions Intensity Across Regions (2SLS)

Dep. Var	SO_2 Emissions-Intensity				Dust Emissions-Intensity			
	Coastal	Non-Coastal	High-Mix	Low-Mix	Coastal	Non-Coastal	High-Mix	Low-Mix
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Export_t	-0.553***	-0.324*	-0.501***	-0.361**	-1.036***	-0.196	-0.741***	-0.529**
	(-4.24)	(-1.92)	(-3.55)	(-2.36)	(-4.85)	(-0.74)	(-3.95)	(-2.44)
	[-0.819, -0.357]	[-0.727, 0.135]	[-0.788, -0.289]	[-0.643, -0.025]	[-1.380, -0.724]	[-0.733, 0.223]	[-1.096, -0.388]	[-0.934, -0.171]
Abatement_t	-0.486***	-0.239*	-0.226*	-0.584***	-0.520*	-0.373	-0.308	-1.036**
	(-4.55)	(-1.84)	(-1.71)	(-4.51)	(-1.67)	(-0.97)	(-0.97)	(-2.07)
	[-0.680, -0.259]	[-0.535, -0.086]	[-0.436, -0.057]	[-0.189, -0.339]	[-1.143, 0.007]	[-0.922, 0.293]	[-0.805, 0.216]	[-2.026, -0.027]
Productivity_t	-0.529***	-0.142**	-0.476***	-0.199**	-0.632**	-0.146	-0.605**	0.035
	(-3.32)	(-1.96)	(-3.40)	(-2.20)	(-2.16)	(-0.91)	(-2.53)	(0.14)
	[-0.901, -0.336]	[-0.332, 0.117]	[-0.737, -0.272]	[-0.410, -0.043]	[-1.076, -0.262]	[-0.317, 0.162]	[-0.983, -0.312]	[-0.399, 0.466]
Tariff_t	0.212	0.030	0.113	0.057	-0.064	0.118	-0.100	0.159
	(1.31)	(0.18)	(0.71)	(0.28)	(-0.34)	(0.58)	(-0.62)	(0.54)
	[-0.090, 0.492]	[-0.298, 0.399]	[-0.213, 0.421]	[-0.363, 0.429]	[-0.539, 0.412]	[-0.295, 0.474]	[-0.439, 0.297]	[-0.386, 0.599]
$\ln(K/L)_{t-1}$	-0.088***	-0.148***	-0.089***	-0.143***	-0.049*	-0.175***	-0.069***	-0.095**
	(-5.46)	(-6.86)	(-4.71)	(-8.09)	(-1.81)	(-7.33)	(-2.60)	(-2.46)
	[-0.126, -0.069]	[-0.193, -0.089]	[-0.117, -0.057]	[-0.179, -0.102]	[-0.114, -0.018]	[-0.228, -0.116]	[-0.137, -0.024]	[-0.186, -0.033]
$\ln(e/\bar{r})_{\text{initial}}$	0.314***	0.269***	0.311***	0.280***	0.345***	0.286***	0.350***	0.272***
	(13.19)	(13.73)	(15.97)	(11.20)	(12.96)	(10.28)	(13.58)	(9.08)
	[0.299, 0.338]	[0.259, 0.301]	[0.295, 0.333]	[0.265, 0.313]	[0.314, 0.366]	[0.270, 0.325]	[0.324, 0.390]	[0.256, 0.307]
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F	51.92	54.12	50.51	63.73	20.24	16.58	15.15	16.16
Kleibergen-Paap LM	78.77	54.16	83.50	67.64	31.10	9.53	25.99	15.61
Hansen J-stat	0.42	0.45	0.48	0.13	0.04	0.02	1.93	0.005
Adj. R^2	0.135	0.116	0.128	0.137	0.112	0.177	0.08	0.05
No. obs.	28487	18314	27773	19016	26545	17464	26152	17847

Notes: Standard errors are clustered at the industry (tariff) level. t-statistics are reported in parentheses where ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively. 95% bootstrap confidence intervals are reported in square brackets. We report the Cragg-Donald Wald F-statistic for weak instruments, Kleibergen-Paap rk LM statistic as an underidentification test, and the Hanson J-statistic of overidentifying restrictions.

peat our analysis seperately for each group of firms.[33]

Among firms located in provinces where pollution disperses quickly, exporting tends to have a larger impact on reducing firm-level emission-intensity. In this sense, our pollution dispersion results are similar to the pattern observed across coastal and inland provinces. The abatement estimates, in constrast, do not reflect the same pattern. Rather, the estimated abatement coefficient among provinces where pollution disperses rapidly is small and insignificant, while the abatement coefficient is large and precisely estimated among provinces with low-ventilation coefficients. Our findings indicate that firms located in provinces where their pollution was more likely to affect local environmental conditions also invested in abatement technologies which had a larger marginal impact on emission reductions.

6.1.3 Initial Non-Exporters

We next consider the estimated impact of exporting and abatement in period t among firms which did not export in period $t-1$; that is, we omit previous exporters from our sample. For instance, we expect that new exporters are likely to be making particularly large investments in capital equipment and/or upgrading technology. To the extent that these firm-level adjustments manifest themselves quickly, new exporters may be in a particulary strong position to mitigate the impact of growth on emissions. Alternatively, if investments come online slowly, new exporters may experience steep increases in emissions as output grows in the short-run.

Columns (1) and (5) of Table 5 indicate that the estimated coefficients for initial non-exporters are slightly larger than their benchmark counterparts (Table 2). The export coefficient for SO_2 and industrial dust fall to -0.55 and -0.99, respectively. The point estimates suggest exporting had a particularly large impact among these rapidly growing firms. In contrast, the abatement coefficient is slightly smaller among initial non-exporters, indicating that their abatement efforts were having a smaller marginal impact on emissions relative to their non-exporting counterparts.

6.1.4 Differential Trends

A potential concern with our benchmark fixed effects structure is that it may not appropriately control for differential trends across industries or regions. Indeed, the impact of exporting and productivity on emissions-intensity is systematically different across coastal and non-coastal regions in Table 5. Although our benchmark results control for these differences with province fixed effects, should there be differential trends across provinces which are correlated with emissions-intensity, exporting, or abatement, we might worry that our estimates partly reflect these underlying trend differences. Likewise, to the extent that these empirical patterns capture the evolution of emissions-intensity across industries and time, industry fixed effects may be insufficient to fully control for changes in industrial composition over time.

To address these concerns we first drop industry and year fixed effects from the benchmark specification and include instead industry-year interacted fixed effects instead. The interacted

[33] For each region, we first determine its median ventilation coefficient over our sample period. Locations are then split into high and low ventilation categories by examining whether it's median ventilation coefficient lies in the top half of all location-specific ventilation coefficients. High ventilation coefficient provinces include Heibei, Neimenggu, Liaoning, Jilin, Heilongjiang, Shanghai, Zhejiang, Shandong, Guangdong, Hainan, Tibet, Gansu, Qinghai, Ningxia and Xinjiang. Low-ventilation regions include Beijing, Shanxi, Anhui, Fujian, Jiangxi, Henan, Hubei, Hunan, Guangxi, Chongqing, Sichuan, Guzhou, Yunnan, Shaanxi, Tianjin and Jiangsu.

Table 5: Initial Non-Exporters, Differential Trends & First-Differences (2SLS)

Dep. Var	SO_2 Emissions-Intensity				Dust Emissions-Intensity			
	Initial Non.	Diff. Trend (1)	Diff. Trend (2)	First-Diff.	Initial Non.	Diff. Trend (1)	Diff. Trend (2)	First-Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Export_t	-0.553***	-0.494***	-0.490***	-0.644***	-0.986***	-0.651***	-0.663***	-0.677**
	(-2.92)	(-4.15)	(-4.12)	(-4.59)	(-4.62)	(-4.40)	(-4.46)	(-4.13)
	[-0.884, -0.043]	[-0.781, -0.192]	[-0.723, -0.257]	[-1.028, -0.258]	[-1.397, -0.583]	[-0.988, -0.313]	[-1.273, -0.107]	[-1.036, -0.237]
Abatement_t	-0.407***	-0.348***	-0.314***	-0.408***	-0.108**	-0.432*	-0.408	-0.455*
	(-4.55)	(-4.04)	(-3.68)	(-4.08)	(-2.10)	(-1.85)	(-1.60)	(-1.81)
	[-0.705, -0.046]	[-0.596, -0.107]	[-0.922, 0.211]	[-0.698, -0.158]	[-0.196, 0.038]	[-1.023, 0.313]	[-2.936, 2.194]	[-1.633, 0.716]
Productivity_t	-0.269***	-0.281***	-0.273**	-0.050**	-0.407**	-0.303*	-0.313*	0.016
	(-2.98)	(-3.56)	(-2.47)	(-2.11)	(-2.67)	(-1.91)	(-1.89)	(0.30)
	[-0.374, -0.197]	[-0.374, -0.203]	[-0.409, -0.035]	[-0.159, 0.005]	[-0.499, -0.272]	[-0.449, -0.194]	[-1.504, 0.344]	[-0.253, 2.945]
Tariff_t	0.052	-0.488**	-0.468**	0.044	-0.122	-0.304	-0.269	-0.083
	(0.17)	(-2.54)	(-2.47)	(0.36)	(-0.32)	(-1.29)	(-1.16)	(-0.63)
	[-0.542, 0.645]	[-0.876, -0.117]	[-1.085, 0.144]	[-0.855, 0.611]	[-0.641, 0.714]	[-0.795, 0.186]	[-1.039, 0.489]	[-0.369, 0.213]
$\ln(K/L)_{t-1}$	-0.108***	-0.096***	-0.098***	-0.009	-0.100***	-0.089***	-0.091***	0.013
	(-6.65)	(-7.43)	(-7.57)	(-0.34)	(-4.91)	(-5.38)	(-5.36)	(0.72)
	[-0.135, -0.068]	[-0.127, -0.071]	[-0.179, -0.065]	[-0.039, 0.013]	[-0.150, 0.067]	[-0.139, -0.055]	[0.015,0.188]	[-0.039, 0.059]
$\ln(e/\bar{r})_{\text{initial}}$	0.293***	0.327***	0.329***		0.296***	0.352***	0.353***	
	(24.19)	(18.83)	(39.03)		(21.44)	(29.34)	(29.12)	
	[0.259, 0.322]	[0.308, 0.346]	[0.307, 0.338]		[0.268, 0.322]	[0.322, 0.377]	[0.215, 0.522]	
Province FE	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Industry FE	Yes	No	No	Yes	Yes	No	No	Yes
Year FE	Yes	No	No	Yes	Yes	No	No	Yes
Province-Year FE	No	No	Yes	No	No	No	Yes	No
Industry-Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F-statistic	27.53	72.15	105.39	14.09	21.19	20.47	24.72	14.74
Kleibergen-Paap LM-statistic	54.68	87.10	85.87	57.15	73.10	62.37	50.35	13.64
Hansen J-statistic	0.348	2.04	—	1.02	1.837	0.573	—	1.34
Adj. R^2	0.080	0.102	0.144	0.070	0.098	0.115	0.117	0.039
No. obs.	21784	46813	46813	22066	20011	44019	44019	20287

Notes: Standard errors are clustered at the industry (tariff) level. t-statistics are reported in parentheses where ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively. 95% bootstrap confidence intervals are reported in square brackets. We report the Cragg-Donald Wald F-statistic for weak instruments, Kleibergen-Paap rk LM statistic as an underidentification test, and the Hanson J-statistic of overidentifying restrictions.

fixed effects flexibly control for general changes in industrial composition, while maintaining our benchmark empirical specification without any further alterations. The updated findings are reported in columns (2) and (6) of Table 5. We observe that the estimated coefficients are remarkably close to their benchmark counterparts in Table 2. In each regression and for nearly every parameter, the estimated point estimate is very similar in sign, magnitude, and statistical significance.

In columns (3) and (6) we drop province-specific fixed effects and include province-year interacted fixed effects instead. The additional fixed effects flexibly control for differential trends across geographic space. They also completely absorb the ventilation coefficient instrument since it varies at the province-year level. We identify the regression coefficients in both stages of the 2SLS exercise despite having two endogenous variables because of the instruments interacted with initial productivity. Again, we observe very similar export and abatement estimates. Collectively, these exercises suggest that our benchmark fixed effects structure is not driving the results or that differential provincial investments are not a key source of bias.

6.1.5 First Differences

We next consider a first-difference specification of equation (23). The differenced specification inherently controls for any unobserved, time-invariant, firm-level heterogeneity. Including industry and province fixed effects control for differential trends across regions and industries. We report our findings for each pollutant in columns (4) and (8) of Table 5.

Similar to the sample of initial non-exporters, the estimated export coefficients are negative, slightly larger in absolute magnitude relative to the benchmark result, and statistically significant. The abatement coefficients are very similar to those in Table (2) and those reported in columns (1) or (5) of Table 5 despite the additional controls. Unlike the previous regressions, the coefficients on the productivity and capital-intensity variables are less strongly correlated with emissions intensity. This is not particularly surprising since both variables are highly persistent and change slowly over time.

6.2 Exporting and Emissions-Intensity: A Closer Look

In this section, we study the degree to which the impact of exporting can be attributed to other observable changes in firm-behavior which are omitted from our simple model. Exporting, for example, is often associated with technology upgrades (Bustos, 2011; Lileeva and Trefler, 2010), investment in new capital stock (Rho and Rodrigue, 2016), or changes in product scope (Nocke and Yeaple, 2014). Likewise, should trade liberalization have changed the relative price of clean and dirty inputs, we might expect that growing firms may disproportionately benefit from new, cleaner energy sources. If these mechanisms lead to changes in the effectiveness of abatement or the environmental efficiency in production, the reported export coefficient could be picking up these unaddressed firm and year specific differences across firms.

Incorporating complementary explanations into our benchmark regression allows us to effectively address two separate econometric concerns. First, the estimated coefficients on the export variable may be capturing other, omitted, firm-level changes which are correlated with exporting, abatement or both. Second, the exercise helps identify underlying mechanisms through which exporting affects firm-level emissions.

Specifically, we consider the following augmented emissions-intensity equation

$$\ln\left(\frac{e_{it}}{\bar{r}_{it}}\right) \quad = \quad \gamma_0 + \gamma_\theta \tilde{\theta}_{it} + \gamma_\delta \Gamma_t^x \delta_{it} + \gamma_\varphi \tilde{\varphi}_{it} + \gamma_\tau \tau_{m,ft} + \gamma_W W_{it} + \varepsilon_{it}^e \tag{24}$$

where W_{it} represents one or more auxiliary variables correlated with exporting, abatement and productivity and γ_W is the associated regression coefficient. In practice W_{it} corresponds to firm and sector measures of research and development, coal-based energy sourcing, capital vintage, and product mix. To capture the degree to which each mechanism particularly affects export-oriented firms we also consider specifications which interact each measure with firm-level export status.

Firm-level research and development, RD_{it}, is a binary variable that takes a value of 1 if firm i has positive R&D expenditures in year t. If R&D-intensive firms use cleaner technology than non-R&D firms, then we would expect its impact on emissions-intensity to be negative. Further, if exporting and $R\&D$ have complementary effects on emissions-efficiency we would likewise expect their interaction to further reduce emissions-intensity to be negative, while the opposite is the case should R&D and exporting offset each other.

Natural gas and coal, the latter of which is relatively emissions-intensive, are common energy sources among Chinese producers. Using firm-level data on the quantity consumed of each fuel type, we calculate the fraction of total firm-level heat content consumed from relatively dirty sources, NRG_{it}:

$$NRG_{it} = \frac{c_{coal} NRG_{it-1}^{coal}}{\sum_j c_j NRG_{it-1}^j}$$

where NRG_{it-1}^j is the quantity of energy source j consumed by firm i in the prior year, c_j is the energy conversion factor for each type of fuel from the US Energy Information Administration and $j \in \{\text{natural gas (NG), coal, petroleum, diesel fuel}\}$. We would generally expect that coal-intensive firms are likely to produce greater amounts of pollution, particularly with respect to SO_2. However, should exporters have stronger incentives to switch energy sources or preferential access to cleaner energy sources at seaboard locations, we would expect that exporters may disproportionately reduce emissions as they grow into global markets.

Capital vintage, VIN_{it}, measures the age of a firm's capital stock. Using data on the year of initial operation and annual observations of new investment in physical capital, we employ perpetual inventory methods to construct a measure of capital vintage for each firm in each year:

$$VIN_{it} = \sum_{\tau=t_{i0}-1}^{t-1} \left[\frac{i_\tau (1-d)^{t-\tau}}{\sum_{\tau=t_{i0}-1}^{t-1} i_\tau (1-d)^{t-\tau}}\right] (t-\tau) \tag{25}$$

where t is the current year, τ is a time index, i_τ is the value of new investment in physical capital in year t, d is the depreciation rate, t_{i0} is firm i's initial year of production, and $(t-\tau)$ measures age of a subset of the firm's capital stock. The term in square brackets is a weight placed on investment in different years, where we explicitly assume that new investment in period t does not become productive (or incorporated into the firms capital stock) until the subsequent year. The numerator captures the remaining value of undepreciated capital from investment in a particular year, while the denominator is a measure of total physical capital.

Among firms born after 1998 we observe the full set of firm-level investments in physical capital.[34] Among firms which are estalished prior to 1998, we assume that capital grew linearly between the date of establishment and 1998.[35]

Firm-level changes in capital-vintage captures indirect technological progress associated with exporting. While exporting is often associated with capital growth (Riaño, 2011; Alessandria and Choi, 2014; Rho and Rodrigue, 2016), few papers have explored the impact of new capital on emissions-intensity. New equipment, even if not purchased with the explicit purpose of reducing emissions, is likely to do so as long as new capital uses energy more efficiently than old capital.

As argued in Nocke and Yeaple (2014) exporting is often associated with changes in firm-level product mix. Following Barrows and Ollivier (2018) we also consider the environmental impact of changes in the set of goods produced and exported. Since our benchmark data sources do not contain product-specific information we compute changes in product mix by further matching our working sample with Chinese customs records.[36] Specifically, let j denote a 6-digit HS code from the Chinese customs data. We define the emissions-intensity of a particular HS code in 1999 as

$$\iota_{j,1999} = \sum_{i \in \Omega_j} s_{ij,99} \frac{e_{i,99}}{\bar{r}_{i,99}}$$

where s_{ij} is the export revenue share of firm i in total exports of good j and $e_{i,99}/\bar{r}_{i,99}$ captures the emissions-intensity of each firm which produces HS code j. We then aggregate over all of the HS codes exported by firms in a given industry

$$MIX_{st} = \sum_{j \in \Omega_s} s_{jt} \iota_{j,1999} \tag{26}$$

where s_{jt} is the share of total export revenue attributed to exports of HS code j from firms which have industry code s. If the industry's product mix shifts towards products which are inherently dirtier (cleaner) it should be captured by MIX_{st}.[37]

Our initial regression exercises treat each new firm-level characteristic as weakly exogenous. This assumption is undoubtedly strong, but plausible in each case; the benefits of R&D or investment in physical capital are typically assumed to manifest themselves in the year subsequent to the year of investment (Aw et al, 2011; Rho and Rodrigue, 2016). Likewise, changes in energy sources or product mix require significant lead time. We further lag each of these variables to ensure that they are predetermined to current firm-level decisions.

Nonetheless, the interactions of each characteristic with firm-level export decisions remain endogenous to current emission-intensity. We augment the initial instrument set to include the firm's lagged export decision and interactions with each new firm-level characteristic. Using

[34] In practice, we assume that first-year capital stock is the firm's investment in physical capital in the year prior to entry and assume a depreciation rate of 9 percent consistent with Brandt, Van Biesebreck and Zhang (2012).

[35] Specifically, we need to calculate the investment flows which generated the initial capital in year t, when we first observe the firm. We assume $\bar{i}_\tau = \frac{d}{1-(1-d)^{t-t_{i0}+1}} k_t$ where k_t is the firm's capital stock in year t, where $\tau < t$. This implies that the initial capital vintage assigned to this firm is $VIN_{initial} = \frac{1}{k_t} \sum_{\tau=t_{i0}-1}^{t} \bar{i}(1-d)^{t-\tau}(t-\tau)$. Although a strong assumption, many firms were established during the early to mid 1990s and, as such, this assumption is relatively modest given this short time frame.

[36] We use standard matching approaches to match our benchmark sample with the Chinese customs records. Details can be found in the appendix.

[37] Although it would be possible to measure export product mix at the firm-level, we would only be able to do so among exporting firms which would rule out specification (24).

the augmented set of explanatory varaibles we report our OLS findings for SO_2 in Table 6 and the analogous 2SLS results in Table 7. For brevity, the corresponding results for industrial dust, which feature nearly identical empirical patterns, are relegated to the appendix.

Tables 6 and 7 consider eleven separate specifications. The first column of each table reproduces our benchmark estimates for comparison purposes. Each pair of subsequent columns consider a single additional co-variate and its interaction with export status. For example, column (2) adds the *R&D* variable, while column (3) includes both *R&D* and its interaction with export status. Finally, the last two columns consider the impact of adding all of the additional explanatory variables simultaneously.

With the exception of column (9), the OLS estimates indicate that the inclusion of alternative explanatory variables, or their interactions with export status, have little impact on the estimated export or abatement coefficients. This does not imply, however, that these additional variables are weakly correlated with emissions-intensity. Rather, the *R&D*, energy and capital vintage variables are all highly significant and have their expected signs. The interactions between the energy, capital vintage and product mix variables with export status likewise suggest important heterogeneous effects. Indeed, the export coefficient is small and insignificant in column (9) when we include its interaction with the product mix variable.

Table 7 reports analogous 2SLS results. Again, the abatement coefficient is likewise stable and very close to the benchmark result in all columns, while the export coefficient is nearly always large, negative and statistically significant. The addition of capital vintage or product mix, when interacted with export status, reduces the export coefficient substantially. The addition of capital vintage interacted with export status reduces our benchmark export coefficient by 50 percent. Although firms with older capital stocks appear to be more emissions-intensive, the impact of vintage on emissions is half as large among exporting firms. One interpretation of the estimated coefficient differences is that capital upgrading among exporters particularly affected the environmental efficiency of production. Alternatively, consistent with Schott (2003) and Boehm et al. (2019), changing input structure may reflect underlying changes in the firm's product mix.

Indded, when we examine changes in product mix directly, we again observe the the addition of these co-variates significantly reduce the benchmark export coefficient. The estimates are consistent with the notion that the mix of products exported by Chinese producers became cleaner over time. This pattern may reflect changing industrial composition towards higher value goods or the offshoring of the dirtiest products to other countries among trade-oriented, coastal firms.

We also consider a LASSO (least absolute shrinkage and selection operator) approach to estimating the specifications in columns (10) and (11) of Tables 6 and 7 in separate estimation exercises (Tibshirani 1996). These regressions test whether each variable, including export status, has additional explanatory power for firm-level emissions-intensity beyond the other regression co-variates. For comparisons with our benchmark IV regressions we implement the LASSO with instrumental variables estimator (Belloni et al, 2016). The LASSO regressions always retain all of our benchmark and additional co-variates and return very similar results to those reported in Tables 6 and 7.[38]

[38]Tables 14 and 15 document a full set of complementary results for industrial dust, while all LASSO regression findings are presented in Table 16.

Table 6: Exporting, Abatement and SO_2 Emissions Intensity (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Export$_t$	-0.114***	-0.101***	-0.103***	-0.107***	-0.096***	-0.113***	-0.137***	-0.115***	-0.035	-0.092***	-0.090**
	(-12.78)	(-9.19)	(-8.60)	(-10.25)	(-6.91)	(-10.44)	(-7.51)	(-10.82)	(-1.00)	(-8.90)	(-2.57)
R&D$_{t-1}$		-0.303***	-0.308***							-0.284***	-0.299***
		(-12.70)	(-10.05)							(-12.55)	(-9.96)
R&D$_{t-1}$ × Export$_t$			0.006								0.014
			(0.33)								(0.084)
NRG$_{t-1}$				1.700***	1.726***					1.678***	1.688***
				(22.05)	(21.66)					(22.02)	(21.38)
NRG$_{t-1}$ × Export$_t$					-0.030						-0.010
					(-1.15)						(-0.39)
K-Vintage$_t$						0.059***	0.069***			0.045***	0.058***
						(6.74)	(5.85)			(4.58)	(5.05)
K-Vintage$_t$ × Export$_t$							-0.014*				-0.019**
							(-1.62)				(-2.20)
Product Mix$_t$								-0.019	-0.009	-0.020	-0.015
								(-0.097)	(-0.44)	(-1.03)	(-0.76)
Product Mix$_t$ × Export$_t$									-0.013***		-0.006
									(-2.33)		(-1.13)
Abatement$_t$	-0.446***	-0.403***	-0.403***	-0.426***	-0.426***	-0.408***	-0.407***	-0.407***	-0.407***	-0.421***	-0.420***
	(-23.06)	(-17.20)	(-17.21)	(-17.10)	(-17.09)	(-17.47)	(-17.45)	(-17.40)	(-17.42)	(-16.89)	(-16.89)
Productivity$_t$	-0.223***	-0.167***	-0.168***	-0.164***	-0.165***	-0.165***	-0.166***	-0.156***	-0.162***	-0.186***	-0.190***
	(-4.00)	(-2.98)	(-2.99)	(-3.14)	(-3.14)	(-2.90)	(-2.91)	(-2.80)	(-2.87)	(-3.45)	(-3.49)
Tariff$_t$	0.234	0.043	0.042	0.097	0.105	0.068	0.069	0.084	0.089	0.070	0.075
	(1.60)	(0.30)	(0.29)	(0.70)	(0.76)	(0.48)	(0.49)	(0.57)	(0.61)	(0.50)	(0.53)
$\ln(K/L)_{t-1}$	-0.140***	-0.105***	-0.105***	-0.099***	-0.099***	-0.118***	-0.119***	-0.117***	-0.118***	-0.089***	-0.089***
	(-15.33)	(-11.58)	(-11.60)	(-11.08)	(-11.09)	(-12.75)	(-12.74)	(-12.61)	(-12.68)	(-10.04)	(-10.10)
$\ln(e/\bar{r})_{\text{initial}}$	0.302***	0.316***	0.316***	0.303***	0.303***	0.318***	0.318***	0.316***	0.317***	0.304***	0.305***
	(14.89)	(14.34)	(14.35)	(13.93)	(13.89)	(14.43)	(14.44)	(14.35)	(14.35)	(13.92)	(13.89)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.174	0.179	0.180	0.205	0.205	0.176	0.176	0.176	0.176	0.209	0.210
No. obs.	47,984	47,984	47,984	47,984	47,984	47,984	47,984	47,984	47,984	47,984	47,984

Notes: t-statistics are reported in parentheses. Standard errors are clustered at the industry (tariff) level. ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively.

Table 7: Exporting, Abatement and SO_2 Emissions Intensity (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Export$_t$	-0.452***	-0.578***	-0.637***	-0.584***	-0.127***	-0.630***	-0.199***	-0.633***	-0.020	-0.586***	-0.105***
	(-4.66)	(-4.25)	(-3.93)	(-4.62)	(-10.31)	(-5.04)	(-9.91)	(-4.56)	(-0.58)	(-4.10)	(-2.66)
R&D$_{t-1}$		-0.152***	-0.572***							-0.133***	-0.306***
		(-3.09)	(-6.43)							(-2.75)	(-11.09)
R&D$_{t-1}$ × Export$_t$			0.405***								0.029
			(3.18)								(1.57)
NRG$_{t-1}$				1.593***	1.700***					1.581***	1.655***
				(26.18)	(28.44)					(26.19)	(27.61)
NRG$_{t-1}$ × Export$_t$					-0.044**						-0.017
					(-2.05)						(-0.77)
K-Vintage$_t$						0.035***	0.079***			0.024**	0.066***
						(3.21)	(7.16)			(2.20)	(6.07)
K-Vintage$_t$ × Export$_t$							-0.029***				-0.031***
							(-3.02)				(-3.30)
Product Mix$_t$								0.032*	0.005	0.030*	-0.002
								(1.90)	(0.46)	(1.76)	(-0.23)
Product Mix$_t$ × Export$_t$									-0.020***		-0.012**
									(-3.72)		(-2.17)
Abatement$_t$	-0.396***	-0.321***	-0.332***	-0.367***	-0.376***	-0.325***	-0.334***	-0.318***	-0.330***	-0.350***	-0.356***
	(-4.65)	(-3.86)	(-4.00)	(-4.25)	(-4.26)	(-3.90)	(-3.92)	(-3.80)	(-3.85)	(-4.08)	(-4.10)
Productivity$_t$	-0.313***	-0.295***	-0.303***	-0.297***	-0.169***	-0.308***	-0.172***	-0.302***	-0.173***	-0.308***	-0.196***
	(-3.94)	(-3.76)	(-3.68)	(-3.81)	(-3.80)	(-3.82)	(-3.62)	(-3.68)	(-3.62)	(-3.82)	(-4.13)
Tariff$_t$	0.147	-0.076	-0.126	-0.039	0.093	-0.077	0.053	-0.078	0.074	-0.061	0.066
	(1.06)	(-0.68)	(-1.07)	(-0.35)	(0.90)	(-0.68)	(0.52)	(-0.68)	(0.72)	(-0.54)	(0.64)
$\ln(K/L)_{t-1}$	-0.112***	-0.081***	-0.086***	-0.069***	-0.098***	-0.084***	-0.118***	-0.083***	-0.118***	-0.064***	-0.091***
	(-9.20)	(-7.20)	(-8.20)	(-5.84)	(-12.23)	(-6.98)	(-14.49)	(-6.58)	(-14.48)	(-5.62)	(-11.33)
$\ln(e/\bar{r})_{\text{initial}}$	0.300***	0.313***	0.312***	0.300***	0.304***	0.314***	0.318***	0.313***	0.316***	0.305***	0.305***
	(38.12)	(56.28)	(54.94)	(54.39)	(56.19)	(55.85)	(58.84)	(56.01)	(58.79)	(53.77)	(56.18)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F-stat	104.92	53.96	36.65	60.18	482.94	64.01	485.44	51.86	484.95	47.83	301.53
Kleibergen-Paap LM-stat	223.96	161.60	147.96	182.04	220.31	193.56	233.57	156.97	233.22	144.81	232.10
Hansen J-stat	0.98	0.40	1.76	1.03	1.78	0.42	1.86	0.40	1.640	3.07	1.764
Adj. R^2	0.136	0.113	0.116	0.136	0.207	0.096	0.179	0.094	0.178	0.136	0.213
No. obs.	46,821	46,821	46,821	46,821	46,821	46,821	46,821	46,821	46,821	46,821	

Notes: t-statistics are reported in parentheses. Standard errors are clustered at the industry (tariff) level. ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively. We report the Cragg-Donald Wald F-statistic for weak instruments, Kleibergen-Paap rk LM statistic as an underidentification test, and the Hanson J-statistic of overidentifying restrictions.

7 Structural Interpretation

This section uses the reduced-form estimates to recover the model's structural parameters. We use our benchmark 2SLS estimates from Table 2 to back out the implied model parameter values for the emissions returns to scale parameter, β, abatement efficiency parameter, α, the elasticity of substitution, σ, and the traded input share parameter, ν, using the structural relationships outlined in Table 1.

Table 8: Implied Structural Parameters

		SO_2		Industrial Dust	
		OLS	2SLS	OLS	2SLS
	Parameter Interpretation	(1)	(2)	(3)	(4)
β	Emissions RTS	0.888	0.553	0.863	0.285
σ	Elasticity of Substitution	10.817	2.690	9.159	1.570
α	Abatement Efficiency	0.647	0.869	0.743	1.128
ν	Traded Input Share	1.003	0.618	0.656	0.229

Notes: The above table documents the implied structural parameters from the estimation of equation (23). The relationships between the reduced-form and structural parameters are documented in Table 1.

The 2SLS estimates of the parameter β, which capture the impact of exporting on abatement, ranges between 0.285 and 0.553 across air pollutants. This parameter indicates that a 100 percent increase in production will increase emissions by at most 55 percent. The OLS estimates, in constrast, suggest a much tighter relationship between firm-expansion and pollution growth. Across pollutants doubling production implies 86-89 percent increase in pollution. Nonetheless, even at the OLS upper bound, our estimates imply that trade-induced expansions increase pollution at a significantly slower rate than the growth in production.

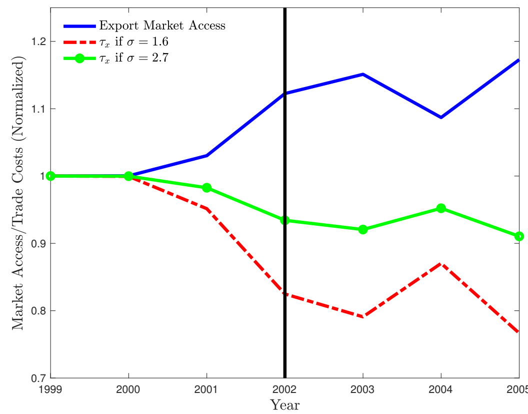
Our 2SLS estimates imply an elasticity of substitution in the range of 1.6-2.7 across pollutants, which similar to those reported elsewhere in the literature (Simonovska and Waugh, 2014; Soderbery, 2015)[39] In general, the implied elasticity of substitution is highly sensitive to the point estimate of β. Case in point: the OLS estimates of β and σ are both much larger than their 2SLS counterparts.

Larger values of β and σ in turn imply smaller values of α, the abatement efficiency parameter. The abatement efficiency parameter is estimated to fall between 0.647 (OLS) and 0.869 (2SLS) for SO_2 and between 0.743 (OLS) and 1.128 (2SLS) for industrial dust. In the context of the workhorse model, a one percent increase in abatement, θ_i, will reduce emissions by roughly $\frac{1}{\alpha}\left(\frac{\theta_i}{1-\theta_i}\right)$ percent. For the median firm, our 2SLS estimates imply that a 10 percent increase in abatement would reduce SO_2 emissions by 12 percent. In contrast, the same investment in abatement only decreases industrial dust emissions by 9 percent.

In principle, the reduced-form estimates also provide a sense of the foreign traded input share. Across air pollutants the 2SLS estimates imply that ν is predicted to lie between 0.23 (industrial dust) and 0.62. While plausible for both air pollutants, it is worth nothing that our point estimate on the input tariff variable, γ_τ, was never precisely estimated in any of our reduced-form regressions and the implied structural values are likewise relatively uncertain.

[39]Further, the implied markups are consistent with the range of manufacturing markups reported in Lu and Yu (2015) and Rodrigue, Sheng and Tan (2020).

Last, the reduced form regressions also identify the implied change in export market access. In Figure 5 the solid blue line plots a spike in export market access upon WTO-accession in 2002. We further characterize the implied change in trade costs up to the normalization of export market size ($\phi = 1$) and the estimated elasticity of substitution (σ). Higher values of σ imply that trade flows are very sensitive to trade costs and, as such, the same change in export market access can be justified by smaller changes in trade costs.



Notes: The above figure plots the implied change in market access trade costs between 1999 and 2005.

Figure 5: Market Access/Trade Costs

The red dashed line captures the implied change in trade costs when $\sigma = 1.6$, our lowest estimated elasticity, while the green depicts the change in trade costs when $\sigma = 2.7$, our largest estimate. In the latter case, trade costs fall by a smaller amount, but trade flows nonetheless grow just as rapidly given the high value of σ.

Table 9: Emissions Taxes

Pollutant	Coefficient of Variation	Average Annual Emissions Taxes (Normalized) 1999	2000	2001	2002	2003	2004	2005
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SO_2	2.770	0.963	0.916	0.937	1.000	1.125	1.124	1.225
Dust	1.572	0.732	0.892	0.840	1.000	0.975	0.939	1.073

Table 9 documents the coefficient of variation for implied firm-level emissions taxes along the average annual emission tax implied by the model's structural parameters under the assumption that all firms use the same production and abatement technology and face the same underlying demand conditions. We relax these assumptions below. We normalize average implied emissions taxes to 1 in 2000.

Our counterfactual experiments employ the structural parameters to back out the implied emissions taxes for each firm in each year using the relationship in equation (14). Table 9 collects summary statistics for the implied emissions taxes under our benchmark assumptions. In column (1) we report the coefficient of variation, or the standard deviation of the implied emissions taxes divided by the mean, while in columns (2)-(8) we document annual levels of emissions taxes after normalizing the level in 2002 to one. The values in columns (2)-(8) do not directly depend on any structural parameters in an of themselves, but nonetheless reflect two key patterns for our model. First, there was remarkable variation in the degree to which firms faced emissions regulation; the standard deviation of emissions taxes is greater than 150% of the mean for both four pollutants. Second, average annual emissions taxes grew over our sample period for both pollutants. For SO_2 there is a 30 percent rise in implied emissions taxes and the largest increases occur after WTO accession. Industrial dust displays a similar empirical pattern, though the post-2002 growth is relatively modest.

7.1 Allowing For Production, Abatement and Demand Heterogeneity

A potential concern with our structural estimates, and the subsequent counterfactual policy analysis based upon them, is that they rely heavily on a high degree of parameter homogeneity across very different producers and require that these relationships remain stable over time. For example, Rodrigue and Tan (2019) and Rodrigue, Sheng and Tan (2020) find evidence of increasing markups over time among Chinese manufacturers. Rising markups suggest that σ fell over time and, as such, other structural parameters may be biased accordingly. We likewise expect that differences in demand or production technology may vary across sectors, regions, ownership-type or time.

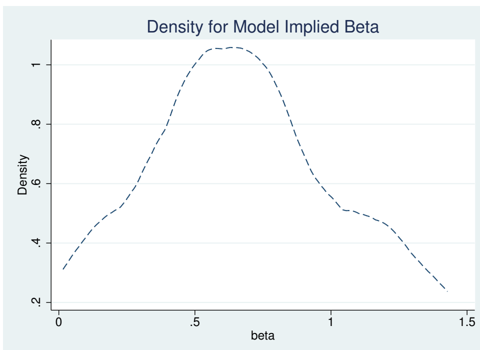
To investigate the degree to which variation in production, abatement or demand conditions affect our structural estimates, we reconsider our benchmark exercises but allow for parameter variation across firms and time on each of these dimensions. Specifically, for a given time period, we re-estimate equation (23) for each set of 'similar' firms in our data. Firms are grouped into sets which share the same location (coastal or non-coastal), and ownership structure (foreign, state-owned or private), the same broad sectoral classification.[40] For each group of firms we separately recover all of the structural parameters in three time periods: the pre-WTO (1999-2001), early post-WTO (2002-2003) and late post-WTO (2004-2005). Using the recovered distributions of reduced-form estimates we back out structural parameters for each firm in each year. Figure 6 displays the full distribution of recovered structural parameters.

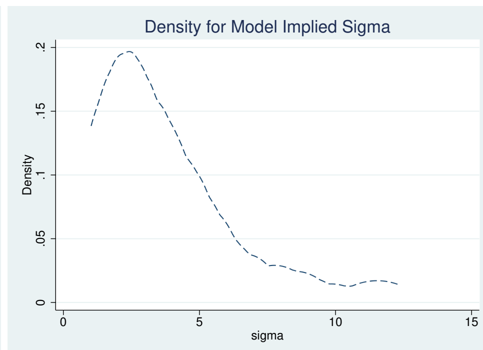
There are two salient features of each distribution. First, there is wide heterogeneity in the recovered structural parameters. This feature is important in that it affects both implied emissions taxes and the responsiveness of individual firms to policy change. Second, the modal estimate of each structural parameter is very close to its full-sample, single-estimate counterpart. For instance, the distribution for the β parameter displays a large amount of mass near 0.5-0.6, which is very close to our single parameter estimate of 0.55 for SO_2 in Table 8. However, it also suggests that there are many firms for which this value of β would be misleading. Indeed, a significant number of sub-groups return values of β which are greater than 1, indicating that increases in production will lead to increasing rates of emissions. Inspection of panels (b), (c) and (d) reveal similar patterns for σ, α and ν. The evolution of trade costs also suggest significant variability across regions, ownership and sector, but are again broadly consistent with the implications from the model which imposes a single-trade cost parameter across all firms in a given year.

7.2 Counterfactual Policy Experiments

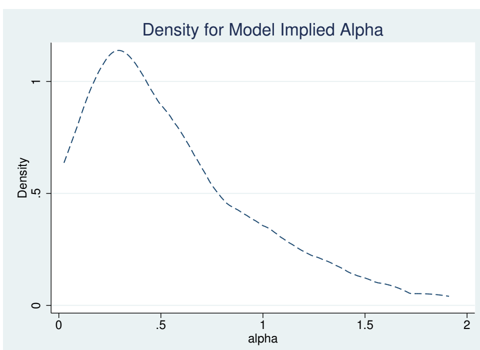
This section leverages our structural model to study the impact of policy change on output, export and emissions growth in China. For parsimony, we restrict attention to the quantitative

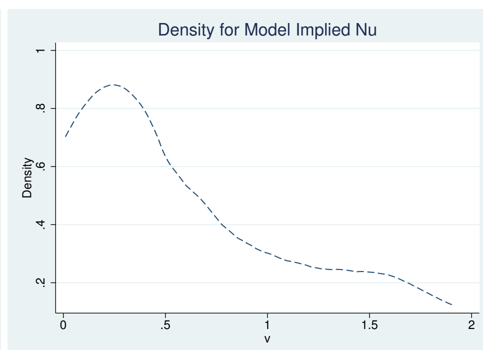
[40] This approach is consistent with a nested CES demand structure for each sub-group of firms.





(a) β (b) σ





(c) α (d) ν

Notes: Panels (a)-(d) report the full distribution of recovered structural parameters - β, σ, α and ν, respectively, when we allow for demand and technological heterogeneity.

Figure 6: Structural Parameters Allowing for Demand and Technological Heterogeneity

model that allows variation in the parameters which govern the firm's demand function and production technology.[41]

We consider three distinct counterfactual policy alternatives to answer the following three questions:

1. Did heterogeneous emissions taxes exacerbate or mitigate the observed emissions growth after China's WTO accession?

2. How rapidly would Chinese emissions taxes have needed to grow to restrict aggregate emissions to the level observed prior to WTO accesion?

3. How much do emissions fall as trade costs rise?

To answer the first question, we compare the observed trajectory of aggregate emissions to one where each firm pays the same uniform emission tax in each year.[42] To keep our experiment as transparent as possible we fix the emissions tax in each year at the mean level observed in our data and recompute each producer's optimal response. In this sense, the first experiment allows us to quantify the degree to which enforced environmental policies disproportionately penalized heavy polluters. Likewise, to the extent that uniform emissions taxation slows (increases) emissions, we quantify the decline (rise) of output and exports under the alternative policy.

The second counterfactual exercise uses the structural model to determine the degree of regulation needed to hold aggregate emissions constant from 2002 onwards. Numerous papers investigate the degree to which trade liberalization complements 'deep intregration,' or the coordination of domestic policy change as countries reduce barriers to global markets (Bagwell et al., 2016). In a similar manner, our last experiment quantifies the (Chinese) environmental benefits to export market access trade costs. We measure the tradeoff between policy induced reductions output and exports and the consequent reductions in emissions.

In each experiment we are careful to account for endogenous firm-level export, abatement and production responses to policy change. Using the model's implied emissions taxes, tariffs and changes in export market access we flexibly estimate the firm's decision to export. Conditional on the firm's export decision, we use the model implied parameters to impute optimal abatement and output choices. We then aggregate all of the firm-level responses to characterize the change in aggregate outcomes. For brevity, we focus on the SO_2 emissions alone.[43]

Uniform Emissions Taxes

In this experiment we consider the impact of uniform emissions taxes. Specifically, we measure the (emissions-weighted) average emission tax applied to each unit of Chinese emissions in each year as

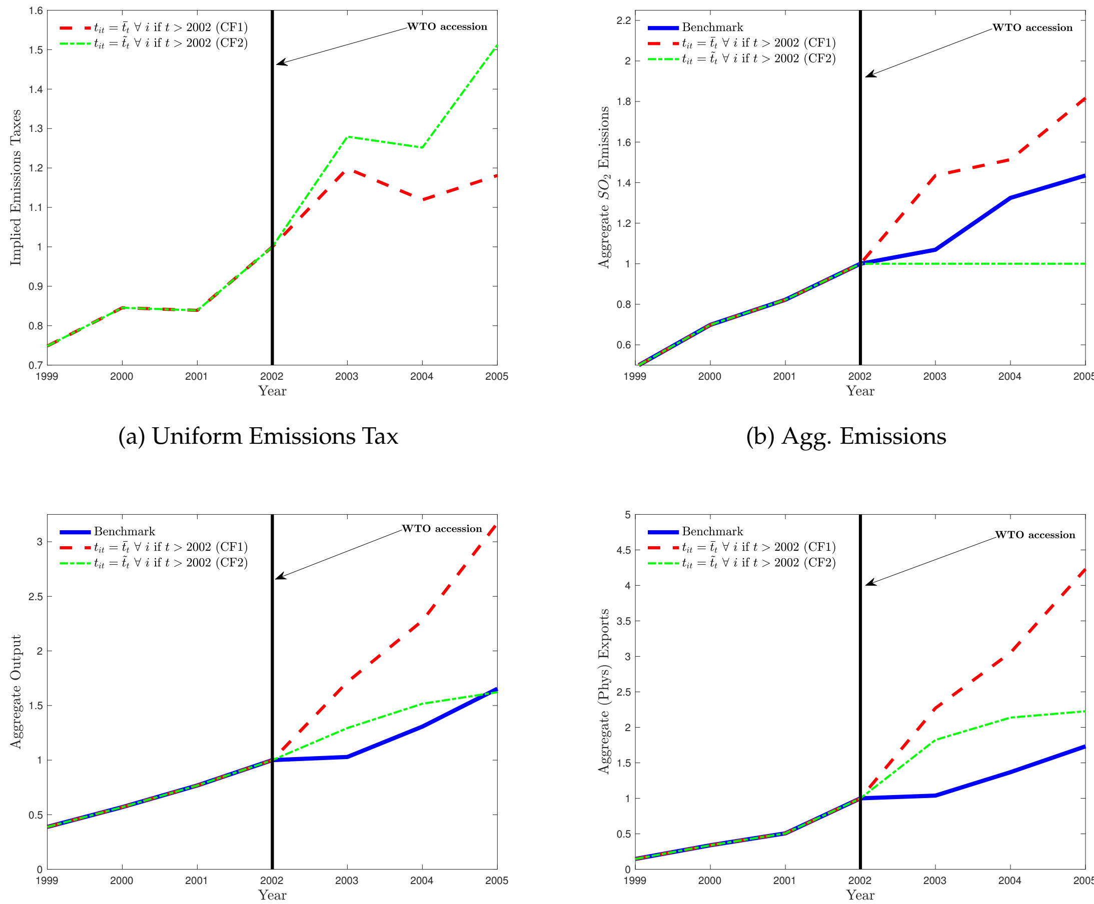
$$\bar{t}_t = \frac{e_{it}}{\sum_i e_{it}} t_{it}$$

[41] A comparison with the quantitative model which imposes homogeneous structural parameters across all firms can be found in the Supplemental Appendix. Regardless of the parameterization assumptions, the counterfactual findings are qualitatively similar, though there are quantitative differences.

[42] Uniform emissions taxes are often posited as an efficient policy tool for reducing global emissions (Shapiro, 2019).

[43] Similar results were found for industrial dust. A detailed description of the counterfactual algorithm can be found in the appendix. We abstract from general equilibrium responses to policy change.

and compute the endogenous firm-level responses from facing $t_{it} = \bar{t}_t$ in every year after 2002. Figure 7 reports the aggregate emissions, output and export consequences of uniform emissions taxation.



(a) Uniform Emissions Tax

(b) Agg. Emissions

(c) Agg. Output

(d) Agg. Exports

Notes: The solid blue lines in panels (b)-(d) plot the implied evolution of aggregate emissions, output and exports in the benchmark model. The red dashed line in panel (a) plots the uniform emissions tax equal to the average implied emissions tax in the data ($\bar{t}$), while the red dashed line plot the counterfacual path of the same aggregate variables under this counterfactual policy in every year after 2002 ($t_{it} = \bar{t}$ after 2002). The green dotted line in panel (a) plots the uniform emissions tax aggregate emissions constant after 2002 ($\tilde{t}_t$), while the green dotted line in panels (b)-(d) plots the counterfacual path of the same aggregate variables under the same emission tax ($t_{it} = \tilde{t}$ after 2002).

Figure 7: Uniform Emissions Taxes and SO_2 Emissions

Moving to uniform emissions taxes causes aggregate emissions to rise; by 2005 aggregate emissions would have been 27 percent greater under uniform taxation then it was under the benchmark, heterogeneous environmental taxation. This suggests that, on average, Chinese policy over the 2002-2005 period generally targeted emissions-intensive firms.

The lost output and exports from targeted emissions taxation is predicted to be substantial. Under the alternative policy of uniform taxation, output is predicted to be 92 percent greater in 2005, while exports rise by 144 percent in the same year. While targeting emissions-intensive firms significantly reduced emissions, it also slowed what would have been even greater Chinese growth.

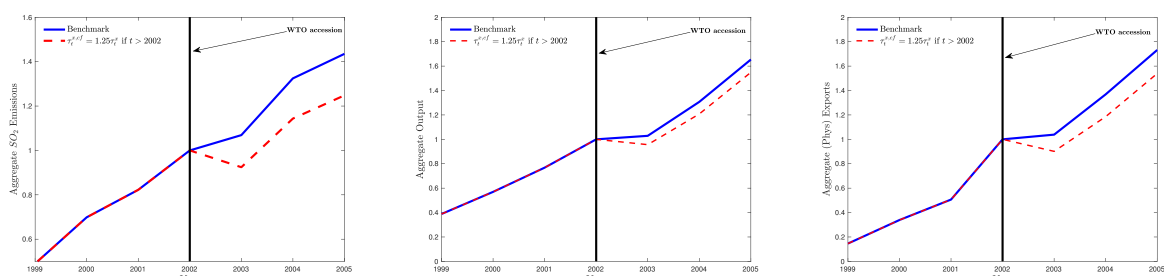
The Economic Costs of Environmental Policy

The second counterfactual policy exercise builds on the first by increasing uniform tariffs to the point such that emissions remain constant from 2002 onwards. Given that trade costs decline and productivity rises over time, higher emissions taxes are required to keep aggregate emissions in check. Nonetheless, as documented in Figure 7, the 2005 emissions tax necessary to keep aggregate emissions constant at their 2002 level is nearly 30 percent higher than the (weighted) average emissions tax in the data.

Although a higher uniform tax does cause output and exports to fall relative to our first counterfactual, it is remarkable that they are similar or greater than their benchmark levels. This reinforces the distortionary nature of heterogeneous emissions taxation; greater uniform taxation is predicted to both provide much greater mitigation of SO_2 emissions and encourage greater export growth relative to our benchmark simulation. For example, the 30 percent increase in the price of emissions causes aggregate 2005 manufacturing output to fall by 48 percent in comparison to the first counterfactual. However, aggregate output only fell by 2 percent relative to the benchmark simulation. Moreover, aggregate exports remain above the benchmark throughout the 2002-2005 period despite the large rise in the price of emissions.

The (Local) Environmental Benefits of Trade Costs

Our third counterfactual considers the impact of rising trade costs on emissions. Specifically, we increase export market access by 25 percent, say due to higher tariffs in foreign markets.[44] We consequently expect exports and output to fall, which will in turn induce reductions in emissions.



(a) Agg. Emissions (b) Agg. Output (c) Agg. Exports

Notes: The solid blue lines in panels (a)-(c) plot the implied evolution of aggregate emissions, output and exports in the benchmark model. The red dashed lines in panels (a)-(c) plot the counterfacual path of the same aggregate variables under the counterfactual policy $\tau_t^{x,cf} = 1.25\tau_t^x$ in every year after 2002.

Figure 8: Trade Costs and SO_2 Emissions

[44]For example, Fajgelbaum et al. (2019) report that the US raised tariffs on 11,207 products from China to the USA. On average, tariffs rose from 3 to 15.5 percent and affected nearly 49 percent of all trade flows from China to the USA.

By 2005 aggregate emissions would have been 13 percent smaller than that under the observed policy, while output and exports fall by 6 and 11 percent, respectively. The relatively large decline in emissions reflects the fact that β is estimated to be greater than one for many large and emissions-intensive producers. Aggregate emissions fall disproportionately relative to output and exports because of the disproportionate decline among these large producers.

In contrast, median firm emissions decline less than output and exports in response to increased trade costs. For the median firm $\beta < 1$ and a smaller scale of production offsets the emissions gains from reduced production.[45] Indeed, these offsetting effects across heterogeneous producers result in a small change in average firm-level abatement. Average investment in abatement is predicted to fall by only 1.5 percent in response to the policy change.

8 Conclusion

This paper demonstrates that Chinese exporters are significantly less-emissions intensive relative to their non-exporting counterparts, at least for two common air pollutants (SO_2 and industrial dust). We also document that this difference cannot be explained by differential rates of abatement alone and extend the standard heterogeneous firms, trade and emissions model to match these stylized facts. Our model features export-driven emission-complementarities, such as changes in product mix or the investment in energy-efficient capital. Using exogenous variation in trade policy and geographic variation in the dispersion of air pollution, we quantify the impact of endogenous export and abatement decisions on firm-level emissions. We find that exporting *reduces* emissions-intensity by at least 45 percent across all air pollutants. Observable changes in energy sourcing, product scope and capital-vintage account for at least half of the empirical relationship between exporting and air emission-intensity. Abatement, in contrast, has a much smaller impact on emissions. For the average firm, endogenous abatement decisions reduced emissions by 4 percent.

Recovering the model's structural parameters from our reduced form estimates we conduct a series of counterfactual experiments in quantify the trade-offs between emissions and output growth. We find that moving to uniform taxation after WTO-accession would have encouraged greater export and output growth, but would have also caused SO_2 emissions to rise by 27 percent. Surprisingly, increasing uniform emission-taxes to the point such that aggregate manufacturing emissions were constant after 2002 slows counterfactual output and export growth, but they are still predicted to remain near or above observed levels in the data. This suggests that increasingly stringent uniform emissions taxes may lead to both lower emissions and allocative efficiency gains in the Chinese manufacturing sector.

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[45] We further explore this aspect of our third counterfactual exercise in the Supplemental Appendix.

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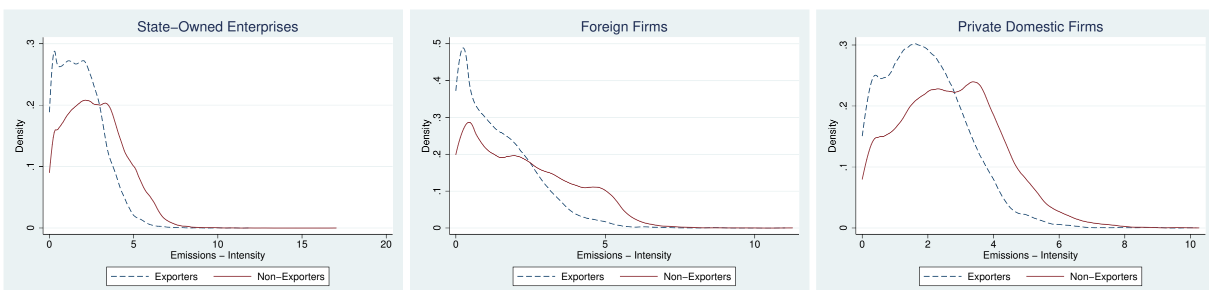
A Tables and Figures

Table 10: Summary Statistics

Sample	Manufacturing Survey			Environmental Survey			Matched Sample		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Revenue	70661.6	16300	625250.4				177637.8	34158.5	986270.4
Export Rev.	13290.7	0	205692.1				24820.1	0	242430.9
Capital	38858.3	4490.8	569630.3				130864.5	17368.2	960519.3
Labor	299.6	117	1348.1				806.04	277	3985.4
Tariffs	12.47	10.3	12.36				12.04	9.4	12.90
SO_2 Emis.				212536.8	7440	2268869	356884.1	12000	2953672
Dust Emis.				105361.1	2750	1026575	155362.3	3635	1320615
SO_2 Abt-Int.				0.091	0	0.211	0.113	0	0.229
Dust Abt-Int.				0.543	0.8	0.404	0.615	0.8	0.381
Productivity							0.038	0.016	0.182

Notes: The above table reports summary statistics for three samples. The leftmost panel reports summary statistics for the manufacturing survey collected by NBS, the center panel reports summary statistics for the environmental survey collected by MEE, and the rightmost panel reports summary statistics for the matched sample used our benchmark regression exercises.



(a) SOEs

(b) Foreign Firms

(c) Private, Domestic Firms

Notes: The solid blue line and the dashed blue line respectively plot the average firm-level SO_2 emissions and abatement among exporting firms. The solid red line with circles and the dashed red line with circles respectively plot the average firm-level SO_2 emissions and abatement among non-exporting firms. Emissions/abatement values are normalized by the average exporter in 2002.

Figure 9: SO_2 Emissions-Intensity Across Export Status

Table 11: First Stage Estimates, (Table 2, All Variables)

Pollutant	SO_2		Dust	
Dep. Variable	Export	Abatement	Export	Abatement
	(1)	(2)	(3)	(4)
Ventilation	0.260*	-0.002	0.269*	-0.399**
	(1.85)	(-0.02)	(1.92)	(-2.35)
Ventilation × Initial Prod.	0.004	0.067***	0.002	0.023***
	(1.28)	(16.56)	(0.61)	(5.82)
Initial Tariff × Initial Prod.	0.122***	-0.004	0.125***	-0.012
	(13.51)	(-1.02)	(13.57)	(-1.40)
Productivity$_t$	0.298***	0.041**	0.318***	-0.454***
	(2.93)	(2.37)	(2.95)	(-3.66)
Tariff$_t$	-0.123	-0.053	-0.130	-0.001
	(-1.38)	(-1.26)	(-1.47)	(-0.01)
$\ln(K/L)_{t-1}$	0.077***	0.026***	0.079***	0.043***
	(13.23)	(8.42)	(13.12)	(6.11)
$\ln(e/\bar{r})_{\text{initial}}$	-0.006***	-0.005***	-0.018***	0.019***
	(-2.74)	(-3.47)	(-7.27)	(5.55)
Province FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: t-statistics are reported in parentheses. Standard errors are clustered at the industry (tariff) level. ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively.

Table 12: First Stage Estimates, (Table 3, Excluded Instruments Only)

Pollutant, Sample	SO_2, SOE		Dust, SOE	
Dep. Variable	Export	Abatement	Export	Abatement
	(1)	(2)	(3)	(4)
Ventilation	0.106	0.048	0.100	-0.047
	(0.64)	(0.50)	(0.60)	(-0.24)
Ventilation × Initial Prod.	0.006	0.066***	0.003	0.017***
	(1.40)	(11.94)	(0.65)	(3.62)
Initial Tariff × Initial Prod.	0.171***	-0.008	0.175***	-0.004
	(14.23)	(-1.51)	(14.07)	(-0.36)
Pollutant, Sample	SO_2, Private		Dust, Private	
Dep. Variable	Export	Abatement	Export	Abatement
	(5)	(6)	(7)	(8)
Ventilation	0.587**	-0.143	0.657**	-0.912***
	(2.15)	(-1.20)	(2.39)	(-2.67)
Ventilation × Initial Prod.	0.005	0.068***	0.003	0.017**
	(0.81)	(9.01)	(0.35)	(1.96)
Initial Tariff × Initial Prod.	0.043***	-0.000	0.041***	-0.030*
	(2.95)	(-0.02)	(2.85)	(-1.73)
Pollutant, Sample	SO_2, Foreign		Dust, Foreign	
Dep. Variable	Export	Abatement	Export	Abatement
	(9)	(10)	(11)	(12)
Ventilation	0.379	0.004	0.473	-0.667*
	(1.10)	(0.03)	(1.33)	(-1.72)
Ventilation × Initial Prod.	-0.010	0.084***	-0.009	0.051***
	(-1.17)	(8.61)	(-0.98)	(4.61)
Initial Tariff × Initial Prod.	0.074***	0.001	0.073***	-0.029
	(3.01)	(0.07)	(2.92)	(-1.32)

Notes: *t*-statistics are reported in parentheses. Standard errors are clustered at the industry (tariff) level. ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively.

Table 13: First Stage Estimates, (Tables 4-5, Excluded Instruments Only)

Pollutant, Sample	SO_2, Coastal		SO_2, Non-Coastal		SO_2, High-Mix		SO_2, Low-Mix	
Dep. Variable	Export	Abatement	Export	Abatement	Export	Abatement	Export	Abatement
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ventilation	0.200	-0.059	0.046	0.108	0.238	-0.013	0.364*	0.147
	(1.06)	(-0.69)	(0.23)	(0.92)	(1.17)	(-0.15)	(1.86)	(1.18)
Ventilation	-0.000	0.069***	0.009*	0.065***	-0.005	0.065***	0.018***	0.077***
× Initial Prod.	(-0.11)	(16.28)	(1.71)	(8.33)	(-1.36)	(13.43)	(3.24)	(16.45)
Initial Tariff	0.113***	-0.012**	0.142***	0.011*	0.111***	-0.003	0.150***	-0.007
× Initial Prod.	(9.85)	(-2.19)	(9.37)	(1.66)	(9.70)	(-0.59)	(9.66)	(-0.95)
Pollutant, Sample	Dust, Coastal		Dust, Non-Coastal		Dust, High-Mix		Dust, Low-Mix	
Dep. Variable	Export	Abatement	Export	Abatement	Export	Abatement	Export	Abatement
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Ventilation	0.241	-0.727***	-0.019	0.509*	0.228	-0.717***	0.322*	0.452
	(1.26)	(-3.37)	(-0.10)	(1.75)	(1.10)	(-3.16)	(1.68)	(1.55)
Ventilation	-0.003	0.023***	0.009	0.026***	-0.006	0.022***	0.015**	0.026***
× Initial Prod.	(-0.74)	(5.12)	(1.60)	(3.42)	(-1.63)	(4.34)	(2.52)	(4.23)
Initial Tariff	0.117***	-0.047***	0.138***	0.058***	0.112***	-0.022**	0.153***	0.013
× Initial Prod.	(9.98)	(-4.29)	(8.96)	(4.08)	(9.79)	(-2.20)	(9.51)	(0.89)
Pollutant, Sample	SO_2, Initial Non.		SO_2, Diff. Trend 1		SO_2, Diff. Trend 2		SO_2, First-Diff	
Dep. Variable	Export	Abatement	Export	Abatement	Export	Abatement	Export	Abatement
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Ventilation	0.460**	0.005	0.231	-0.013	-	-	0.165	-0.141
	(2.10)	(0.05)	(1.50)	(-0.18)	-	-	(1.29)	(-1.52)
Ventilation	0.002	0.076***	0.003	0.068***	0.002	0.067***	-0.005	0.037***
× Initial Prod.	(0.32)	(14.89)	(0.95)	(16.78)	(0.73)	(16.96)	(-1.03)	(4.34)
Initial Tariff	0.099***	-0.006	0.088**	-0.010***	0.087***	-0.010**	0.089***	0.003
× Initial Prod.	(7.29)	(-1.03)	(11.78)	(-2.61)	(11.92)	(-2.54)	(3.96)	(0.35)
Pollutant, Sample	Dust, Initial Non.		Dust, Diff. Trend 1		Dust, Diff. Trend 2		Dust, First-Diff	
Dep. Variable	Export	Abatement	Export	Abatement	Export	Abatement	Export	Abatement
	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
Ventilation	0.450**	-0.481**	0.232	-0.345**	-	-	0.230*	-0.364
	(1.99)	(-1.88)	(1.50)	(-1.98)	-	-	(1.74)	(-1.52)
Ventilation	0.000	0.012**	0.001	0.025***	0.001	0.024***	-0.008	0.015**
× Initial Prod.	(0.06)	(2.45)	(0.43)	(6.20)	(0.22)	(6.03)	(-1.60)	(2.18)
Initial Tariff	0.108***	0.019	0.090***	0.015*	0.089***	0.014*	0.094***	0.013
× Initial Prod.	(7.55)	(1.40)	(11.72)	(1.95)	(11.85)	(1.82)	(4.13)	(0.56)

Notes: *t*-statistics are reported in parentheses. Standard errors are clustered at the industry (tariff) level. ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively.

Table 14: Exporting, Abatement and Dust Emissions Intensity (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Export_t	-0.138***	-0.116***	-0.120***	-0.117***	-0.106***	-0.129***	-0.139***	-0.131***	-0.068*	-0.103***	-0.102***
	(-13.67)	(-10.25)	(-9.47)	(-11.21)	(-6.25)	(-11.60)	(-7.42)	(-11.95)	(-1.78)	(-9.79)	(-2.64)
$\text{R\&D}_{t-1}$		-0.322***	-0.336***							-0.302***	-0.330***
		(-16.88)	(-9.78)							(-11.59)	(-9.68)
$\text{R\&D}_{t-1} \times \text{Export}_t$			0.013								0.028
			(0.71)								(1.52)
NRG_{t-1}				2.145***	2.170***					2.126***	2.141***
				(20.77)	(20.22)					(20.80)	(20.08)
$\text{NRG}_{t-1} \times \text{Export}_t$					-0.028						-0.015
					(-0.88)						(-0.47)
K-Vintage_t						0.053***	0.057***			0.037***	0.046***
						(4.70)	(4.37)			(3.35)	(3.55)
$\text{K-Vintage}_t \times \text{Export}_t$							-0.005				-0.013
							(-0.64)				(-1.47)
Product Mix_t								0.003	0.011	0.006	0.009
								(0.16)	(0.54)	(0.33)	(0.49)
$\text{Product Mix}_t \times \text{Export}_t$									-0.011*		-0.004
									(-1.61)		(-0.75)
Abatement_t	-0.228***	-0.199***	-0.199***	-0.266***	-0.265***	-0.203***	-0.203***	-0.201***	-0.202***	-0.261***	-0.261***
	(-20.54)	(-16.88)	(-16.89)	(-25.87)	(-25.62)	(-17.36)	(-17.35)	(-17.15)	(-17.24)	(-3.24)	(-25.18)
Productivity_t	-0.279***	-0.238***	-0.239***	-0.207***	-0.207***	-0.233***	-0.233***	-0.225***	-0.229***	-0.229***	-0.233***
	(-3.59)	(-3.11)	(-3.12)	(-3.05)	(-3.05)	(-3.04)	(-3.04)	(-2.97)	(-3.01)	(-3.24)	(-3.26)
Tariff_t	0.173	0.073	0.071	0.132	0.140	0.105	0.105	0.112	0.119	0.094	0.097
	(1.05)	(0.44)	(0.43)	(0.84)	(0.89)	(0.63)	(0.63)	(0.67)	(0.71)	(0.60)	(0.62)
$\ln(K/L)_{t-1}$	-0.159***	-0.123***	-0.123***	-0.115***	-0.115***	-0.138***	-0.138***	-0.136***	-0.137***	-0.103***	-0.104***
	(-15.69)	(-12.00)	(-12.00)	(-11.63)	(-11.64)	(-13.22)	(-13.20)	(-13.00)	(-13.03)	(-10.06)	(-10.59)
$\ln(e/\bar{r})_{\text{initial}}$	0.331***	0.336***	0.336***	0.320***	0.321***	0.337***	0.337***	0.336***	0.336***	0.320***	0.320***
	(13.70)	(13.41)	(13.40)	(12.96)	(12.86)	(13.47)	(13.47)	(13.41)	(13.41)	(12.88)	(12.80)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.191	0.190	0.190	0.220	0.220	0.186	0.186	0.185	0.185	0.224	0.224
No. obs.	45,157	45,157	45,157	45,157	45,157	45,157	45,157	45,157	45,157	45,157	45,157

Notes: t-statistics are reported in parentheses. Standard errors are clustered at the industry (tariff) level. ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively.

Table 15: Exporting, Abatement and Dust Emissions Intensity (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Export_t	-0.715***	-0.634***	-0.744***	-0.474***	-0.505***	-0.674***	-0.150***	-0.700***	-0.013	-0.502***	-0.019
	(-6.04)	(-4.38)	(-4.33)	(-3.26)	(-2.99)	(-5.03)	(-5.56)	(-4.70)	(-0.28)	(-3.22)	(-0.37)
$\text{R\&D}_{t-1}$		-0.136**	-0.650***							-0.128**	-0.292***
		(-2.53)	(6.78)							(-2.36)	(-7.67)
$\text{R\&D}_{t-1} \times \text{Export}_t$			0.514***								0.049**
			(3.79)								(2.39)
NRG_{t-1}				2.533***	2.277***					2.456***	2.753***
				(7.24)	(5.73)					(7.07)	(8.93)
$\text{NRG}_{t-1} \times \text{Export}_t$					0.474**						0.030
					(2.40)						(0.71)
K-Vintage_t						0.028**	0.063***			0.019	0.046***
						(2.13)	(4.96)			(1.49)	(3.50)
$\text{K-Vintage}_t \times \text{Export}_t$							-0.009*				-0.010
							(-1.60)				(-0.90)
Product Mix_t								0.066***	0.031**	0.055***	0.032**
								(3.60)	(2.52)	(2.95)	(2.45)
$\text{Product Mix}_t \times \text{Export}_t$									-0.022***		-0.020***
									(-3.40)		(-2.76)
Abatement_t	-0.479**	-0.314	-0.399**	-0.645***	-0.749***	-0.329*	-0.444**	-0.315	-0.412**	-0.597**	-0.788***
	(-2.04)	(-1.56)	(-1.97)	(-2.70)	(-3.16)	(-1.64)	(-2.33)	(-1.56)	(-2.15)	(-2.50)	(-3.33)
Productivity_t	-0.337**	-0.349***	-0.335***	-0.167	-0.076	-0.323***	-0.141	-0.359***	-0.156*	-0.204	-0.030
	(-2.24)	(-3.02)	(-2.92)	(-1.24)	(-0.61)	(-3.07)	(-1.43)	(-3.04)	(-1.62)	(-1.54)	(-0.20)
Tariff_t	0.028	-0.081	-0.156	0.004	-0.082	-0.080	0.070	-0.090	0.090	-0.026	0.078
	(0.17)	(-0.60)	(-1.09)	(0.03)	(-0.53)	(-0.58)	(0.55)	(-0.65)	(0.71)	(-0.19)	(0.60)
$\ln(K/L)_{t-1}$	-0.095***	-0.873***	-0.089***	-0.068***	-0.072***	-0.091***	-0.126***	-0.089***	-0.127***	-0.063***	-0.080***
	(-5.32)	(-6.41)	(-6.67)	(-4.30)	(-4.64)	(-6.21)	(-11.13)	(-5.88)	(-11.49)	(-4.18)	(-5.74)
$\ln(e/\bar{r})_{\text{initial}}$	0.321***	0.327***	0.329***	0.318***	0.315***	0.328***	0.340***	0.326***	0.338***	0.316***	0.325***
	(30.07)	(46.11)	(46.71)	(53.27)	(47.20)	(45.88)	(54.91)	(44.34)	(54.01)	(51.99)	(66.11)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F-stat	20.58	19.16	14.59	13.56	14.83	19.51	12.14	19.45	12.01	13.58	15.64
Kleibergen-Paap LM-stat	42.69	58.15	59.07	41.17	43.85	59.22	61.40	59.03	60.79	41.23	44.01
Hansen J-stat	0.02	0.75	0.04	0.02	0.84	0.72	1.90	0.55	1.83	0.017	0.763
Adj. R^2	0.165	0.113	0.094	0.130	0.113	0.099	0.169	0.092	0.174	0.137	0.126
No. obs.	44,028	44,028	44,028	44,028	44,028	44,028	44,028	44,028	44,028	44,028	44,028

Notes: t-statistics are reported in parentheses. Standard errors are clustered at the industry (tariff) level. ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively. We report the Cragg-Donald Wald F-statistic for weak instruments, Kleibergen-Paap rk LM statistic as an underidentification test, and the Hanson J-statistic of overidentifying restrictions.

Table 16: Exporting, Abatement and Emissions-Intensity (LASSO)

Dep. Var	SO_2 Emissions-Intensity				Dust Emissions-Intensity			
Lasso	Linear	Linear	Linear IV	Linear IV	Linear	Linear	Linear IV	Linear IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Export_t	-0.092***	-0.092***	-0.586***	-0.105***	-0.107***	-0.120***	-0.515***	-0.005
	(-12.79)	(-3.05)	(-4.31)	(-2.79)	(-13.51)	(-3.85)	(-3.34)	(-0.10)
$\text{R\&D}_{t-1}$	-0.287***	-0.309***	-0.128***	-0.306***	-0.306***	-0.330***	-0.124**	-0.293***
	(-15.07)	(-13.10)	(-2.67)	(-11.96)	(-14.50)	(-12.64)	(-2.28)	(-7.78)
$\text{R\&D}_{t-1} \times \text{Export}_t$		0.016		0.029*		0.026*		0.048**
		(1.14)		(1.70)		(1.65)		(2.40)
NRG_{t-1}	1.702***	1.701***	1.581***	1.655***	2.160***	2.195***	2.479***	2.756***
	(42.59)	(39.35)	(34.11)	(36.25)	(45.13)	(42.81)	(7.21)	(8.99)
$\text{NRG}_{t-1} \times \text{Export}_t$		-0.027		-0.017		-0.019		0.032
		(-1.49)		(-0.81)		(-0.94)		(0.77)
K-Vintage_t	0.052***	0.065***	0.024**	0.066***	0.042***	0.055***	0.021*	0.045***
	(6.06)	(6.46)	(2.24)	(6.15)	(4.38)	(4.87)	(1.65)	(3.50)
$\text{K-Vintage}_t \times \text{Export}_t$		-0.021***		-0.031***		-0.016**		-0.006
		(-2.87)		(-3.41)		(-1.96)		(-0.54)
Product Mix_t	-0.003	0.005	0.030*	-0.002	0.025**	0.033***	0.050***	0.026**
	(-0.36)	(0.55)	(1.84)	(-0.24)	(2.44)	(3.10)	(2.74)	(2.11)
$\text{Product Mix}_t \times \text{Export}_t$		-0.006		-0.012**		-0.003		-0.021***
		(-1.60)		(-2.36)		(-0.73)		(-2.95)
Abatement_t	-0.417***	-0.416***	-0.350***	-0.356***	-0.266***	-0.264***	-0.605**	-0.784***
	(-31.26)	(-31.09)	(-5.53)	(-5.90)	(-38.63)	(-38.41)	(-2.55)	(-3.33)
Productivity_t	-0.206***	-0.222***	-0.308***	-0.196***	-0.242***	-0.248***	-0.194	-0.015
	(-4.45)	(-4.78)	(-5.13)	(-4.24)	(-4.74)	(-4.84)	(-1.50)	(-0.14)
Tariff_t	-0.358***	-0.471***	-0.061	0.066	-0.281**	-0.358***	-0.021	0.084
	(-3.50)	(-4.60)	(-0.50)	(0.60)	(-2.52)	(-3.21)	(-0.16)	(0.66)
$\ln(K/L)_{t-1}$	-0.098***	-0.100***	-0.064***	-0.091***	-0.108***	-0.108***	-0.061***	-0.079***
	(-13.28)	(-13.41)	(-5.88)	(-11.91)	(-12.95)	(-12.92)	(-4.03)	(-5.71)
$\ln(e/\bar{r})_{initial}$	0.308***	0.310***	0.301***	0.305***	0.325***	0.326***	0.320***	0.329***
	(-91.68)	(91.81)	(82.21)	(90.36)	(92.23)	(92.24)	(52.64)	(65.94)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	46,821	46,821	46,821	46,821	44,028	44,028	44,028	44,028

Notes: t-statistics are reported in parentheses. ***, **, * represent statistical significance at the 1, 5 and 10 level of significance, respectively.