The Curious Case of the Missing Chinese Emissions*

Joel Rodrigue
Vanderbilt

Dan Sheng
Nankai

Yong Tan
NUFE

June 2020

Abstract

This paper characterizes the growth sulfur dioxide emissions among Chinese manufacturers during the WTO accession period. By failing to account for contemporaneous changes in markups, we demonstrate that standard emissions analyses overemphasize within-firm reductions in emissions-intensity, while undervaluing the role of resource reallocation across firms. We derive an unbiased decomposition of aggregate emissions and find that emissions increased nearly one-for-one with the scale of the Chinese manufacturing sector. Although improved technology mitigated emissions growth by 14 percent between 2000 and 2005, these gains were completely offset by resource reallocation towards dirty producers over the same time frame.

Keywords: China, emissions, markups

*Contact: Rodrigue (joel.b.rodrigue@vanderbilt.edu), Tan (yongtan_econ@163.com). The authors thank Rick Bond, Mario Crucini, Emir Malikov, Michelle Marcus, Sarah Quincy, Matt Zaragoza-Watkins, and seminar participants at UNLV.

1 Introduction

China's accession to the WTO is perhaps the most significant shock to the global economy in recent history. The environmental consequences of rapid, trade-induced economic growth have concurrently generated consternation both at home and abroad; Chinese policymakers are increasingly concerned that becoming "the factory of the world" has come at the cost of bearing a disproportionate share of global environmental degradation, while the impact of rising Chinese pollution has made headlines across the globe.

Indeed, standard estimates of aggregate Chinese manufacturing production suggest that it rose by nearly 150 percent between 2000 and 2006. Exports grew even faster; real exports rose by more than 250 percent over the same five-year period. Given these stark changes to the global manufacturing landscape, we would naturally expect that Chinese manufacturing pollution would also rise rapidly. Surprisingly, we find that emissions, and particularly those tied to the trade intensive manufacturing sector, did not grow nearly as fast.

This is not to say that China did not experience a large rise in pollution. Rather, aggregate measures of sulfur dioxide (SO_2) grew by roughly 20 percent between 2000 and 2005, while manufacturing driven emissions increased by just over 75 percent. The observed growth in air pollution is a significant, and a justified, cause for concern both in China and abroad. Nonetheless, the stark difference in the observed rates of growth begs the question: why didn't Chinese emissions grow more?

To answer this question we appeal to a unique data set which tracks firm-level sulfur dioxide (SO_2) emissions in China. Mapping this data to corresponding production surveys and balance-sheet data we investigate the seemingly muted response of Chinese emissions to the expansion of the manufacturing sector. Following a rich literature in environmental economics (Antweiler et al, 2001; Levinson, 2009; Shapiro and Walker, 2018) we adapt workhorse environmental emission-growth decomposition methods to identify key determinants of Chinese manufacturing emissions growth.

One possible answer, rooted in economic theory, is simply that the manufacturing sector has inherent economies of scale. If scale economies allow firms to produce greater amounts of output for a fixed amount of (energy) input, we might expect that firm-level expansions induce differential growth rates between production and emissions. However, the observed difference between the growth of the Chinese manufacturing sector and the growth of Chinese manufacturing emissions is too large to be explained by economies of scale alone. For economies of scale to explain emissions growth, a given bundle of inputs would need to produce nearly twice as much output in 2005 than it did in 2000. While numerous empirical studies confirm that a range manufacturing industries benefit from modest increasing returns to scale, standard estimates suggest that firm-level scale economies are nearly an order of magnitude too small (De Loecker, 2011).

A second potential solution is that green (emissions-unintensive) industries grew relatively quickly during the WTO-accession period. The conventional decomposition suggests the exact opposite. Dirty industries, supported by notoriously weak regulation and enforcement during this period, arguably form a non-trivial source of China's comparative advantage on world markets (Jia, 2012; Wu et al, 2013). Not surprising, these emissions-intensive industries also grew at a disproportionately rapid rate after China's WTO accession.

A third explanation for the missing emissions is that sector-specific emissions-intensity declined at precisely the same time that China grew into world markets. The so-called 'technique effect,' turns out to explain the large majority of the decline in measured emissions-intensity in China, much like previous studies of the US manufacturing. In this US context, the adoption of stringent air quality standards has been found to be the key determinant of increased abatement efforts, reductions in observed emissions-intensity and lower aggregate emissions despite a growing manufacturing sector (Shapiro and Walker, 2018). Could this possibly be the case in China? It seems unlikely. If modest regulation helps explain the disproportionate growth of dirty industries, it would be surprising to find it simultaneously inducing substantial within-firm environmental upgrading.

Alternatively, declines in emissions-intensity could be driven by rapid technological improvement. To investigate this possibility we consider a production setting which nests a wide set of standard environmental production frameworks (e.g. Antweiler et al., 2001; Forslid et al, 2018; Shapiro and Walker, 2018) to broadly characterize the production, efficiency and emissions of individual manufacturing firms. We show that standard measures of the technique effect, and the presumptive source of emissions-reductions in previous literature, potentially suffers from severe mismeasurement. In particular, we argue that variation in measured firm-level emissions-intensity can be completely explained by changes in (a) production technology, (b) market structure, and (c) regulation. We demonstrate that omitting changes in market structure (markups) or imposing strong technological assumptions can significantly bias standard conclusions.

Building on the literature studying the estimation of production functions and firm productivity (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; De Loecker, 2011; De Loecker and Warzynski, 2012; Ackerberg et al., 2015; De Loecker et al., 2016, Gandhi et al., 2019), we construct measures of emissions-technology and markups which vary across industries, ownership, location, size, and time. In fact, our analysis more generally argues that the 'conventional decomposition' (Levinson, 2009) may be particularly biased in a setting where market structure, and markups, are changing over time. By treating deflated revenues as a measure of production the conventional decomposition mismeasures technological changes by conflating systematic variation in markups with improvements in environmental efficiency.[1]

Accounting for the difference in markups across firms leads us to consider an alternative approach based on the firm's optimal pricing condition. After correcting for firm-level markup variation we find that there are no more 'missing' emissions from Chinese manufacturing; rather aggregate emissions grow roughly one-for-one with our corrected measure of economic scale.

This is not to suggest that there were not large, underlying changes to the Chinese manufacturing

[1]This difference analogous to the argument made in regards differences between physical and revenue based measures of total factor productivity (Foster et al, 2008).

sector. Indeed, our corrected decomposition indicates that technology improvement in the *nature* of production, as measured by the elasticity of output with respect to emissions, or increased *efficiency*, as captured by changes in marginal costs, mitigated observed emissions growth by as much as 15 percent. Consistent with the finding of rapid Chinese productivity growth throughout the 2000-2005 period, it is the latter effect, firm-and-product specific efficiency gains, that account for nearly all of the emissions-intensity declines among individual manufacturers.

These gains, however, are entirely offset by the disproportionate growth of emissions-intensive Chinese manufacturers. Unlike preceding approaches, we start with firm-and-product specific optimality conditions as the basis for our decomposition. As such, our reallocation term benefits from having theoretically grounded weights for specific firm and product specific bundles and allows us to conclude that, in aggregate, resource reallocation increased aggregate emissions growth by 16-23 percent. Moreover, we find that 92-93 percent of the emissions-encouraging reallocation occurs between incumbent firms rather than across products within firms or due to the rapid entry of new producers.

Last, we argue that distinguishing between revenue and physical emissions-intensity provides a natural metric for the implied degree of regulation faced by any firm in any year even in the absense of direct regulartory information. We construct a firm-specific measure of its regulatory burden and characterize the implied changes in Chinese regulation over the 2000-2005 period. Consistent with the historical record, a large degree of variation across firms, industries, regions and ownership structure. In particular, our estimates are consistent with the notion that foreign firms face the greatest degree of regulatory scrutiny, while state-owned enterprises face the least.[2] In aggregate, increased regulation mitigated at 4-8 percent of Chinese emissions gorwth.

These findings have direct policy implications. The standard decomposition exercise is often motivated by a perfectly-competitive economic environment (Antweiler et al, 2001; Levinson, 2009) or one with constant markups (Forslid et al, 2018; Shapiro and Walker, 2018). Conventional assumptions of slow (or invariant) production technology along with a fixed market structure imply that the only possible determinant of emissions-intensity variation is regulation. In this sense we argue that biased measures of emissions-intensity are likely to give changes in environmental regulation outsized importance in determination of firm-level environmental performance.

Our research is closely tied to the literature studying the relationship between aggregate, industry and firm-level emissions (Grossman and Krueger, 1993; Levinson, 2009), and particularly those in an open-economy context (Antweiler, Copeland and Taylor, 2001; Copeland and Taylor, 2003; Cherniwchan, 2017; Forslid et al, 2018; Shapiro and Walker, 2018). We build on this rich literature to characterize the determinants of emissions growth in China.

We also contribute to the growing number of studies at the intersection of trade, growth, and pollution in the Chinese context. Like Yan and Yang (2010), who analyze carbon dioxide emissions growth through the lens of input-output tables, we are also interested in characterizing sources of aggregate emis-

[2]Other intuitive empirical patterns emerge from our cross-ownership findings: foreign producers are most productive and the most profitable, state-owned are the least efficient, and private enterprises produce with the smallest margins.

sions growth. In contrast, we focus on sulfur dioxide growth among individual Chinese manufacturers. Similarly, our findings map into the literature aimed at quantifying the impact of domestic environmental regulation on aggregate (Nam et al 2013, 2014; Qi et al 2014; Zhang et al 2014, 2016a, 2016b), regional (Zhang et al 2013, Springmann et al 2015, Kishimoto et al 2017, Wong et al 2017) or firm-level (Cao and Karplus, 2014 and Karplus and Zhang, 2017) emissions in China.[3] Given that there is little data capturing the degree to which environmental regulation was enforced over our sample, all of the above studies focus on a time subsequent to our analysis. By recovering changes in implicit emissions taxes we are able to link our sample period to more recent studies of Chinese environmental policy.

We build on the rich literature studying the impact of globalization, and trade liberalization in particular, on environmental outcomes.[4] Existing work by Copeland and Taylor (1994, 1995), Ederington et al. (2005) and Levinson and Taylor (2008) argues that trade liberalization may increase pollution in countries that have a (potentially regulation driven) comparative advantage in pollution-intensive industries. We study whether emissions-intensive firms and industries grew disproportionately fast duing the WTO-accession period. Our new decomposition approach allows us to quantify the degree to which technological improvement mitigated Chinese environmental degradation, as highlighted in Grossman and Krueger (1995), Antweiler et al. (2001) and Frankel and Rose (2005) among others.

Last, our work sheds new light on the abundance of papers quantifying the differential impact of regional emissions growth on consequent health and economic outcomes across Chinese provinces (Dean 2002; Ebenstein et al. 2015, de Sousa et al. 2015, and Bombardini and Li 2019, Callaway et al. 2020).[5] While we do not characterize health or economic impacts of emissions growth per se, our proposed decomposition quantifies key sources of emissions growth, components of which are arguably exogenous to firm-level decisions and can be used to better understand the mechanisms driving environmental outcomes across time and space.

The next section documents the institutional background during our period of study, particularly as it pertains to environmental policy. Section 3 documents key patterns in our data and formally defines the mystery of missing emissions through the lens of the standard emissions decomposition. Section 4 links the standard decomposition to firm-level pricing behavior and characterizes the nature of markup-induced bias in the conventional environmental decomposition. Section 5 provides an alternative approach and describes our estimation methodology. Section 6 presents our empirical results. Section 7 concludes.

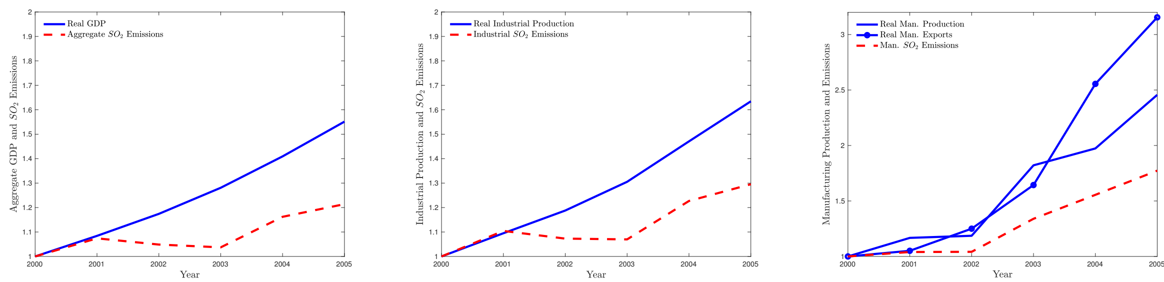
[3] Cao and Karplus (2014) study the drivers of energy, electricity and carbon intensity among a sample of 800 Chinese firms between 2005 and 2009. Although we observe similar trends, the Cao and Karplus (2014) study differs from ours in the outcome variables under consideration, the mechanisms evaluated in the paper, the sample of firms, and the strigency of of environmental regulation during the time period under study.

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

[5] A large literature studies the health costs of industrial pollution in China. See, for example, Hao et al (2007), Cropper (2012), Chen et al (2013), Tanaka (2015), or He (2016). Lin et al (2014) quantifies the impact of US-China trade on US air quality.

2 Institutional Background

China's economic tranformation, dating back to the mid-1970s, stands as one of longest sustained periods of rapid economic growth in recorded history. Since the mid 1990s, China's continued transition to a market-oriented economy is punctuated by the expansion of the energy-intensive and export-oriented manufacturing sector (Zhu, 2012). Already one of the world's leading producers of manufactured goods, China's accession to the WTO in December 2001 lead to even greater output and export growth. As evidenced in Figure 1, China's real GDP and real industrial production grew by 55 and 63 percent over the 2000-2005 period, respectively. As widely reported, much of the increase in aggregate output was driven by the rapid rise of the manufacturing sector which grew by nearly 150 percent over the same time period.



(a) Aggregate (b) Industry (c) Manufacturing

Notes: Figure 1a plots real Chinese GDP and aggregate SO_2 emissions over the 2000-2005 period, Figure 1b plots real Chinese industrial production and industrial SO_2 emissions, Figure 3 plots real manufacturing production (deflated revenue), real manufacturing exports, and aggregate manufacturing SO_2 emissions. All values in 2000 are normalized to 1. Sources: NBS (GDP, Manufacturing Production, Exports), World Bank (Real Industrial Production), MEE (Emissions).

Figure 1: Production and Emissions

It is no surprise the aggregate emissions and aggregate manufacturing emissions also rose quickly over same period or that these stark changes produced significant social, health, and environmental concern among domestic policymakers (see CCINED 2003, 2004 for examples). The difference in the rate of growth between emissions and standard measures of production is surprising; by 2005 aggregate and industrial SO_2 emissions are estimated to be *only* 21 and 30 percent greater than that in 2000 despite the fact that comparable measures of output grew twice as fast over the same time period.

The gap between standard measures of production and emissions is particularly curious due to the regulatory framework during our sample period (or the lack thereof).[6] Chinese air quality standards were broadly outlined in 1979, while the first legislative document outlining penalties for excessive emissions,

[6]China has had an agency dedicated to addressing domestic environmental quality since 1973. In 1998 the Chinese government upgraded the state environmental agency to a ministry-level agency, which then became the State Environmental Protection Administration (SEPA). In 2008, SEPA was promoted to the level of a national ministry, The Ministry of Environmental Protection (MEP), which in turn renamed The Ministry of Ecology and Environment (MEE) in 2018. MEE is responsible for setting pollution standards and regulation, organizes environmental quality monitoring, mandates the collection of regional and establishment-specific pollution information, and is the primary source of firm-level data for this study.

was implemented 1989 (Jin et al, 2016).[7] Despite the existing regulation Chinese air pollution grew rapidly thereafter and there was little evidence of policy enforcement.[8]

Across all environmental programs, a key feature of the institutional setting is that national state agencies had little role in local implementation, verification or enforcment. Rather, over our 2000-2005 sample period, determining compliance to environmental legislation and the enforcement of penalties for violations to existing policies were primarily *local* responsibilities. Across China there were roughly 3060 Environmental Protection Bureau (EPBs) which were responsible for the enforcement of enviromental standards and the administration of penalties for policy violations. Under the discharge permit system (DPS), local EPBs are mandated to issue permits that limit both the quantities and concentrations of pollutants to regulate the air emissions and wastewater discharge for every establishment in their jurisdiction. However, the EPBs do not directly report to higher state ministries, but rather are typically administered by the local township, district or prefecture government.[9]

Despite the clear environmental mandate for local EPBs there is an equally apparent conflict across governmental objectives: during this time period local administrators were typically promoted based on the rate of *local* economic development (Jia, 2012; Wu et al, 2013), not the enforcment of national environmental policy. As a result, EPBs were often lenient toward polluters which generated fiscal revenues for local authorities and firms which were responsible for substantial local employment (OECD, 2009). For example, state-owned firms were known to have received special treatment, lower emissions penalties, or advantageous lines of credit to install and implement abatement technology.

This should not suggest, however, that EPBs, when empowerd by the local government, are without the means to influence firm behavior. Once non-compliance is established, EPB inspectors usually issue warning letters and then, if the firm continues not to comply with environmental policy, the EPB can impose fines on the establishment, fine the manager directly, and/or withdraw the firm's operating permit altogether. In practice, fines are the most common form of non-compliance penalty and are enforced in nearly 60 percent of all recorded instances of non-compliance. In 2004, the EPBs imposed sanctions in approximately 80,000 cases across China with aggregate monetary penalties of 460 million RMB (56 million US dollars). While this may be relatively modest in aggregate, they do not imply that the individual penalties were insigificant for firms which were found to be non-compliant.[10]

[7] It was later revised in 1995, with specific emphasis on sulfur dioxide emissions.

[8] In 2006, China introduced significant new regulation of SO_2 emissions in the national government's 11^{th} Five-Year Plan. We do not extend our sample beyond 2006 as we lack key variables for the measurement of technology and markups after 2006. Callaway et al. (2020) study the impact of the 11^{th} Five-Year plan on firm-level emissions responses over the 2006-2010 period.

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

[10] In 2003 EPBs also started publishing the names of non-compliant firms to induce greater public pressure on polluters. In conjunction with state-owned banks the EPB can penalize non-compliant polluters by affecting their loan conditions. More recently, EPBs have been granted the ability to ban firms from exporting (2007) or access capital among publically held firms (2008).

3 Data

Our primary data source is an annual survey of Chinese enterprises collected by Ministry of Ecology and Environment (MEE) over the 2000-2005 period. This data includes information capturing the total weight of SO_2 emitted by a firm over the course of a calendar year.[11] The data reports pollution at the *firm-level* rather than the plant or establishment level. If a firm has multiple plants, our data reports aggregated total pollution across plants in the same firm.

MEE also provides data on a limited number of firm characteristics including: the location of each firm (city/province), domestic revenues, and energy consumption by energy type (coal, natural gas, diesel fuel, heavy oil). Following a methodology pioneered by the US EPA, it also reports the amount of pollution *generated* by the firm given its input consumption and the emission factor assigned to each input by the EPA. Using observed variation in pollution generation and emissions, the data allows us to characterize the variation in abatement across the distribution of heterogeneous firms.

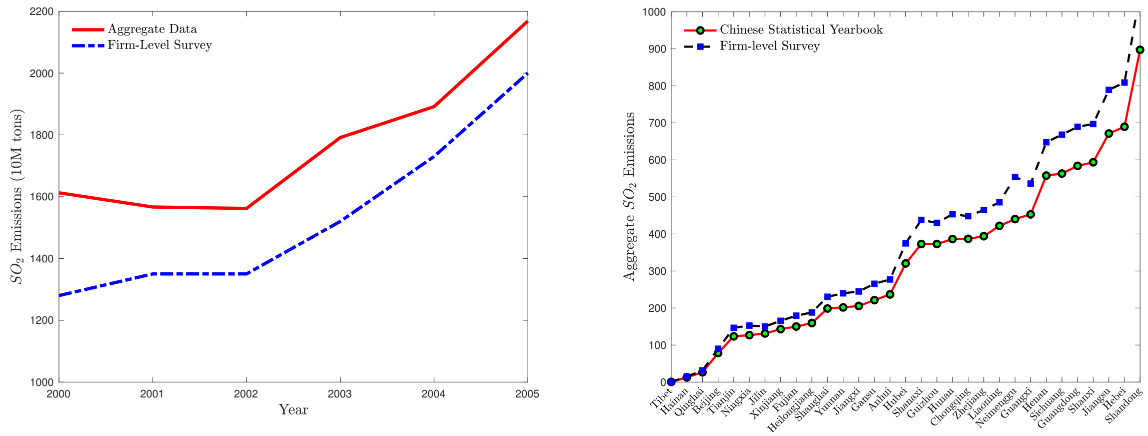
There are three sample features of our data which are important to state at the outset. First, our firm-level data does not include all industrial polluters, but nonetheless tracks aggregate changes in pollutants very closely. Although MEE surveys the universe of polluting establishments, our sample only includes firms from the top 80 percentiles of the firm-level pollution distribution in each year. To check the accuracy of the our data we aggregate all of the firm-specific emissions data and compare it to the aggregate statistics produced by the Chinese Ministry of Ecology and the Environment.[12] In panel (a) of Figure 2 it is clear that the aggregated firm-level SO_2 emissions tracks the officical aggregate emissions statistics closely. The survey captures 79 percent of total industrial SO_2 emissions in 2000, 85-86 percent between 2001-2003, and 91-92 percent of total industrial emissions over the last two years of our sample.

As a second check of our data, we also examine the degree to which it captures the spatial distribution of pollutants. Specifically, we aggregate our firm-level data for each province and calculate the provincial average level of pollution over our sample period. We then compare the computed average provincial pollution levels to provincial averages reported by MEE over the same time frame. Panel (b) of Figure 2 plots aggregate SO_2 emissions for each Chinese province from both data sources. Not only do both data sources track each other closely, but we also find significant variation across provinces in the aggregate level of pollution.

The environmental data set does not record numerous key variables for our analysis: we are missing measures of physical output, employment, capital use, intermediate material purchases, and any measure of firm-efficiency. Given that technology and scale have long been associated with improvements in firm-

[11] A detailed description of emission measurement is provided in the appendix.

[12] Aggregate industrial statistics are published regularly by the Ministry of Ecology and Environment in Annual Reports available at http://english.mee.gov.cn/Resources/Reports/. We crosschecked the accuracy of the SO_2 data from the Ministry of Ecology and the Environment with US Satellite Data and find that they exhibit similar patterns over time and space. Although independent estimates of SO_2 emissions have previously been found to be higher than those reported in official statistics (Streets and Waldhoff 2000; Streets et al. 2000; Ohara et al. 2007; Cao et al. 2009), our primary concerns are systematic discrepancies across locations or over time. We do not find any significant evidence of systematic reporting bias. A description of this exercise and our results can be found in the appendix.



(a) SO_2 Emissions Over Time

(b) SO_2 Emissions Across Provinces

Notes: Panel (a) plots annual emissions of SO_2. The solid red represents the value reported by MEE in annual reports, while the dashed blue line represents the aggregated value from our firm-level survey. Panel (b) plots the average provincial emissions of SO_2 over our sample period. The red line with circles represents the value reported by MEE, while the blue line with squares represents the aggregated value from our firm-level survey.

Figure 2: Aggregate vs Firm-Level Data

level emissions intensity, these are particularly significant omissions. Moreover, the pollution dataset does not distinguish between domestic, state or foreign-owned firms and does not report any indication of industrial affiliation. It is well-known that access to export markets, size, technological capacity, and the incentive to escape environmental regulation varied significantly with firm-ownership, firm-location, and industry in China.

To fill in these missing dimensions of our data set, we match the firm-level pollution data with balance sheet information from annual manufacturing surveys and production data from the Annual Survey of Industrial Firms. Matching these data sets inherently restricts attention to the Chinese manufacturing sector.

The manufacturing survey only covers firms with revenues of at least 5 million RMB and not all large manufacturing firms are necessarily large polluters. As such, not all of the manufacturing firms are contained in the pollution data set. Despite these caveats, we are able to match 49 percent of the firms in the manufacturing survey to corresponding data in the pollution survey.

3.1 The Mystery Defined

To characterize the sources of emissions growth we follow a standard decomposition of aggregate emissions (Grossman and Krueger (1993), Copeland and Taylor (2003, 2004), Levinson (2009), Shapiro and Walker (2018)) which breaks the growth of aggregate air emissions E into three components: scale, composition and technique. This is typically written as

$$E = \sum_s e_s = \sum_s v_s \iota_s = V \sum_s w_s \iota_s \tag{1}$$

where V is total output, traditionally measured as deflated revenue (or value-added), v_s is the revenue of sector s, w_s is the revenue share of sector s and ι_s is the emission coefficient of sector s, measured as the amount of pollution per dollar of revenue, $\iota_s = e_s/v_s$. Writing this relationship in vector notation and computing the total differential yields the benchmark decomposition equation:

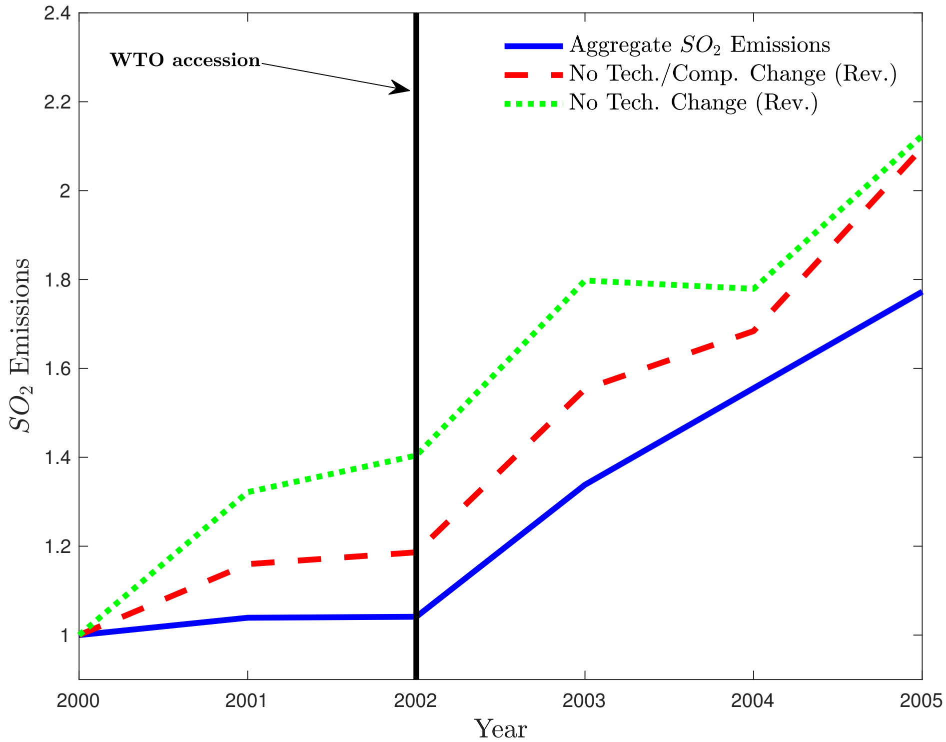
$$\frac{dE}{E} = \frac{dV}{V} + \frac{d\mathbf{w}}{\mathbf{w}} + \frac{d\boldsymbol{\iota}}{\boldsymbol{\iota}}. \tag{2}$$

The first term in equation (2) captures the change in aggregate emissions which can be explained by the increase in the size of Chinese manufacturing industry (the 'scale' effect). As in previous studies we use aggregate (deflated) revenue, V, as a benchmark measure of total production. The second term measures the contribution to aggregate emissions from changes in the composition of industries which comprise manufacturing (the 'composition' effect). To the extent that China had a comparative advantage in dirtier industries, perhaps due to less stringent environmental regulation, we would expect that the disproportionate growth of these industries would also cause aggregate emissions to rise. The third term, typically named the 'technique' effect, captures systematic changes in average emissions-intensity or emissions per dollar of deflated revenue.

We illustrate the relative importance of each channel through two thought experiments. First, we ask how much would Chinese manufacturing emissions have grown if industrial composition and emissions intensity remained unchanged from 2000 onwards? Given that the Chinese economy grew rapidly over the WTO accession period, we would expect aggregate emissions to exhibit similar growth. Second, if we allow industrial composition to change, but hold emissions-intensity fixed at its 2000 value, how much would aggregate emissions have grown? Figure 3 plots the results where we have normalized aggregate SO_2 emissions in 2000 to one.

The solid blue line captures actual pollution growth and documents that aggregate SO_2 emissions grew by 77 percent. Moreover, almost all of the growth in pollution has occured since China's accession to the WTO in 2002. The two counterfactual paths for emissions reveal puzzling results. The dotted green line captures the impact of holding emissions-intensity, or a broad-sense of industrial technology, fixed at its 2000 value. By 2005 aggregate emissions are predicted to be roughly 32 percentage points greater than the already strong increases we observe in the data. It is in this sense that the standard framework suggests that emissions are 'missing' from the Chinese manufacturing sector; while standard measures of aggregate production grew by 150 between 2000 and 2005, emissions rose by less than 75 percent. Typically, this finding is interpreted as broadly capturing changes in the nature of production over the same time.

The concurrent change in industrial composition makes the observed pattern of emissions even more



Notes: The blue solild line plots the aggregate SO_2 emissions among Chinese manufacturing firms (normalized to 1 in 2000). The red dashed (green dotted) line plots the counterfactual path of aggregate emissions when we hold emissions-intensity fixed at its value in 2000 (hold emissions-intensity and industrial composition fixed at their values in 2000).

Figure 3: Decompositing Aggregate Emissions

surprising. The red dashed line holds emissions-intensity fixed at 2000 levels, but also requires that industrial composition does not change over time. We observe that the red dashed line lies between the solid blue line and the dottted green line throughout the entire sample period. In this sense WTO-accession is strongly associated with the growth of dirtier industries in China and is broadly consistent with the pollution haven hypothesis (Eskeland and Harrison, 2003; Ederington et al., 2005; Levinson and Taylor, 2008): as trade with Western countries grew after 2002, pollution-intensive industries escaped Western regulation by relocating to China.

In practice, the decline in emission-intensity may reflect various underlying changes. Improvements in technology or firm-level productive efficiency, changes in the mix of products produced by multi-product firms, increasing firm-level returns to scale, changes in market power and/or the reallocation of market share towards cleaner firms are all possible explanations for falling emissions-intensity. To shed light on the possible sources of emissions-intensity improvements, we follow Melitz and Polanec (2015) to decompose changes in average emissions-intensity into components originating from within-firm improvements in emissions intensity, the reallocation of market share towards dirtier firms, and the entry and exit of firms into the Chinese manufacturing industry.[13]

Specifically, we define *weighted* average emissions-intensity as $\iota^w_{st} \equiv \sum_{i \in s} w_{it}\iota_{it}$ and decompose the change in average emissions-intensity as

$$\Delta\iota^w_{st} = \underbrace{\underbrace{\sum_{i\in\mathcal{C}_s}(\iota_{i,05}-\iota_{i,00})\bar{w}_i}_{\text{Within-Firm}} + \underbrace{\sum_{i\in\mathcal{C}_s}(w_{i,05}-w_{i,00})\bar{\iota}_i}_{\text{Across-Firm}}}_{\text{Continuing Firms}} + \underbrace{(\bar{\iota}_{\mathcal{C}_s,00}-\bar{\iota}_{\mathcal{X}_s,00})\sum_{i\in\mathcal{X}_s} w_{it}}_{\text{Exiting Firms}} + \underbrace{(\bar{\iota}_{\mathcal{E}_s,05}-\bar{\iota}_{\mathcal{C}_s,05})\sum_{i\in\mathcal{E}_s} w_{it}}_{\text{Entrants}} \quad (3)$$

where e_{it} and w_{it} represent the emission-intensity and revenue share of firm i, in sector s, in year t. The variables $\bar{\iota}_i$ and $\bar{w}_i$ are firm i's average emissions-intensity and average revenue-share, and $\mathcal{C}$, $\mathcal{E}$ and $\mathcal{X}$ capture the set of continuing firms, new entrants and exiting firms, respectively, over our sample period.

Table 1 documents the decomposition of the average change in emissions-intensity. Column (1) reports the average firm-level of emission intensity in the initial year of the data, while column (2) records the change in average emissions intensity, the outcome variable of equation (3). Average manufacturing emissions-intensity fell by 24.5 percentage points across industries. These are remarkably large changes; the observed decline in emission-intensity represents 18 percent of its initial value.

We break down the total percentage point change (column 2) into the total contribution from continuing firms (column 3), the contributions from new entrants (column 6) and the contribution from exiting firms (column 7). It is clear that despite the rapid entry of new Chinese manufacturers over our sample period, the decline in average emissions-intensity was almost exclusively driven by continuing firms.

Columns (3) and (4) further decompose the total impact of continuing firms into a term which cap-

[13]Barrows and Ollivier (2018) consider an industry decomposition based on Foster et al. (2008). As argued in Melitz and Polanec (2015) these methods can potentially bias the importance of firm entry and exit, an issue of particular relevance over our sample period.

Table 1: Decomposition of Aggregate Manufacturing SO_2 Intensity, 2000-2005

Initial Avg. Pol. Intensity	Total % Point Change	Continuing Firms			New Entrants	Exiting Firms
		Total	Within	Across		
(1)	(2)	(3)	(4)	(5)	(6)	(7)
24.50	-4.48	-6.94	-6.44	-0.54	-0.45	2.90

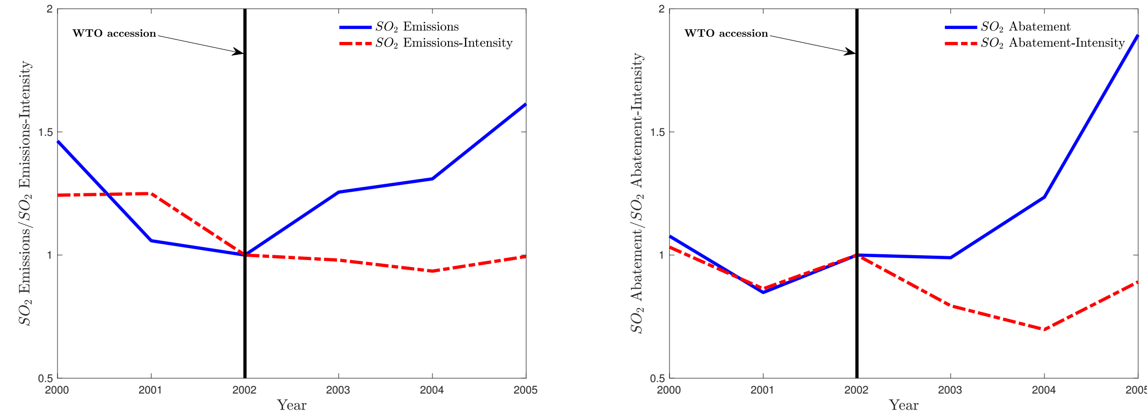
Notes: This table documents the percentage point change in average SO_2 emissions-intensity. Column (1) reports the weighted average emissions-intensity in the initial year. Column (2) documents the total percentage point change. Columns (3), (6) and (7) document the contribution from continuing firms, new entrants and exiting firms, respectively. Columns (4) and (5) decompose the contribution from continuing firms (column 3) into within-firm (column 4) and reallocation components (column 5).

tures within-firm emissions-intensity changes, given the firm's market share, ('Within') and a term capturing the reallocation of firm-level market share towards (or away from) emissions-intensive firms, given its emissions-intensity ('Across'). The former term captures the degree to which large firms were induced to reduce their emissions-intensity over the sample period, while the latter term measures the degree to which relatively clean firms were more likely to grow faster than their emissions-intensive counterparts. Examining these two columns we observe that the reduction in emissions-intensity among continuing firms appears to be almost exclusively driven by within-firm changes. A typical interpretation of this result is that firms improved environmental performance through fundamental changes in the nature of production: upgrading production technology, purchasing cleaner inputs, directly investing in abatement, or changing their product mix towards less emissions-intensive products. In contrast, column (5) suggests that firms with relatively clean production over the 2000-2005 period do not appear to grow much faster than those firms which are systematically more emissions-intensive.

Both of these findings are surprising, particularly in light of the conventional industry-level decomposition. On one hand, the industry-level decomposition finds that relatively dirty industries in equation (2) grew rapidly, while relative firm-level growth does not appear to vary significantly across firm-level emissions-intensity in equation (3).

On the other hand, firm-level emissions-intensity dropped rapidly. The observed declines in average emissions intensity are consistent with the notion that improved production techniques are the primary driver of firm-level or industry-level environmental performance. In the US context, it is argued lower emissions-intensity has primarily been achieved through greater abatement; that is, greater investment in the technology associated with reducing emissions (Shapiro and Walker, 2018). Could that be the case in China? This seems unlikely: there is little evidence of stringent environmental enforcement over our sample period and, if anything, existing evidence suggests local incentives were clearly tilted towards encouraging rapid economic growth at the expense of environmental concerns (Jia, 2012; Wu et al, 2013).

Nonetheless, we again turn to our firm-level sample to examine if this is a likely source of changes



(a) SO_2 Emissions

(b) SO_2 Abatement

Notes: The blue solild lines in panels (a)-(b) respectively plot the average (revenue-weighted) firm-level SO_2 emissions and abatement among Chinese manufacturing firms (normalized to 1 in 2002). The red dashed lines plot average emissions-intensity and abatement-intensity over the same time period. The average fraction of generated emissions which are abated over the sample period is roughly 10 percent.

Figure 4: Firm-Level Emissions and Abatement

in Chinese firm-level environmental performance. We first compute the change in average firm-level emissions and emissions-intensity over our sample period and plot these series in Figure 4.

While average firm-level emissions grew rapidly after 2002, average emissions-intensity declined throughout the 2000-2005 period. If firm-level abatement is to explain the divergence in average emissions and emissions-intensity, we would expect that both the total firm-level of abatement and the intensity of firm-level abatement to rise concurrently. To investigate this possibility, we use a unique measure of abatement as provided by the MEE data set. Specifically, the data records a consumption-based measure of pollution *generated* by the firm (e.g. the amount of sulfur-based fuel directly consumed plus expected emissions generated during production) and the amount of pollution *removed* prior to emissions. To get a sense of the changes over time we plot both the average level of abatement along with abatement-intensity, defined as total abatement per unit of deflated revenue, in panel (b) of Figure 4.

Average firm-level abatement rises continuously over the 2000-2005 period and the rate of growth is particularly sharp after 2002. Despite this, rather than rising, average firm-level abatement-intensity distinctly declines after WTO accession. While this pattern suggests that it is unlikely that rising abatement can explain the observed changes in emissions-intensity alone, it is consistent with the established view that there was little increase in environmental regulation or enforcement prior to 2006.

4 Accusation: Markup Bias

We propose that emissions-intensity, as traditionally measured, mischaracterizes the relationship between production and emissions. Revenue-based emissions-intensity can be expressed as a multiplicative function of firm-level markups, unobserved emissions regulation, and an underlying technological component governing the fundamental emissions-intensity of production. Employing cost-weighted measures of emission growth, we find that observed declines in average emissions-intensity suggest that the 'missing Chinese emissions' are much smaller than that implied revenue-based decomposition. A cost-based analysis reduces the contribution of improved production techniques by one half .

4.1 Technology, Markups and Emissions: A Second Look

To illustrate the relationship between markups, production technology and emissions, we describe an economic environment consistent with a large class of models examining production and emissions in an open economy setting (Antweiler et al, 2001; Shapiro and Walker, 2018; Forslid et al., 2018). Denote the production function for a given firm i in year t as

$$x_{it} = f_p(a_{it}, m_{it}^1, ..., m_{it}^K, \omega_{it}) \tag{4}$$

where output x is a function of K productive inputs, firm-specific productivity ω_{it} and the firm's investment in abatement, a_{it}. The only restrictions imposed on $f_p()$ is that it is continuous and twice differentiable with respect to its arguments and at least one input is variable in the current period. Following the above literature we also assume that a_{it} is flexibly chosen by the firm every period and is a continuous function of productive inputs and productivity:

$$a_{it} = a(m_{it}^1, ..., m_{it}^K, \omega_{it}).$$

We then model firm-level emissions e_{it} as an increasing function of output x_{it} but a decreasing function of abatement a_{it},

$$e_{it} = e(a_{it}, x_{it}). \tag{5}$$

To make our case we introduce two assumptions, commonly satisfied in the literature.

Assumption 1 *The emissions function (5) is invertable in any of its arguments. That is,*

$$a_{it}^j = e_a^{-1}(x_{it}, e_{it}) \textit{ and } x_{it}^j = e_x^{-1}(a_{it}, e_{it})$$

Assumption 2 *The production function (4) is invertable in any of its variable inputs. That is,*

$$m_{it}^k = x_k^{-1}(a_{it}, m_{it}^1, ..., m_{it}^k, m_{it}^{k+1}, ..., m_{it}^K, \omega_{it}, x_{it})$$

Using assumption 1 we invert the emissions function (5) and insert it into the production function. Using assumption 2 we then isolate production as a function of productive inputs $(m_{it}^1, ..., m_{it}^K)$, firm-specific productivity (ω_{it}), and emissions (e_{it}):

$$x_{it} = f_e(e_{it}, m_{it}^1, ..., m_{it}^K, \omega_{it}) \tag{6}$$

where we refer to $f_e(\cdot)$ as the emissions augmented production function. We treat the price of emissions as the implicit emissions tax, t_s, on production in sector s.

4.1.1 Output Elasticities and Markups

De Loecker and Warzynski (2012) demonstrate that standard profit maximization implies

$$\gamma_{it}^{mk} = \mu_{it} \frac{w_t^{mk} m_{it}^k}{p_{it} x_{it}}$$

where γ_{it}^{mk} is the output elasticity of productive input k, μ_{it} is the firm's markup, and w_t^{mk} is the price of variable input m^k. The same logic holds for our emissions-augmented production function under assumptions (1) and (2). That is, letting γ_{it}^e denote the output elasticity of emissions from equation (6), we can write

$$\gamma_{it}^e = \mu_{it} \frac{t_s e_{it}}{p_{it} x_{it}}$$

Rearranging terms we can use the above equation to write the firm's optimal emissions-intensity as

$$\frac{e_{it}}{r_{it}} = \frac{\gamma_{it}^e}{\mu_{it}} t_{st}^{-1} \tag{7}$$

This equation relates emissions-intensity to output-elasticities, markups, and regulation. Notice that firm-level costs or efficiency are completely absent from the RHS of above equation, except for their potential influence on the firm's markup.

Alternatively, variation in emissions-intensity could reflect changes in the elasticity of output with respect to emissions, γ_{it}^e, or changes in regulation. In practice, common modelling assumptions imply constant markups and time-invariant constant returns to scale in production (as in Antweiler et al, 2001; Levinson, 2009; Shapiro and Walker, 2018).[14] Failing to account for the role of heterogeneous markups may have particularly pronounced implications for environmental policy evaluation.

Letting $\tilde{r}_{it}$ represent deflated revenue and imposing the assumptions of constant markups and common constant production technology, we write the conventional measure firm-level environmental performance, $e_{it}/\tilde{r}_{it}$, in terms of the firm's first order condition

$$\Delta \log \left(\frac{e_{it}}{\tilde{r}_{it}} \right) = \Delta \log \left(\frac{e_{it}}{r_{it}} \right) + \Delta \ln(\tilde{P}_t) = \Delta \ln(\tilde{P}_t) - \Delta \ln(t_{st}) \tag{8}$$

[14]With perfect competition and constant technology equation (7) reduces to $e_{it}/r_{it} = \gamma^e/t_{st}$ since $\mu = 1$. Under CES demand $\mu = (\sigma)/(\sigma - 1)$ where σ is the constant elasticity of substitution.

where $\tilde{P}_t$ is an industry price deflator. In the absence of significant policy change, equation (8) suggests variation in emissions-intensity should largely be driven by increases in the average industrial price level. To the extent that China had a comparative advantage in 'dirty' industries, we might expect that prices in these industries grew relatively rapidly after WTO accession. As such, even without variation in markups we might expect standard measures of emissions-intensity growth to be biased upwards among high growth industries.

Allowing markups to vary across firms and time, equation (8) can be expressed as

$$\Delta \log \left(\frac{e_{it}}{\tilde{r}_{it}} \right) = \Delta \ln(\tilde{P}_t) - \Delta \ln(\mu_{it}) - \Delta \ln(t_{st})$$

If markups grew relatively rapidly among the dirtiest producers within individual industries, standard emissions-intensity measures, and the consequent policy conclusions, may be biased in the exact opposite direction.

We would not generally expect that emissions-intensity measured in physical units of output would share the same properties. Rearranging the firm's first order condition we write physical emissions-intensity as

$$\frac{e_{it}}{x_{it}} = mc_{it} \frac{\gamma_{it}^e}{t_{st}} \tag{9}$$

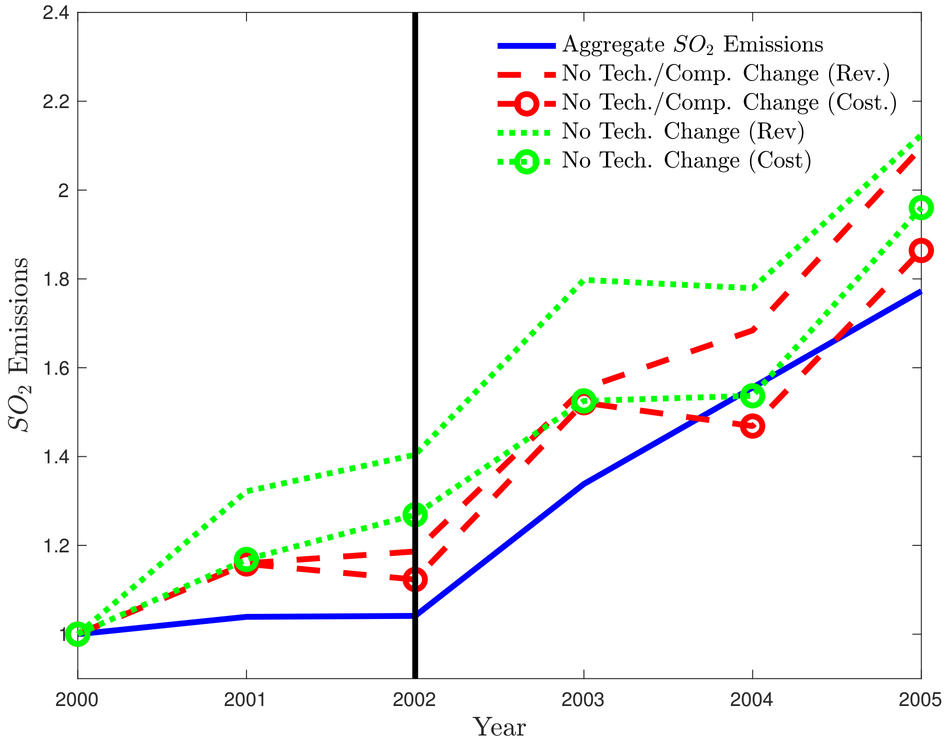
where mc_{it} is the marginal cost of firm i in year t. Any argument of marginal costs should also affect emissions-intensity in quantities. Thus, improvements in technical efficiency, access to cheaper inputs, quality upgrading or even changes in product mix might influence the evolution of physical emissions-intensity even though these will only be correlated with the changes in revenue-based emissions-intensity to the degree that they indirectly influence firm-level markups.

4.2 Cost-Based Decomposition Analysis

How important is the difference between costs and revenues for the interpretation of the conventional emissions decomposition? While it may be desirable to draw conclusions based on equation (9), aggregating units of output across different products, firms, and industries, poses a complementary challenge. A straightforward way to get a sense of the scope of the difference between these approaches is to return to the benchmark decomposition analysis, but use an alternative measure of economic activity for decomposition weights.

In this case rather than using deflated revenue to construct industry or firm-level weights, we measure real variable cost expenditures to distinguish growth in input-use and contemporaneous changes in markups.[15] For instance, we again employ equation (2) but measure V by total variable cost expenditures, while v_s is now the variable costs of production in sector s, w_s is the variable cost share of sector s and ι_s is the cost-based emission-intensity coefficient of sector s, measured as the amount of pollution

[15] In practice, we use the sum of materials expenditures and the wage bill as a measure of total firm-level variable costs. We adjust firm-level wages following Hsieh and Klenow (2009) to account for missing compensation in the firm-level survey.



The blue solild line plots the aggregate SO_2 emissions among Chinese manufacturing firms (normalized to 1 in 2000). The red (green) lines plot the counterfactual path of aggregate emissions when we hold emissions-intensity fixed at its value in 2000 (hold emissions-intensity and industrial composition fixed at their values in 2000). The counterfactual lines with circles use variable cost weights, while the counterfactual lines without circles employ revenue weights.

Figure 5: Decomposing Aggregate SO_2 Emissions

per unit of expenditure on variable inputs.

As in our benchmark analysis, the variable cost-based decomposition again captures changes in scale, industrial composition and technique. It should also mitigate the impact of markup variation under the assumptions that firms produce under roughly constant returns to scale, there is little change in product mix or quality, and markups do not vary significantly over time. We relax these admittedly strong assumptions in Section 5.

Figure 5 illustrates substantial differences between the revenue and cost based decompositions, particularly after WTO accession. In the first exercise, we hold technology, as proxied by emissions-intensity, constant at its level in 2000. The revenue-based counterfactual is plotted by the green dotted line, while its variable cost based counterpart is represented by the green dotted line with circles. Clearly, the cost-based line is always significantly closer to the observed path of emissions than the revenue based line. While the revenue-based counterfactual emissions are 20 percent greater than observed emissions in 2005, the cost-based counterfactual implies roughly half the additional emissions growth (10.6 percent).

This also has implications for counterfactual industrial composition. The dashed red line represents the revenue-based counterfactual emissions path when we hold both technology and industrial composition fixed at their 2000 values, while the dashed red line with circles documents corresponding cost-based counterfactual emissions. After accounting for changes in industrial composition, revenue-based counterfactual emissions remain 18 percent greater than observed emissions. The small difference with the first counterfactual is reflective of the dominant role that changes in technique are estimated to have on the path of emissions growth. In contrast, the corresponding cost-based exercise implies differential growth which is only 5 percent greater in 2005 than the observed data. Not only does it appear that the revenue-based decomposition potentially overstates the overall impact of technological change, but it may also lead to misleading conclusions regarding the relative importance of compositional changes in the greater economy.

Turning to the firm-level decomposition of average emissions-intensity we again find significant differences when we quantify equation (3) using revenue or variable cost measures. Table 2 reports both the cost-based decomposition alongside the original revenue-based decomposition for comparison. As expected, the average firm-level measure of emissions-intensity is 5 percentage points higher when it is constructed using variable costs since revenues reflect both costs and markups. Nonetheless, the average percentage change in emissions-intensity is even greater when we use the variable cost-based measure. The total decline in average emissions-intensity falls by 31 percent when we employ the cost-based measure, but only 18 percent in revenue-based exercise.[16]

At first glance, this result appears inconsistent with our characterization of aggregate emissions growth. However, again, the variation across exercises reflect subtle but important differences in measurement between industrial emissions-intensity, $\iota_{st} = \frac{\sum_{i \in s} e_{it}}{\sum_{i \in s} v_{it}}$, and the weighted average emissions-intensity, $\iota_{st}^{w} = \frac{\sum_{i \in s} v_{it} e_{it}}{\sum_{i \in s} v_{it}}$. Stronger correlation between the changes in weights and emissions can explain the larger decline the cost-based decomposition. The differences across exercises also highlights the importance of choosing appropriate weights since they appear to offer contradictory implications. We return to this issue in Section 5.

Table 2: Decomposition of Aggregate Manufacturing SO_2 Intensity, 2000-2005

Decomposition Type	Initial Avg. Pol. Intensity	Total % Point Change	Continuing Firms: Total	Continuing Firms: Within	Continuing Firms: Across	New Entrants	Exiting Firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Revenue	24.50	-4.48	-6.94	-6.44	-0.54	-0.45	2.90
Cost	29.53	-9.17	-11.64	-9.42	-2.24	-1.81	4.28

Notes: This table documents the percentage point change in weighted average SO_2 emissions intensity. Column (1) reports the average emissions-intensity in the initial year. Column (2) documents the total percentage point change. Columns (3), (6) and (7) document the contribution from continuing firms, new entrants and exiting firms, respectively. Columns (4) and (5) decompose the contribution from continuing firms (column 3) into within-firm (column 4) and reallocation components (column 5). The first row measures average emissions-intensity using revenue weights, while the second row uses variable cost weights.

[16] We compute these figures by dividing column (2) by column (1) in Table 2.

Although both exercises confirm a significant role for within-firm changes, the cost-based decomposition suggests a significantly larger role for cross-firm reallocation. Still, the reallocation term in both exercises suggest that cleaner firms grew faster than their counterparts, which contradicts the notion that Chinese growth was fueled by regulation driven comparative advantage. More precisely, it again reinforces the fact that decomposition weights mask a host of firm-level changes that have potential emissions implications. Changes in product mix, product quality, or returns to scale - on top of changes in markups - are all potential confounding explanations in either approach to decomposition analysis.

5 Firm-Level Sources of Aggregate Emissions Growth

Although the cost-based decomposition provides substantially different implications than that based on deflated revenue, it raises nearly as many concerns as the former. Did emissions rise due to changing returns to scale or was it induced by increasingly strict policy enforcement? Were the large number of new producers an important source of aggregate emissions growth even if, on average, they are typically quite small? Was Chinese resource reallocation biased towards clean or dirty producers or products? If so, what weights should be applied to within or across firm reallcation? To address these questions we develop a decomposition of aggregate emissions based on the firm's optimal emissions and production decisions.

Unlike conventional approaches (whether cost or revenue based) our decomposition has four important virtues:

1. Microfoundations: Each decomposition component is directly linked to the determinants of the firm's optimal level of emissions. This is true of both the underlying firm-level changes and the weights placed on each source of emissions growth.

2. Policy: Rather than having policy implicitly affect scale, reallocation or technique, our decomposition specifies a direct impact of policy on emissions (as mediated through the firm's abatement decisions).

3. Entry and Exit: We distinguish the role of net entry, at the firm or product-level, as it reflects growth in the scale of the economy from firm/product-churning which instead captures systematic differences in the nature of production across entrants, exiting firms and incumbents.

4. Quantification: Each subcomponent can be estimated from a straightforward extension of standard product-level estimation of production functions, markups and marginal costs (De Loecker et al., 2016).

Bridging the gap between optimal firm-level emissions and the structure of our data requires extending our argument to the firm-product level since multi-product firms account for the large majority of total Chinese manufacturing production (Tan et al., 2015). While equation (9) directly links production to emissions, it implicitly assumes that each firm only produces one product. Barrows and Ollivier (2018) highlight that within-firm product churning was an important determinant of Indian emissions growth. This is likely to also be the case in China where product scope is reported to have grown rapidly over the WTO accession period (Kee and Tang, 2016). Extending condition (9) to the firm-product level yields

$$e_{ijt} = \frac{mc_{ijt} x_{ijt} \gamma_{ijt}^e}{t_{st}}. \tag{10}$$

where j indexes firm i's products, $j \in \mathcal{I}_i$. Summing over individual firms and products we directly link the firm's optimal emissions choices in a given year to aggregate manufacturing emissions

$$E_t \equiv \sum_i e_{it} = \sum_i \tau_{it} f_{it} \tag{11}$$

where $\tau_{it} \equiv 1/w_{it}^e$ is a measure of the emissions policy faced by each firm in each year and $f_{it} \equiv \gamma_{it}^e c_{it} = \gamma_{it}^e \sum_j mc_{ijt} x_{ijt}$ is a measure of firm-level primitives: technology, marginal costs, scale, product-mix, etc. We proceed to decompose aggregate emissions growth, $\Delta E_5 = E_5 - E_0$, as the sum of five components

$$\Delta E_t = S_t + P_t + T_t + R_t + C_t \tag{12}$$

where

1. S: Scale (Extensive and Intensive Margins)
2. P: Policy (Implied Emissions Taxes)
3. T: Technology (Emission-Biased Technological Change and Efficiency)
4. R: Reallocation (Across Firms and Products)
5. C: Churning (Net Entry of Firms and Products)

We discuss each of the above categories and their interpretation below.[17] For transparency, we focus on the end points of our sample, 2000 ($t = 0$) and 2005 ($t = 5$) and characterize three types of firms or products: entrants ($\mathcal{E}$), exiters ($\mathcal{X}$), or continuing firms/products ($\mathcal{C}$). For a given variable v, we denote the average value for a particular group $\mathcal{G} \in \{\mathcal{C}, \mathcal{E}, \mathcal{X}\}$ in a particular year as $v_t^{\mathcal{G}}$. Similarly, let $\bar{v}$ represent the simple average of v over the sample period, $\bar{v} = 0.5v_5 + 0.5v_0$ and, analogously, $\bar{v}^{\mathcal{G}}$ is $\bar{v}^{\mathcal{G}} = 0.5v_0^{\mathcal{G}} + 0.5v_5^{\mathcal{G}}$.[18] Last, unless otherwise noted, Δv represents the long difference in any particular variable, $\Delta v = v_5 - v_0$. While the discussion below focuses on the interpretation of individual

[17] Arguably, many of the above categories could be combined. For instance, distinguishing churning and scale are largely matters of taste. Nonetheless, because each component is directly tied to the firms first order conditon, each underlying component has an intuitive economic interpretation.

[18] We use simple averages between the two end points of our sample when constructing averages in our decomposition exercise. However, as in Melitz and Polanec (2015), similar results could be found for any particular intertemporal weight on the beginning or end period.

components of the aggregation exercise, a detailed derivation of each term from equation (12) can be found in the appendix.

Scale

Aggregate emissions, holding all features of production constant, increase with the size of an economy by construction. Nonetheless, it is not obvious whether increases in emissions present themselves as increases in the output of existing producers, the expansion of firm product scope or a rise in the number of producers themselves. Letting $\bar{N} = 0.5N_5 + 0.5N_0$ represent the average total number of firms in each year, each of these sources of economic expansion can be aggregated as

$$S_t = \underbrace{\bar{e}^{\mathcal{C}}(N_5^{\mathcal{E}} - N_0^{\mathcal{X}})}_{\text{No. of firms}} + \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\bar{\gamma}_i^e(n_i^{\mathcal{E}} - n_i^{\mathcal{X}})}_{\text{No. of products}} + \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{\gamma}_i^e\sum_{j\in\mathcal{I}_i^{\mathcal{C}}}\overline{mc}_{ij}\Delta x_j}_{\text{Average output growth}}$$

where $\Delta x_j = \frac{1}{N_j^{\mathcal{C}}}\sum_{i\in\mathcal{C}}(x_{ij5} - x_{ij0})$ captures average output growth, $c_i = \sum_j mc_{ijt}x_{ijt}$ measures firm costs, $\gamma_{it}^e = \sum_j(e_{ijt}\gamma_{ijt}^e)/e_{it}$ is the average firm-level output elasticity of emissions, and $\mathcal{I}_i^{\mathcal{C}}$ is the set of products produced by firm i continuously over the 2000-2005 period.

The first term captures the growth in the number of Chinese producers over 2000-2005 period evaluated at the average emissions-level among continuing firms, while the second captures increases in product-scope, holding firm-level taxes, costs and technology constant over time. Note that it is inflated by the fraction $\bar{N}/N^{\mathcal{C}}$ since the average number of firms is greater than the number of continuing firms. The last term captures the growth in the intensive margin of output. The growth of each product is evaluated at the average marginal cost for each firm in over the sample, but average growth is not firm-specific. In this sense, we consider this term an increase in economic 'scale.' Deviations from this average will be associated with reallocation across heterogenous producers below.

Policy

Changes in environmental policy are likely to have both direct and indirect impacts on firm-level emissions. For instance, if greater Chinese enforcement of environmental policy were to induce firms to increase abatement efforts we would expect firm-level emissions to fall. This type of action would be captured by our policy component. In contrast, if greater enforcement caused firms to invest in new, cleaner technology this type of indirect policy effect is not captured by P_t but is instead implicitly part of the technological change component below. We write the contribution from changes in effective policy as

$$P_t = \frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\overline{\gamma_i^e c_i}\Delta\tau_i$$

Again, we hold technology, efficiency and production constant when evaluating the policy contribution.[19] We allow, however, the implied emission tax to vary firm-by-firm in our decomposition. Although legislated environmental penalties are common to firms in the same location and year, it is plausible that individual firms faced different levels of regulatory *enforcement* during this time frame.

Technology

The output elasticity of emissions evolves as firms grow. This, in turn, affects the degree to which technological change is biased towards emissions (EBTC). We are capturing only the contribution from the change in technological parameter on emissions, γ^e_{it}, holding input shares for product j in firm i, ϱ_{ijt}, fixed over the sample period.

$$T_t = \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\sum_{j\in\mathcal{I}_i^{\mathcal{C}}}\bar{\varrho}_{ij}\Delta\gamma^e_{ij}}_{\text{EBTC}} + \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{\gamma}^e_i\sum_{j\in\mathcal{I}_i^{\mathcal{C}}}\bar{x}_{ij}\Delta mc_{ij}}_{\text{Efficiency}}$$

At the same time, it is widely reported that Chinese productivity grew rapidly over the WTO accession period which, in turn, reduced marginal costs. Holding production fixed, a reduction in marginal costs is equivalent to a decline in input demand and a potential source of emissions savings.

Reallocation

We distinguish two types of reallocation which contribute to emissions growth. The first term captures traditional across firm reallocation. In particular, we measure whether output growth, Δx_{ij}, grew relatively rapidly among firms facing lower emissions taxes (higher τ), higher input demand (higher mc) and/or greater technological dependence on emissions (higher γ^e). Rather, than arbitrarily assigning a weighting variable, these weights originate from the optimal emissions condition itself.

$$R_t = \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{\gamma}^e_i\sum_{j\in\mathcal{I}_i^{\mathcal{C}}}\overline{mc}_{ij}(\Delta x_{ij}-\Delta x_j)}_{\text{Across Firms}} + \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\sum_{j\in\mathcal{I}_i^{\mathcal{C}}}\bar{\gamma}^e_{ij}\Delta\varrho_{ij}}_{\text{Across Products (Within-firm)}}$$

The second reallocation term captures the degree to which changes in product shares, $\Delta\rho_{ij}$, are similarly correlated with firm-level variation in emissions taxes, costs, and technology. We distinguish this type of reallocation from product churning, or the entry and exit of new products. Although it is computed only for products which were produced continuously over the sample period, it nonetheless captures the degree to which continuing products were increasingly (or decreasingly) important over time. Indeed,

[19] A subtle difference here is that we are holding the combination of technology γ^e_i and costs c_i constant, $\overline{\gamma_i c_i} = 0.5\gamma_{i5}c_{i5} + 0.5\gamma_{i0}c_{i0}$. Above, $\bar{c}_i$ and $\bar{\gamma}_i$ independently entered the firm-level weight for product growth. As demonstrated in the appendix the origin for this difference is the inherent nesting structure of our decomposition approach.

the across-products term can be can be expressed as the sum of a term capturing reallocation among continuing products and a term measuring the change in the importance of continuing products.[20]

Churning

The accelerated rate of firm and product churning is one of the most distinctive features of China's WTO accession. To the extent that entering or exiting firms (products) systematically differ from incumbent firms (continuing products) in their resource demand or emissions-intensity, we might also suspect that they are a potential source of emissions growth. We compute the contribution from firm and product churning as

$$
\begin{aligned}
C_t \quad = \quad & \underbrace{N^{\mathcal{E}}(e_5^{\mathcal{E}} - e_5^{\mathcal{C}}) + N^{\mathcal{X}}(e_0^{\mathcal{C}} - e_0^{\mathcal{X}})}_{\text{Firm-Level Churning}} + \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \bar{\tau}_i \bar{c}_i [n_i^{\mathcal{E}}(\gamma_{i5}^{\mathcal{E}} - \gamma_{i5}^{\mathcal{C}}) + n_i^{\mathcal{X}}(\gamma_{i0}^{\mathcal{C}} - \gamma_{i0}^{\mathcal{X}})]}_{\text{Product-Level Emissions Churning}} \\
& + \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \bar{\tau}_i \bar{\gamma}_i^e [n_i^{\mathcal{E}}(c_{i5}^{\mathcal{E}} - c_{i5}^{\mathcal{C}}) + n_i^{\mathcal{X}}(c_{i0}^{\mathcal{C}} - c_{i0}^{\mathcal{X}})]}_{\text{Product-Level Cost Churning}}
\end{aligned}
$$

where the average output elasctity of emissions and the average cost of production in a particular group of firms are respectively $\gamma_{it}^{\mathcal{G}} = \frac{1}{n_i^{\mathcal{G}}} \sum_{j \in \mathcal{I}_i^{\mathcal{G}}} \varrho_{ijt} \gamma_{ijt}$, $\mathcal{G} \in \{\mathcal{C}, \mathcal{E}, \mathcal{X}\}$, and $c_{it}^{\mathcal{G}} = \frac{1}{n_i^{\mathcal{G}}} \sum_{j \in \mathcal{I}_i^{\mathcal{G}}} mc_{ijt} x_{ijt}$.

The first component of C_t captures the contribution of firm-level net entry analogously to that in Melitz and Polanec (2015). It computes average emissions among entrants (or exiting firms) relative to their incumbent contemporaries and weights each of these by the number of firms in each group. The second component captures systematic differences in the emissions intensity of production among new and obsolete products firm-by-firm, while the last term measures product-level changes in the cost of production. Notably, this last term includes variation in input demand driven by differences in marginal costs and total production as these both enter the firm-level cost term c_i.

5.1 Quantifying the Determinants of Emissions

In this section, we describe our (straightforward) adaptation of De Loecker et al. (2016) to recover firm-level markups, marginal costs, emissions output elasticities, and the effective price of emissions

[20] In particular, we can rewrite the second term as

$$
\underbrace{\frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \bar{\tau}_i \bar{c}_i \sum_{j \in \mathcal{I}_i^{\mathcal{C}}} \bar{\gamma}_{ij}^e \Delta \rho_{ij}}_{\text{Across Products (Within-firm)}} \quad = \quad \frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \bar{\tau}_i \bar{c}_i \left(\bar{\Psi}_i \sum_{j \in \mathcal{I}_i^{\mathcal{C}}} \bar{\gamma}_{ij}^e \Delta s_{ij}^{\rho} + \Delta \Psi_i \sum_{j \in \mathcal{I}_i^{\mathcal{C}}} \bar{\gamma}_{ij}^e \bar{s}_{ij}^{\rho} \right)
$$

where Ψ_i captures the importance of continuing products in resource demand for firm i, $\Psi_{it} = \sum_{j \in \mathcal{I}_i^{\mathcal{C}}} \rho_{ijt}$, while s_{ijt}^{ρ} is the normalized share of resource demand among continuing products, $s_{ijt}^{\rho} = \rho_{ijt}/\Psi_{it}$. The first subterm across products captures reallocation across continuing products, after normalizing their importance to the firm, while the second term captures the rising or declining importance of resource reallocation towards (or away from) continuing products within individual firms.

regulation in China. We assume that firm i produces product j in year t according to the augmented production function

$$x_{ijt} = f_e(l_{ijt}, k_{ijt}, m_{ijt}, e_{ijt})e^{\omega_{it}} \tag{13}$$

where x_{ijt} is physical production of good j. Relative to production function (6) we maintain the standard assumption in De Loecker et al. (2016) that firm productivity is log additive to total production.[21] We restrict attention to traditional productive inputs including labor, capital and materials along with firm-level SO_2 emissions in our augmented production setting.

We write the log emissions-augmented production function as

$$\ln x_{ijt} = \ln f_e(l_{ijt}, k_{ijt}, m_{ijt}, e_{ijt}; \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{ijt} \tag{14}$$

where $\boldsymbol{\beta}$ is the vector or parameters governing $f_e(\cdot)$ and ε_{ijt} captures measurement error in firm-level output of product j. To make a minimal assumption on the structure of our augmented production function we assume that f_e takes a translog form.

We do not generally observe productive inputs; capital (k_{ijt}), labor (l_{ijt}) and intermediate materials (m_{ijt}) are quite possibly measured with bias. More productive firms are likely to hire more skilled workers, have newer and more efficient capital, or use higher quality inputs. Likewise, we observe neither the share of productive inputs allocated to any particular product or the emissions generated by any production process. Following De Loecker et al. (2016) we write the log value of any particular (unobserved) input m_{ijt} used in production of any of firm i's $j = 1, ..., J_i$ products, $\nu_{ijt} \in \{\ln l_{ijt}, \ln k_{ijt}, \ln m_{ijt}, \ln e_{ijt}\}$ as $\nu_{ijt} = \rho_{ijt} + \nu_{it} - w_{ijt}$ where ν_{it} is the firm-level input (e.g. deflated materials expenditures, emissions), ρ_{ijt} is the (unobserved) allocation of the input to a given product within the firm, and w_{ijt} is the (unobserved) firm-specific input price. We then write the log production function as

$$\ln x_{ijt} = f_e(\boldsymbol{\nu}_{ijt}; \boldsymbol{\beta}) + A(\rho_{ijt}, \boldsymbol{\nu}_{ijt}; \boldsymbol{\beta}) + B(w_{ijt}, \rho_{ijt}, \boldsymbol{\nu}_{ijt}; \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{ijt}. \tag{15}$$

The first unobserved term, $A(\cdot)$, arises from the unobserved input allocation parameters ρ_{ijt}, while the second, $B(\cdot)$, is due to unobserved input prices w_{ijt}.[22]

De Loecker et al. (2016) propose an approach to estimate the production function parameters $\boldsymbol{\beta}$ while addressing both sources of potential bias. To address the first source of bias, multi-product production, we estimate product-specific augmented production functions using data from single-product producers alone. Dropping all multiproduct firms potentially induces sample-selection bias since single-product firms are expected to be systematically less productive than multi-product producers. We follow their approach to correct for this potential source of bias by introducing a control variable which captures the

[21] Note that this would be the case in workhorse models of trade and the environment such as Shapiro and Walker (2018).

[22] The functional form of $A(\cdot)$ and $B(\cdot)$ follow directly from the assumption of an augmented translog production function. We report these in the appendix.

probability of exiting the estimation sample because of multiproduct production.[23]

Bias arising from unobserved input prices, $B(\cdot)$, is approximated by a control of variables which correlate with unobserved product quality. These include firm-level measures of market share and their interactions with firm-level state variables. Under the assumption that the proxy variables can entirely capture the variation in unobserved input prices, we recover unbiased estimates of the parameters $\boldsymbol{\beta}$ from augmented production function (15).[24]

After correcting for potential endogeneity arising from selection bias $A(\cdot)$ or unobserved input prices $B(\cdot)$, the vector of augmented production function parameters is estimated using a control function approach (Olley and Pakes, 1996). In particular, we follow the approach proposed by Levinsohn and Petrin (2003), where we assume that unobserved productivity, ω_{it}, follows a first-order Markov process and that we can proxy for its absence with the inverted material demand function. To estimate the production function parameters, we implement the Wooldridge (2009) GMM estimation procedure industry-by-industry where moment conditions are formed on the joint error term of shocks to productivity and the measurement error in output, ε_{ijt}. That is, for each of the 24 2-digit industries in our data, we separately recover a product-specific production function for each 5-digit product classification within the 2-digit industries.[25]

The procedure also returns estimates of the parameters which govern the input price function, $B(\cdot)$, and thereby estimates of unobserved input prices, w_{ijt}. Perhaps the most important input price in this context is the unobserved effective price of emissions. The recovered vector of prices for emissions provides a measure of effective emissions regulation in the Chinese manufacturing sector. In particular, the implied emissions tax captures all constraints on emissions and production and provides a summary of the regulatory environment as it pertains to firm-level emissions.

Using the implied input prices, we then recover the input allocation shares, ρ_{ijt}, and unobserved firm-level productivity, ω_{it}, among multiproduct producers. For the firm with J products we construct a system of $J+1$ equations in $J+1$ unknowns: the first J equations are the production functions as described in equation (15), while the last is simply the restriction that all input allocations must sum to one, $\sum_j \rho_{ijt} = 1$. We solve this system of equations for each individual firm-year pair.

Input prices, w_{ijt}, and input allocations, ρ_{ijt}, in turn allow us to estimate the physical quantity of any specific input, including SO_2 emissions, allocated to any particular product within a particular firm-year pair. The input allocations imply firm, year and product-specific output-elasticities. The output elasticity for emissions, γ^e_{ijt}, measures the emissions-intensity Chinese production as governed by the structure of production. Systematic changes in γ^e_{ijt} capture the degree to which changes in the nature of manufacturing production, conditional on firm productivity, influenced the evolution of emissions over

[23] The sample selection correction in De Loecker et al. (2016) closely resembles the correction for endogenous firm exit in Olley and Pakes (1996).

[24] As noted in De Loecker et al. (2016) this approach requires that input prices are not a function of the level of the input itself.

[25] We note that there are more than 24 2-digit industries in the raw data, but not all are sufficiently large to use as an estimation sample. Thus, we merge small related industries into a final sample of 24 2-digit industries.

time.

Finally, output elasticities combined with expenditure shares allow us to recover markups and marginal costs. As argued in section 4.1, the former may be primary source of bias in conventional decomposition analysis should they vary significantly across firms and time. Declines in marginal costs, highlighted among Chinese manufacturers during the WTO accession period, are a potential source of real environmental gains.

6 Results

We present results in two steps. First, we document the estimated markups, marginal costs, emissions-elasticities, and the implied emissions taxes. Second, we measure the contribution from each source of emissions growth according to our proposed decomposition of aggregate emissions.

6.1 Markups, Marginal Costs, Technology & Taxes

Table 3 documents emissions output elasticities for all of the 2-digit industries in our data. The first two columns report the mean and median firm-and-product specific elasticities, γ_{ijt}^{e}, while columns 3 and 4 compute long differences over the 2000-2005 period, $\Delta\gamma_{ij}^{e} = \gamma_{ij,05}^{e} - \gamma_{ij,00}^{e}$. Our benchmark exercise restricts attention to firms for which the estimated emissions elasticity was positive. Negative emissions-elasticities may reflect a number of different sources of unmodeled and unobserved heterogeneity which we address below.

Our benchmark single-technology, emissions output elasticities are estimated to be quite large; across industries the median firm-level elasticity ranges from 0.071 to 0.859. Roughly two thirds of the median output elasticities lie between 0.1 and 0.3. Among firms in this range, a 10 percent increase in emissions is associated with a 1-3 percent increase in output, ceteris paribus. Rapid firm-level growth will likely lead to large increases in emissions unless there are signficant changes in the structure of production or in the price of emitting pollution.

The long difference in the output elasticities of emissions over 2000 to 2005 period are reported in columns (3) and (4) for the benchmark sample. Median (average) output elasticity declined significantly in 17 (16) of 24 sectors and increased modestly in nearly all other industries. Weighting firms by measures of economic activity (e.g. cost or revenue shares) further reinforces the notion that emissions-intensity did in fact decline over time. In this sense, we do find that the environmental performance Chinese production did improve throughout the WTO accession period. Whether it significantly mitigated aggregate emissions growth, depends on its comovement with the other determinants of emissions growth. However, ignoring the evolution of output elasticity of emissions would lead standard decomposition analysis to underestimate the impact of technological improvement on the evolution of aggregate emissions.

As noted above, our benchmark results drop all observations where firm-product pairs report negative

Table 3: Emissions Output Elasticities

	Single-Technology				Multiple-Technology			
	Levels		Δ's 2000-5005		Levels		Δ's 2000-5005	
Sector	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mineral products	0.324	0.270	-0.435	-0.110	0.328	0.239	-0.345	-0.440
electricity generation	0.283	0.212	-0.149	0.014	0.240	0.139	-0.064	-0.157
food products	0.141	0.124	0.023	-0.049	0.188	0.136	0.022	-0.066
alcoholic beverages	0.092	0.071	0.066	0.038				
cloth	0.212	0.171	-0.176	-0.183	0.218	0.175	-0.019	-0.186
clothing and apparel	0.395	0.361	-0.185	-0.147	0.299	0.202	-0.041	-0.124
wooden furniture	0.496	0.517	-0.285	-0.451	0.524	0.464	-0.194	-0.345
paper products	0.613	0.859	0.241	0.099	0.862	0.852	-0.056	-0.245
fuel, diesel & gas	0.329	0.299	-0.042	-0.180	0.331	0.294	-0.072	-0.176
chemical products	0.197	0.147	0.114	-0.028	0.588	0.505	-0.094	-0.238
rubber products	0.255	0.184	0.452	0.670	0.517	0.351	-0.118	-0.256
tires & conveyor belts	0.508	0.535	-0.121	-0.121	0.564	0.590	-0.148	-0.202
plastic products	0.111	0.075	-0.561	-0.503	0.134	0.113	0.261	0.203
glass & ceramic products	0.186	0.156	-0.264	-0.101	0.415	0.266	0.012	-0.031
crude steel	0.230	0.223	0.122	0.052	0.954	1.536	0.612	0.677
high quality steel & steel plates	0.196	0.190	-0.306	-0.187	1.100	1.611	0.436	0.238
heavy metal products	0.344	0.304	0.157	0.136	0.412	0.354	0.349	0.274
light metal products	0.393	0.396	0.340	0.488	0.614	0.497	-0.006	-0.006
auto parts	0.146	0.093	-0.086	-0.104	0.476	0.320	-0.328	-0.331
wheels, gears, & mining equip.	0.249	0.211	-0.826	-0.423	0.538	0.392	0.171	-0.001
transportation equipment	0.221	0.191	-0.643	-0.714	0.709	1.953	0.094	-0.549
abatement equip. & heavy mach.	0.189	0.128	-0.318	-0.105	0.876	2.403	0.158	-0.064
comm. cables & elec. wires	0.270	0.225	-0.241	-0.112	0.224	0.186	-0.010	-0.119
measuring tech., printers, etc	0.616	0.839	-0.075	-0.191	0.682	0.635	-0.521	-0.268

Notes: Columns (1) and (2) report the estimated mean and median emissions output elasticities, while columns (3) and (4) report the mean and median change in output elasticity over the 2000-2005 period for the single-technology approach. Columns (5)-(8) report the same information for the multiple-technology approach. Each calculation is performed separately for 24 2-digit manufacturing sectors. There are insufficient observations to recover estimates for the alcoholic beverage industry when employing the multiple-technology approach.

emissions elasticities. This occurs in a non-trival part of our sample: for roughly 30 percent of the firm-product pairs the benchmark estimates indicate that the overall level of emissions will decline as output rises.[26] We consider a number of possible explanations for this result. First, we examine the degree to which these firms are concentrated in a particular industry. Although they are largely concentrated in a handful of industries, they do appear in most of our 24 industries. We also check whether these estimates are capturing differences in technology across foreign, state-owned or domestic firms. In general, the negative emissions elasticities are equally present across all three types of ownership.

We study the robustness of our benchmark, single-technology results by allowing for greater technological heterogeneity across firms. First, we estimate the augmented production function under the assumption that a single-technology is sufficient to capture the production function for each of the 360 (5-digit) products in the data set. Upon recovering the estimates, we break each 5-digit product classification into two groups: firm-product pairs which have positive estimated emissions elasticities and firm-product pairs with negative emissions elasticities. We then repeat the production function estimation routine for each product classification and each group under the assumption that the two groups of firms produce the same product with different production technologies.[27] That is, we estimate 2 production functions for each product (or 720 separate production functions total). After accounting for this potential source of unobserved (technological) heterogeneity over 90 percent of all firm-product pairs are estimated to have positive emissions elasticities.[28]

Columns (5)-(8) of Table 3 report complementarity emissions-elasticities and their changes for our multiple technology approach to production function estimation. For most industries the multiple-technology approach yields very similar estimates of the output elasticity of emissions. However, in at least seven industries it is clear that allowing for multiple technologies significantly increased the mean and median output elasticity of emissions. The largest changes occur in the production of abatement equipment[29], transportation equipment, crude steel, high quality steel, chemical products, mining equipment and rubber products. After allowing for multiple technologies, we observe that the estimated elasiticites in these industries are substanially higher than those from the benchmark exercise and, in two cases, are greater than one. Inaccurate measures of emissions elasticities will clearly bias any characterization of the contribution of technological change on emissions growth. As we document below, they also have the potential to generate misleading estimates of marginal costs, markups and the incidence of the regulatory environment.

The augmented production function estimates provide a second, and equally important, measure of technological progress: changes in marginal costs. Table 4 displays significant variation in marginal costs

[26] It is not uncommon for the De Loecker et al. (2016) method to produce negative output elasticities for a small number of observations. The large fraction of negative estimates is rather more concerning.

[27] The intuition here is similar to that exposited in Kasahara, Schrimpf and Suzuki (2017).

[28] We could, in principle, continue to repeat this process until we had eliminated all negative emissions elasticities. In practice, the vast majority of industries have too few negative emissions elasticities to reliably use in a further round of estimation.

[29] The abatement equipment and heavy machinery industry captures the production of concrete machinery, compaction machinery, air pollution prevention and control equipment, water pollution prevention and control equipment, and noise and vibration control equipment among other related products.

Table 4: Marginal Costs

Sector	Single-Technology				Multiple-Technology			
	Levels		Δ's 2000-5005		Levels		Δ's 2000-5005	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mineral products	19.575	0.175	5.842	2.468	10.431	0.384	3.623	1.980
electricity generation	69.321	4.153	2.597	0.223	325.221	6.161	1.041	0.109
food products	27.178	4.017	0.649	-0.140	23.434	7.323	0.553	0.046
alcoholic beverages	68.523	11.188	1.984	0.074				
cloth	194.705	55.592	2.605	0.046	510.310	80.520	1.367	0.079
clothing and apparel	167.261	55.393	0.837	-0.067	855.899	133.451	0.816	0.165
wooden furniture	7.366	1.061	1.334	0.082	3.594	1.941	0.493	0.124
paper products	116.807	2.716	1.622	0.194	239.122	4.146	0.745	-0.261
fuel, diesel & gas	13.376	1.418	2.936	0.540	13.771	2.640	1.679	0.467
chemical products	47.938	6.361	2.049	0.078	42.779	9.553	-0.243	-0.333
rubber products	98.065	8.049	0.965	0.273	66.985	9.881	-0.122	-0.247
tires & conveyor belts	286.760	34.888	-0.001	-0.001	496.765	35.987	-0.224	-0.672
plastic products	786.656	520.394	-0.192	-0.999	1215.611	701.992	-0.549	-1.000
glass & ceramic products	43.547	1.761	0.948	0.001	26.453	1.154	0.709	0.018
crude steel	27.055	2.630	2.876	0.413	18.275	0.860	0.855	1.406
high quality steel & steel plates	36.220	1.994	3.718	1.645	3.085	0.127	3.172	5.189
heavy metal products	116.354	14.258	1.047	0.013	85.735	11.388	0.847	0.032
light metal products	110.974	7.740	0.626	0.152	56.375	6.395	1.470	1.470
auto parts	218.282	44.334	4.902	1.061	396.784	34.365	1.410	0.374
wheels, gears, & mining equip.	105.104	13.684	2.141	0.140	117.360	16.339	0.172	-0.145
transportation equipment	114.267	13.857	3.774	1.857	73.764	6.265	0.096	0.123
abatement equip. & heavy mach.	467.731	82.306	6.302	3.892	697.576	30.205	3.226	6.882
comm. cables & elec. wires	86.528	4.731	2.384	0.254	93.041	7.551	0.959	0.379
measuring tech., printers, etc	46.296	0.991	1.294	0.768	25.887	1.030	1.159	0.140

Notes: Columns (1) and (2) report the estimated mean and median marginal costs, while columns (3) and (4) report the mean and median change in marginal costs over the 2000-2005 period for the single-technology approach. Columns (5)-(8) report the same information for the multiple-technology approach. Each calculation is performed separately for 24 2-digit manufacturing sectors. There are insufficient observations to recover estimates for the alcoholic beverage industry when employing the multiple-technology approach.

across industries and time. In particular, we find that the (simple) average of the change in marginal costs grew over the WTO accession period. As demonstrated in the next section, these changes are somewhat misleading: changes in marginal costs are negatively correlated with the firm-and-product level weights. That is, firms with declining marginal costs account for a much larger share of production in a majority of industries. Accordingly they also receive a greater weight in the decomposition analysis.

Table 5 documents *firm-level* markups for each 2-digit industry in our data. Formally, the first-order condition holds at the firm-product level

$$r_{ijt} = \mu_{ijt} \frac{m_{ijt} w_{ijt}^m}{\gamma_{ijt}^m} \tag{16}$$

and our estimation procedure returns estimates of m_{ijt}, γ_{ijt}^m, and w_{ijt}^m. Because we only observe firm-level revenues, r_{it}, not firm-product revenues, r_{ijt}, we cannot identify firm-and-product specific markups with our data.[30] Summing over products in equation (16) and dividing both sides by $\sum_j \frac{m_{ijt} w_{it}^m}{\gamma_{ijt}^m}$ provides us with an input-weighted measure of firm-level markups

$$\mu_{it} \equiv \sum_j \lambda_{ijt} \mu_{ijt} = \frac{r_{it}}{\sum_j \frac{m_{ijt} w_{ijt}^m}{\gamma_{ijt}^m}} \text{ where } \lambda_{ijt} = \frac{\frac{m_{ijt} w_{ijt}^m}{\gamma_{ijt}^m}}{\sum_j \frac{m_{ijt} w_{ijt}^m}{\gamma_{ijt}^m}} \tag{17}$$

Using intermediate materials as a variable input, we recover firm-level markups according to equation (17).

Our estimated markups generally fall into a similar range to those reported in Lu and Yu (2015). In general, we estimate fewer industries where the median firm-level markup is negative; in our estimation exercise this only occurs in the fuel industry. The difference in findings across papers may plausibly be driven by differences in the sample period or firm-level coverage. The sample period in Lu and Yu (2015) begins in 1998, when markups were potentially smaller prior to WTO accession, while our sample begins in 2000. Similarly, we include both small, single-product firms along with large, multi-product firms in our estimation sample while Lu and Yu (2015) focus exclusively on single-product producers.

De Loecker et al. (2016), which estimates markups among Indian manufacturers during a period of trade liberalization, provides another benchmark to which we can compare our markup estimates. Across 11 sectors they report median markups which range from 15 to 127 percent. Excluding the one or two industries with negative median markups, we estimate median markups which range from 4 to 162 percent in the single-technology exercise and 2 to 108 percent in the multiple-technology approach.

In both experiments, we consistently observe significant increases in Chinese markups over time. On one hand, we find that average markups increase in 17 (14) of the 24 (23) industries in the single-technology (multiple-technology) exercise. If we weight firms by a measure of firm size we find that average markups increase in almost all industries over time. Rising markups suggest that the revenue-based measures emissions-intensity would almost surely bias the standard decomposition analysis and lead researchers to overestimate the role of technological improvement on the path of aggregate emissions. On the other hand, median markups increase in roughly half of the industries in either exercise. Whether, markups matter for our overall decomposition conclusions crucially depend on the weight on an individual firm's contribution to aggregate emissions growth.

Finally, given our estimates of firm-level markups, marginal costs and emissions elasticities, we recover the implied price of emissions, under the assumption that each unit (kilogram) of emissions has the same price regardless of which product the firm is producing. The implied prices, along with their changes over time are reported in Table 6 and are measured in units of 1000 RMB (or \$120.77 USD) per kilogram of SO_2 emissions. To interpret this value we must recall that it reflects the full implied price of increasing emissions across all regulatory and non-regulatory margins even if they are not necessarily intended to restrict emissions per se. That is, it reflects the full cost of quotas, taxes, fines, loan conditions, restricted export market access and public pressure, among other regulatory conditions.

[30] Recall, we are able to identify m_{ijt}, w_{ijt}^m, and γ_{ijt}^m because we observe firm and product specific production, x_{ijt}.

Table 5: Markups

	Single-Technology				Multiple-Technology			
	Levels		Δ's 2000-5005		Levels		Δ's 2000-5005	
Sector	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mineral products	1.463	1.358	0.016	-0.094	1.075	0.985	0.083	-0.084
electricity generation	1.385	1.292	0.172	0.137	1.117	1.021	-0.029	-0.106
food products	1.136	1.091	0.193	0.161	1.145	1.056	0.164	0.161
alcoholic beverages	1.132	1.057	0.052	0.014				
cloth	1.120	1.062	0.005	-0.076	1.187	1.152	-0.013	-0.061
clothing and apparel	2.544	2.628	0.176	0.139	1.757	1.424	0.055	-0.003
wooden furniture	1.445	1.304	0.056	-0.052	1.308	1.261	0.051	-0.026
paper products	1.620	1.469	0.040	-0.027	1.524	1.392	0.000	0.060
fuel, diesel & gas	0.795	0.704	-0.052	-0.136	0.832	0.674	-0.045	-0.117
chemical products	1.239	1.193	0.056	-0.022	1.329	1.196	0.255	0.301
rubber products	1.237	1.100	0.204	0.138	1.516	1.382	0.203	0.241
tires & conveyor belts	1.232	1.078	0.004	0.004	1.418	1.073	0.092	0.340
plastic products	1.037	1.005	0.097	0.036	1.074	1.029	0.111	0.095
glass & ceramic products	1.251	1.217	-0.036	-0.092	1.242	1.311	-0.044	-0.092
crude steel	1.381	1.346	0.027	-0.013	1.466	1.394	-0.181	-0.145
high quality steel & steel plates	1.282	1.251	-0.260	-0.324	0.564	0.570	-0.552	-0.552
heavy metal products	1.859	1.811	0.082	0.025	1.916	1.896	0.168	0.128
light metal products	1.334	1.219	0.123	0.091	1.175	1.198	0.345	0.345
auto parts	1.080	1.037	-0.187	-0.335	1.348	1.280	-0.015	-0.062
wheels, gears, & mining equipment	1.559	1.516	-0.031	-0.126	1.532	1.517	0.088	0.212
transportation equipment	2.075	2.133	0.134	0.110	2.023	1.977	0.213	-0.450
abatement equip. & heavy mach.	1.842	1.816	0.193	0.061	1.783	1.894	0.074	0.261
comm. cables & elec. wires	1.400	1.315	-0.133	-0.156	1.218	1.117	-0.112	-0.124
measuring tech., printers, etc	1.713	1.672	-0.024	0.038	1.473	1.486	-0.075	-0.027

Notes: Columns (1) and (2) report the estimated mean and median markups, while columns (3) and (4) report the mean and median change in markups over the 2000-2005 period for the single-technology approach. Columns (5)-(8) report the same information for the multiple-technology approach. Each calculation is performed separately for 24 2-digit manufacturing sectors. There are insufficient observations to recover estimates for the alcoholic beverage industry when employing the multiple-technology approach.

It also reflects all unmeasured costs associated with increasing production which would lead to greater emissions. For instance, shortages in skilled-labor, increasing costs of upgrading capital, or higher tariffs in export markets are all implicit taxes on production. If they are fully incorporated into current markups and prices, then the implied emissions-tax will not reflect these characteristics of production. However, should prices and markups adjust slowly over time to changing market conditions, the implied emissions-taxes will capture the full cost of increasing production including costs which are not directly aimed at reducing emissions themselves.

Columns (2) and (6) display large differences in the implied emissions taxes across the single and multiple-technology estimation approaches. For instance, in the first row the median emission tax in the mineral products industry is 211 RMB (25.48 USD) per kilogram. In comparison, the median implied emissions-tax in the multiple-technology approach is only 54 RMB (6.25 USD) per kilogram. This pattern is consistent across industries: in all but one case (three cases) the median (average) emissions tax is lower in the multiple-technology exercise. Moreover, the multiple-technology implied emission taxes are often an order of magnitude smaller.

Table 6: Implied Emissions Taxes

	Single-Technology				Multiple-Technology			
	Levels		Δ's 2000-5005		Levels		Δ's 2000-5005	
Sector	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mineral products	0.607	0.211	2.361	2.340	0.653	0.054	2.774	1.065
electricity generation	5.535	1.597	1.294	0.413	0.647	0.028	2.044	0.250
food products	5.485	1.611	1.992	0.625	1.355	0.330	1.902	0.219
alcoholic beverages	6.456	2.925	2.176	0.527				
cloth	2.789	1.088	2.552	0.317	1.004	0.334	1.597	0.247
clothing & apparel	5.080	2.143	1.973	0.222	1.108	0.273	1.386	0.042
wooden furniture	0.787	0.390	2.088	0.640	0.213	0.170	0.497	0.191
paper products	1.652	0.677	1.447	0.310	0.719	0.320	1.463	0.404
fuel, diesel & gas	1.204	0.369	3.074	0.594	0.451	0.232	2.317	0.764
chemical products	1.737	0.488	2.119	0.304	1.438	0.110	0.226	0.040
rubber products	5.016	1.937	2.579	0.510	1.307	0.352	6.483	0.460
tires & conveyor belts	5.122	1.975	0.617	0.617	3.547	1.751	-0.329	-0.076
plastic products	0.686	0.127	1.583	0.241	0.883	0.029	2.005	0.724
glass & ceramic products	1.031	0.289	3.475	1.323	0.316	0.055	4.446	-0.118
crude steel	3.726	0.901	4.080	1.543	1.493	0.076	4.483	1.972
high quality steel & steel plates	4.502	1.321	3.091	0.721	2.272	0.043	0.397	-0.989
heavy metal products	10.331	5.988	3.728	1.709	2.714	1.302	6.593	1.533
light metal products	6.527	3.298	2.280	2.656	3.309	2.272	0.092	0.092
auto parts	8.293	4.306	3.416	1.293	0.251	0.015	5.991	1.583
wheels, gears, & mining equip.	7.595	3.620	4.715	1.426	2.508	0.675	5.173	2.107
transportation equipment	1.937	0.792	1.287	-0.122	4.526	5.430	0.815	0.282
abatement equip. & heavy mach.	11.474	9.262	4.302	1.451	6.543	7.889	1.830	0.996
comm. cables & elec. wires	17.266	21.361	2.499	0.875	2.312	0.838	3.793	0.982
measuring tech., printers, etc	6.376	2.971	-0.066	-0.761	2.590	1.524	0.415	-0.526

Notes: Columns (1) and (2) report the mean and median implied emissions taxes, while columns (3) and (4) report the mean and median change in the implied emissions taxes over the 2000-2005 period for the single-technology approach. Columns (5)-(8) report the same information for the multiple-technology sample. Each calculation is performed separately for 24 2-digit manufacturing sectors. There are insufficient observations to recover estimates for the alcoholic beverage industry when employing the multiple-technology approach.

It is less clear whether the estimated price of emissions are high or low relative to international standards. Our estimated prices are an order of magnitude larger than average US prices for spot sulfur dioxide emissions allowances over the same period.[31] This is not particularly surprising, the frictions associated with increasing production, and thus emissions, are manifold. What is perhaps more interesting is that while it is widely cited that production distortions declined over the WTO accession period, our estimates suggest that the cost of emitting SO_2 rose. The rise in mean and median emissions taxes in Table 6 are consistent with rise in SO_2 taxation, policy enforcement or both. The degree to which this was a quantitatively important determinant of emissions growth depends both on the size of the individual changes but also their correlation with other firm-level attributes. For instance, even if many small, private firms experience increases in implied emissions taxation, this mechanism will not necessarily play a large role in mitigating emissions growth if large, emissions-intensive producers are left unchecked. Our decomposition approach provides theoretically consistent weights to capture the impact of regulatory change.

6.1.1 Ownership Differences

Tables 10-14 (in the appendix) document differences in emissions elasticities, markups, marginal costs and implied emissions taxes across foreign-owned, state-owned and domestic (privately-held) firms.[32] In general, the estimated differences across industries correspond to our prior expectations. For instance, consider the set of industries where each type of ownership is present over the entire sample period. In 9 of the 16 industries foreign firms are estimated to have the lowest median marginal costs and the largest markups. In contrast, state-owned firms are estimated to have the largest median marginal costs in 11 of the same 16 industries. The lowest median markups are found among domestic firms in 8 industries, state-owned firms in 6 industries and foreign firms in 2 industries. In this sense, our findings confirm that foreign owned enterprises are the most efficient and profitable, while the state-owned are least efficient and domestic firms often operate with smallest margins.

Turning to implied emissions taxes we again observe the highest level of taxation among foreign firms in 12 out of 16 industries. Private and state-owned firms faced the weakest (median) regulatory burden in 4 and 9 industries, respectively. Collectively this suggests that foreign producers faced disproportionately strict regulation relative to their domestic counterparts. Finally, there is no obvious pattern across ownership with respect to emissions elasticities. On one hand, privately-owned domestic firms have the largest median emissions-intensities in 8 of 16 industries, while the same is true among state-owned firms in only 3 industries. On the other hand, the lowest median elasticities are found among privately-owned firms in 5 industries, state-owned firms in 6 industries and foreign-owned firms in 7

[31] See the EIA website for historical spot price data: https://www.eia.gov/todayinenergy/detail.php?id=1330# (accessed March 5, 2020). At their height over the 2003-2008, US spot prices reached nearly $2,000 USD per ton of SO_2 emissions. This is nonetheless smaller than the implied prices from our estimation exercise.

[32] Tables 10-14 restrict attention to the multiple-technology approach. The same qualitative patterns are found using the single-technology approach.

industries.[33]

6.2 Decomposition Results

Tables 7 and 8 document our benchmark decomposition findings. Table 7 breaks down aggregate emissions growth into its five primary components (scale, policy, technology, reallocation and churning) while Table 8 examines the underlying determinants of each component. We provide decomposition results for both single and multiple-technology estimation routines, but note that they are generally quite similar.[34]

Table 7: Sources of Aggregate SO_2 Emissions Growth

	Percentage Contribution				
Approach	Scale	Policy	Technology	Reallocation	Churning
Single-Technology	101.08	-4.22	-14.03	15.49	1.68
Multiple-Technology	97.53	-8.19	-13.69	23.41	0.94

Notes: Table 7 documents the contribution from each source of emissions growth according to the decomposition equation (12).

It is clear that there are two key drivers of emissions growth in China: the rapid expansion in the scale of China's economy and the reallocation of economic activity towards relatively emissions-intensive activities. Neither source of emissions growth is particularly surprising, but their relative magnitudes are revealing. Indeed, after correcting for measurement bias, we find that the increased scale of Chinese manufacturing accounts for 98-101 percent of total emissions growth. Although previous analysis also emphasizes economic scale (e.g. Levinson 2009, Shapiro and Walker 2018), emissions growth has not generally been found to move one-for-one with economic growth in contexts outside of China.

The second key driver of emissions growth is the reallocation of economic activity towards dirtier production. In fact, reallocation of resources towards dirtier production increased aggregate emissions growth by 16-23 percent. This is broadly consistent with the notion that China's economic growth has come at the cost of becoming a global pollution haven. Moreover, because the reallocation term only captures changes within pre-existing firms and products, it also suggests that the largest changes are not due to the rapid entry of new firms and products. In fact, despite rapid entry and exit among of new firms and products, marginal firms and products represent a sufficiently small amount of economic activity that their collective contribution of emissions growth is below two percent.

The scale, reallocation and churning terms sum to more than 100 percent because implied policy change and improved technology act to offset aggregate emissions growth. We find that, in aggregate, implied changes in emissions regulation mitigated 4-8 percent of aggregate emissions growth. Although modest, this result is line with existing research which highlights that, at the time, the prevailing regulation was ineffective even if SO_2 emissions were an increasing domestic concern (Shi and Xu, 2018).

[33]The median elasticity was nearly identical for foreign and domestic firms in two industries.

[34]Tables 7 and 8 report decomposition results after trimming outliers. Starting with the full sample, we consistently trimmed one percentile from the top and bottom of the distribution of firm-level contributions of each subcomponent in Table 8. We then collected the remaining firms and recomputed the entire decomposition.

In contrast, technological improvement is estimated to have reduced emissions by 14 percent which is substantial given China's rate of economic growth. For our aggregated sample of manufacturing firms this would suggest that technological improvement has reduced China's annual SO_2 emissions by 1.5 million tons. On one hand, this effect is remarkable, particularly given the scope of China's emissions growth during the WTO accession period. On the other hand, it stands in sharp contrast to existing results which suggest that improved production techniques may be sufficient to mitigate the environmental consequences of economic growth (e.g. Antweiler et al., 2001).

Table 8: Subcomponents of SO_2 Emissions Growth

Approach	Component Share	Subcomponent Share		
		Scale		
		Number of firms	Number of Products	Average Output Growth
Single-Technology	101.38	0.01	-21.92	121.92
Multiple-Technology	98.32	0.03	-5.10	105.07
		Technology		
		EBTC	Efficiency	
Single-Technology	-14.05	4.65	95.35	
Multiple-Technology	-13.68	8.61	91.39	
		Reallocation		
		Across-Firm Reallocation	Across-Product (Within-Firm) Reallocation	
Single-Technology	15.52	92.67	7.33	
Multiple-Technology	23.40	92.16	7.84	
		Churning		
		Firm-Level	Product-Level Emissions	Product-Level Cost
Single-Technology	1.68	-0.77	22.81	77.96
Multiple-Technology	0.94	2.77	57.11	40.12

Notes: Table 8 documents the contribution from each subcomponent of emissions growth in the decomposition equation (12).

Table 8 identifies the underlying determinants for each of the four multi-faceted primary components of emissions growth: scale, reallocation, technology and churning. It is striking that each primary component is largely driven by one key economic subcomponent. For economic scale, is it clearly the average growth of existing firm-product pairs. This is not to say that there wasn't significant net entry. Rather, even in our sample of large manufacturers the number of new establishments increasesd by over 10 percent. The small contribution of entry is instead driven by the fact that, on average, firm-level emissions are small relative to the aggregate cost-weighted output growth. Likewise, we find that average firm-level product scope declined. This, in turn, has a mitigating impact of economic scale on emissions.[35]

Turning to the technological component, we observe that changes in emissions output-elastiticities accounts 5-9 percent of the total technological contribution to emissions growth. Although modest, our decomposition suggests EBTC alone reduced the path of aggregate emissions by one percent alone. In contrast, lower marginal costs and improved firm-level productivity, mitigated aggregate emissions-growth to a much greater extent. Indeed, the reduction marginal costs accounts for over 90 percent of

[35]The decline in firm-level product scope is consistent with various models of multiproduct firms during periods of trade liberalization. See Bernard et al. (2011) or Mayer et al. (2014) for examples. Our decomposition findings do not imply that export scope declined.

the technological contribution to aggregate emissions and reduced the total growth of manufacturing emissions by at least 13 percent. In a companion paper, Rodrigue, Sheng and Tan (2020), we study the degree to which WTO accession induced changes in Chinese firm-level production technology which were complementary to within-firm improvements in environmental performance. We find evidence that the technological improvements in firm-level environmental performance are manifest through new investment in physical capital, a reduction in the dependence on coal-based energy, and underlying changes in product mix.

The third panel of Table 8 studies the reallocation term and is the most important determinant of Chinese emissions growth outside of the rapid expansion of economic scale. Notably, the lion's share of reallocation occurs at the firm-level rather than the product-level. This feature is consistent with the notion that although energy-intensity may vary across products within-firms, energy sources are likely to be relatively firm-specific. Moreover, the large firm-level reallocation term suggests that large firms with access to cheap, but dirty, energy sources grew particularly quickly relative to their industry averages in the aftermath of WTO accession.

The bottom panel of Table 8 decomposes the modest contribution from firm and product churning. Although both the single and multiple-technology suggest that churning accounts for little overall emissions growth, the underlying sources vary significantly across exercises. For instance, in the single-technology case most of the churning component arises from within-firm changes in average product production cost. This finding is consistent with the notion that the total production cost of continuing products, which typically represent the firm's chief output, is significantly larger than that of dropped products. In contrast, the multiple-technology exercise suggests a larger role for product-level emissions churning. As China grew into world markets, new products were most likely to appear in industries in line with China's comparative advantage and the least emissions-intensive goods were likely to be dropped from the firm's production set.

7 Conclusion

This paper documents the growth of firm-level emissions among Chinese manufacturers during the WTO accession period (2000-2005). We demonstate that heterogeneous markups bias standard emissions growth analysis and may potentially lead to a misleading relationship between firm-level measures of emissions-intensity and emissions-regulation.

After correcting for sources of measurement bias, we find that aggregate manufacturing emissions rose one-for-one with the scale of the Chinese manufacturing sector. This does not imply that there were not important technological, compositional and regulatory changes during this time frame. Rather, increased regulation appears to have restrained emissions growth 4-8 percent, while technological advances further mitigated the advance of aggregate emissions by 14 percent. These environmental gains were offset by the disproportionate growth of emissions-intensive firms. Indeed, we find resource reallocation towards the dirtiest producers exacerabated emissions growth by 16-23 percent.

References

Ackerberg, Daniel, Kevin Caves, and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators," *Econometrica*, 83(6): 2411-2451.

Antweiler, Werner, Brian R. Copeland, M. Scott Taylor. 2001. "Is Free Trade Good for the Environment?" *American Economic Review*, 91(4): 877-908.

Barrows, Geoffrey and Hélène Ollivier. 2018. "Does Trade Make Firms Cleaner? Theory and Evidence from Indian Manufacturing," *Journal of Environmental Economics and Management*, 88(March): 134-158.

Bernard, Andrew B., Stephen J. Redding and Peter K. Schott. 2011. "Multiproduct Firms and Trade Liberalization," *Quarterly Journal of Economics*, 26(3): 1271-1318.

Bombardini, Matilde and and Bingjing Li. 2019. "Trade, Pollution and Mortality in China," *Journal of International Economics*, forthcoming.

Callaway, Brantly, Tong Li, Joel Rodrigue, Yuya Sasaki and Yong Tan. 2019. "Environmental Regulation and Firm-Level Pollution: Evidence from China's Eleventh Five-Year Plan," mimeo.

Cao, Jing, Mun S. Ho, and Richard Garbaccio. 2009. "China's 11th Five-Year Plan and the Environment: Reducing SO2 Emissions," *Review of Environmental Economics and Policy*, 3(2): 231-250.

Cao, Jing and Valerie J. Karplus, V. 2014."Firm-Level Determinants of Energy and Carbon Intensity in China," *Energy Policy*, 75: 167-178.

CCICED, 2003. *Recommendations of CCICED to the Government of China*. Retrieved June 7, 2019 from http://www.cciced.net/cciceden/Events/AGM/2003nh/News/201205/t20120515_80041.html

CCICED, 2004. *Task Force on WTO and Environment 2004 Report*. Retrieved June 7, 2019 from http://www.cciced.net/cciceden/Events/AGM/2004nh/News/201205/t20120515_80010.html

Chen, Yuyu, Avraham Ebenstein, Michael Greenstone, and Hongbin Li. 2013. "Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy," *Proceedings of the National Academy of Sciences of the United States of America*, 110(32): 12936-12941.

Cherniwchan, Jevan. 2017. "Trade liberalization and the environment: Evidence from NAFTA and U.S. manufacturing," *Journal of International Economics*, 105: 130-149.

Cherniwchan, Jevan, Brian R. Copeland, and M. Scott Taylor. 2017. "Trade and the environment: new methods, measurements, and results," Annual Review of Economics, 9(August): 59-85.

Cole, Matthew A., Robert J.R. Elliott, and Kenichi Shimamoto. 2005. "Industrial characteristics, environmental regulations and air pollution: an analysis of the UK manufacturing sector," *Journal of Environmental Economics and Management*, 50(1): 121-143.

Cole, Matthew A., Robert J.R. Elliott, and Eric Strobl. 2008. "The environmental performance of firms: The role of foreign ownership, training, and experience," *Ecological Economics*, 65(3): 538-546.

Copeland, Brian R. and M. Scott Taylor. 1994. "North-South Trade and the Environment." *Quarterly Journal of Economics*, 109(3): 755-787.

Copeland, Brian R. and M. Scott Taylor. 1995. "Trade and Transboundary Pollution." *American Economic Review*, 85(4): 716-737.

Copeland, Brian R., and M. Scott Taylor. 2003. *Trade and the Environment: Theory and Evidence.* Princeton, NJ: Princeton University Press.

Copeland, Brian R. and M. Scott Taylor. 2004. "Trade, growth and the environment," *Journal of Economic Literature*, 42(1): 7-71.

Cropper, Maureen. 2012. "What are the Health Effects of Air Pollution in China?" In: Heal, Geoffrey (eds) *Is Economic Growth Sustainable?* London: Palgrave-Macmillan.

Dean, Judith M. 2002. "Does trade liberalization harm the environment? A new test," *Canadian Journal of Economics*, 35(4): 819-842.

De Loecker, Jan. 2011. "Product Differentiation, Multi-Product Firms and Estimating the Impact of Trade Liberalization on Productivity," *Econometrica*, 79(5): 1407-1451.

De Loecker, Jan and Frederic Warzynski. 2012. "Markups and Firm-Level Export Status," *American Economic Review*, 102(6): 2437-2471.

De Loecker, Jan, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik. 2016. Prices, Markups, and Trade Reform, *Econometrica*, 84(2): 445-510.

de Sousa, José, Laura Hering, and Sandra Poncet. 2015. "Has trade openness reduced pollution in China?," CEPII Working Paper No 2015-11 - July.

Ebenstein, Avraham, Maoyang Fan, Michael Greenstone, Guojun He, Peng Yin, Maigeng Zhou. 2015. Growth, Pollution, and Life Expectancy: China from 1991-2012. *American Economic Review*, 105(5): 226-231.

Ederington, Josh, Arik Levinson, and Jenny Minier. 2005. "Footloose and Pollution Free," *Review of Economics and Statistics*, 87(1): 92-99.

Eskeland, Gunnar S. and Ann E. Harrison. 2003. "Moving to greener pastures? Multinationals and the pollution haven hypothesis," *Journal of Development Economics*, 70(1): 1-23.

Forslid, Rikard, Toshihiro Okubo, and Karen Helene Uttveit-Moe. 2018. "Why are Firms that Export Cleaner? International Trade, Abatement and Environmental Emissions," *Journal of Environmental Economics and Management*, 91: 166-183.

Foster, Lucia, John Haltiwanger and Chad Syverson. 2008. 'Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98(1): 394-425.

Frankel, Jeffrey A. and Andrew K. Rose. 2005. "Is Trade Good or Bad for the Environment? Sorting Out the Causality," *Review of Economics and Statistics*, 87(1): 85-91.

Gandhi, Amit, Salvador Navarro and David Rivers. 2019. "On the Identification of Gross Output Production Functions," *Journal of Political Economy*, forthcoming.

Global Modeling and Assimilation Office (GMAO) (2015), MERRA-2 tavgU_2d_aer_Nx: 2d, diurnal, Time-averaged, Single-Level, Assimilation, Aerosol Diagnostics V5.12.4, Greenbelt, MD, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: April 17, 2019, 10.5067/KPUMVXFEQLA1

Grossman, Gene M. and Alan B. Krueger. "Economic Growth and the Environment," *Quarterly Journal of Economics*, 110(2): 353-377.

Hao, Jiming, Kebin He, Lei Duan, Junhua Li, Litao Wang. 2007. "Air pollution and its control in china." *Frontiers of Environmental Science & Engineering in China*, 1(2): 129-142.

He, Guojun, Maoyong Fan, and Maigeng Zhou. 2016. "The effect of air pollution on mortality in China: Evidence from the 2008 Beijing Olympic Games," *Journal of Environmental Economics and Management*, 79: 18-39.

Jia, Ruixue. 2012. "Pollution for Promotion," Working Paper, UC San Diego.

Jin, Yana, Henrik Andersson and Shiqui Zhang. 2016. "Air Pollution Control Policies in China: A Retrospective and Prospects," *International Journal of Environmental Research and Public Health*, 13(12), 1219: 1-22.

Karplus, Valerie J., and Xiliang Zhang. 2017. "Incentivizing firm compliance with China's national emissions trading system," *Economics of Energy and Environmental Policy*, 6(2): 73-86.

Kasahara, Hiroyuki, Paul Schrimpf and Michio Suzuki. 2017. "Identification and Estimation of Production Functionwith Unobserved Heterogeneity," mimeo.

Kishimoto, Paul Natsuo, Valerie J. Karplus, Min Zhong, Eri Saikawa, Xu Zhang, and Xiliang Zhang. 2017. "The impact of coordinated policies on air pollution emissions from road transportation in China," *Transportation Research Part D: Transport and Environment*, 54: 30-49.

Levinsohn, James and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 70(2): 317-341.

Levinson, Arik and M. Scott Taylor. 2008. "Unmasking the Pollution Haven Effect," *International Economic Review*, 49(1): 223-254.

Levinson, Arik. 2009. "Technology, International Trade, and Pollution from US Manufacturing," *American Economic Review*, 99(5): 2177-2192.

Lileeva, Alla and Daniel Trefler. 2010. "Improved Access to Foreign Markets Raises Plant-level Productivity...For Some Plants," *Quarterly Journal of Economics*, 125(3): 1051-1099.

Lin, Jintai, Da Pan, Steven J. Davis, Qiang Zhang, Kebin He, Can Wang, David G. Streets, Donald J. Wuebbles, and Dabo Guan. 2014. "China's International Trade and Air Pollution in the United States," *Proceedings of the National Academy of Sciences*: 111(5), 1736-1741.

Lu, Yi and Linhui Yu. 2015. "Trade Liberalization and Markup Dispersion: Evidence from China's WTO Accession," *American Economic Journal: Applied Economics*, 7(4): 221-253.

Mayer, Thierry, Marc J. Melitz and Gianmarco I.P. Ottaviano. 2014. "Market Size, Competition, and the Product Mix of Exporters," *American Economic Review*, 104(2): 495-536.

Ministry of Ecology and Environment (MEE). 2007a. "National Calculation of Emitted Pollutants," State Council Notice (Guo Fa [2007] No. 36), annex.

Ministry of Ecology and Environment (MEE). 2007b. "Accounting Methods for Industrial Pollution Source and Discharge," technical report.

Melitz, Marc J. and Sašo Polanec. 2015. "Dynamic OlleyPakes productivity decomposition with entry and exit," *RAND Journal of Economics*, 46(2): 362-375.

Nam, Kyung-Min, Caleb J. Waugh, Sergey Paltsev, John M. Reilly and Valerie J. Karplus. 2013. "Carbon co-benefits of tighter SO2 and NOX regulations in China." *Global Environmental Change*, 23(6): 1648-1661.

Nam, Kyung-Min, Caleb J. Waugh, Sergey Paltsev, John M. Reilly and Valerie J. Karplus. 2014. "Synergy between Pollution and Carbon Emissions Control: Comparing China and the U.S." *Energy Economics*, 46: 186-201.

OECD. 2009. *Ensuring Environmental Compliance: Trends and Good Practices*, OECD Publishing, Paris, https://doi.org/10.1787/9789264059597-en.

Ohara, Toshimasa, Hajime Akimoto, Jun-ichi Kurokawal, Nobuhiro Horii, Kazuyo Yamaji, Xiaoyuan Yan, and Taiki Hayasaka. 2007. "An Asian emission inventory of anthropogenic emission sources for the period 1980-2020," *Atmospheric Chemistry and Physics*, 7: 4419-4444.

Olley, Steven G. and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6): 1263-1297.

Qi, Tianyu, Xiliang Zhang, and Valerie J. Karplus. 2014. "The energy and CO2 emissions impact of renewable energy development in China." *Energy Policy*, 68: 60-69.

Shapiro, Joseph S. and Reed Walker. 2018. "Why is Pollution from U.S. Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade," *American Economic Review*, 108(12): 3814-3854.

Springmann, Marco, Da Zhang, and Valerie J. Karplus. 2015. "Consumption-Based Adjustment of Emissions-Intensity Targets: An Economic Analysis for China's Provinces," *Environmental and Resource Economics*, 61(4): 615-640.

Streets, David G., Nancy Y. Tsai, Hajime Akimoto, and Kaoru Oka. 2000. "Sulfur dioxide emissions in Asia in the period 1985-1997," *Atmospheric Environment*, 34: 4413-4424.

Streets, David G. and Stephanie T. Waldhoff. 2000. "Present and future emissions of air pollutants in China: SO_2, NO_x and CO," *Atmospheric Environment*, 34: 363-374.

Tan, Yong, Jian Han, and Yeqing Ma. 2015. "Multi-productfirms, product scope, and the policy of export tax rebate," *China Economic Review*, 35: 33-46.

Tanaka, Shinsuke. 2015. "Environmental Regulations on Air Pollution in China and Their Impact on Infant Mortality," *Journal of Health Economics*, 42: 90-103.

Wong, Christine and Valerie J. Karplus. 2017. "China's War on Air Pollution: Can Existing Governance Structures Support New Ambitions?" *China Quarterly*, 1-23.

Wooldridge, Jeffrey M. 2009. "On estimating firm-level production functions using proxy variables to control for unobservables," *Economic Letters*, 104(3): 112-114.

Wu, Jing, Yongheng Deng, Jun Huang, Randall Morck, and Bernard Yeung. 2013. "Incentives and Outcomes: China's Environmental Policy," NBER Working Paper No. 18754.

Yan, Yunfeng and Laike Yang. 2010. "China's Foreign Trade and Climate Change: A Case Study of CO2 Emissions," *Energy Policy*, 38(1): 350-356.

Zhang, Da, Valerie J. Karplus and Cyril Cassisa and Xiliang Zhang. 2014. "Emissions trading in China: Progress and prospects," *Energy Policy*, 75: 9-16.

Zhang, Da, Sebastian Rausch, Xiliang Zhang, and Valerie J. Karplus. 2013. "Quantifying regional economic impacts of CO2 intensity targets in China," *Energy Economics*, 40: 687-701.

Zhang, Da, Marco Springmann, and Valerie J. Karplus. 2016. "Equity and Emissions Trading in China," *Climatic Change*, 134(1-2): 131-146.

Zhang, Xiliang, Valerie J. Karplus, Tianyu Qi, Da Zhang, and Jiankun He. 2016. "CO2 Emissions in China: How far can new efforts bend the curve?" *Energy Economics*, 54: 388-395.

Zhu, Xiaodong. 2012. "Understanding China's Growth: Past, Present, and Future," *Journal of Economic Perspectives*, 103(24): 103-124.

A Decomposition Derivation

As in the main text, we focus on the end points of our sample, 2000 ($t = 0$) and 2005 ($t = 5$) and characterize three types of firms or products: entrants ($\mathcal{E}$), exiters ($\mathcal{X}$), or continuing firms/products ($\mathcal{C}$). For variable v, we denote the average value for a particular group $\mathcal{G} \in \{\mathcal{C}, \mathcal{E}, \mathcal{X}\}$ in a particular year as $v_t^{\mathcal{G}}$, while $\bar{v}$ represents the simple average of v over the sample period, $\bar{v} = 0.5v_5 + 0.5v_0$ and, analogously, $\bar{v}^{\mathcal{G}}$ is $\bar{v}^{\mathcal{G}} = 0.5v_0^{\mathcal{G}} + 0.5v_5^{\mathcal{G}}$. Finally, Δv generally represents the long difference in any particular variable, $\Delta v = v_5 - v_0$.

We note that aggregate emissions can always be represented as the sum of emissions from individual producers, $E_t = \sum_i e_{it}$, or equivalently,

$$\begin{aligned} E_0 &= \sum_i e_{i0} = \sum_{i \in \mathcal{C}} e_{i0} + \sum_{i \in \mathcal{X}} e_{i0} \\ &= N^{\mathcal{C}} e_0^{\mathcal{C}} + N^{\mathcal{X}} e_0^{\mathcal{X}} = N_0 e_0^{\mathcal{C}} + N^{\mathcal{X}} (e_0^{\mathcal{X}} - e_0^{\mathcal{C}}) \end{aligned}$$

and we analogously write $E_5 = N_5 e_5^{\mathcal{C}} + N^{\mathcal{E}}(e_5^{\mathcal{E}} - e_5^{\mathcal{C}})$. The changes in aggregate emissions can then be expressed as

$$\begin{aligned} \Delta E_t &\equiv E_5 - E_0 \\ &= \bar{N} \Delta e^{\mathcal{C}} + \underbrace{\bar{e}^{\mathcal{C}} (N^{\mathcal{E}} - N^{\mathcal{X}})}_{\text{S: No. of firms}} + \underbrace{N^{\mathcal{E}} (e_5^{\mathcal{E}} - e_5^{\mathcal{C}}) + N^{\mathcal{X}} (e_0^{\mathcal{C}} - e_0^{\mathcal{X}})}_{\text{C: Firm-Level Churning}} \end{aligned}$$

where $\bar{N} = 0.5N_5 + 0.5N_0$ represents the average total number of firms in each year. The first term captures the growth in average emissions among continuing firms. The second and third terms form components of the 'scale' and 'churning' components of our decomposition. Following the approach in Melitz and Polanec (2015), we further decompose the first term as follows.

$$\begin{aligned} \bar{N} \Delta e^{\mathcal{C}} &= \frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \overline{\gamma_i^e c_i} \Delta \tau_i + \frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \bar{\tau}_i (\gamma_{i5}^e c_{i5} - \gamma_{i0}^e c_{i0}) \\ &= \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \overline{\gamma_i^e c_i} \Delta \tau_i}_{\text{P: Policy}} + \frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \bar{\tau}_i \bar{\gamma}_i^e \Delta c_i + \frac{\bar{N}}{N^{\mathcal{C}}} \sum_{i \in \mathcal{C}} \bar{\tau}_i \bar{c}_i \Delta \gamma_i^e \end{aligned} \tag{18}$$

The first term captures changes in the price of emissions and forms the second component of our decomposition. In contrast to existing decomposition approaches the 'weights' in any term are not chosen but are determined by the underlying first order optimality conditions. For example, in the first term $\Delta\tau_i$ is weighted by the relevant firm size measure, $\overline{\gamma_i^e c_i}$, instead of an adhoc weight (e.g. revenue weights). The second and third terms reflect changes in technology, reallocation across of production, and changes product mix. We clarify the contribution of each of these margins below.

Expanding the last term in equation (18) we have

$$
\begin{aligned}
\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\Delta\gamma_i^e &= \frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\left(\sum_j \varrho_{ij5}\gamma_{ij5}^e - \sum_j \varrho_{ij0}\gamma_{ij0}^e\right) \\
&= \frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\left[\left(\sum_{j\in\mathcal{I}^{\mathcal{C}}}\left(\bar{\gamma}_{ij}^e\Delta\varrho_{ij}+\bar{\varrho}_{ij}\Delta\gamma_{ij}^e\right)\right)+\sum_{j\in\mathcal{I}^{\mathcal{E}}}\varrho_{ij5}\gamma_{ij5}^e-\sum_{j\in\mathcal{I}^{\mathcal{X}}}\varrho_{ij0}\gamma_{ij0}^e\right] \\
&= \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\sum_{j\in\mathcal{I}^{\mathcal{C}}}\bar{\gamma}_{ij}^e\Delta\varrho_{ij}}_{\text{R: Across Products (Within-Firm)}}+\underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\sum_{j\in\mathcal{I}^{\mathcal{C}}}\bar{\varrho}_{ij}\Delta\gamma_{ij}^e}_{\text{T: EBTC}}+\underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i\bar{\gamma}_i^e(n_i^{\mathcal{E}}-n_i^{\mathcal{X}})}_{\text{S: No. of products}} \\
&\quad+\underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{c}_i[n_i^{\mathcal{E}}(\gamma_{i5}^{\mathcal{E}}-\gamma_{i5}^{\mathcal{C}})+n_i^{\mathcal{X}}(\gamma_{i0}^{\mathcal{C}}-\gamma_{i0}^{\mathcal{X}})]}_{\text{C: Product-Level Emissions Churning}} \qquad (19)
\end{aligned}
$$

Following the same steps for the second term of equation (18) yields

$$
\begin{aligned}
\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{\gamma}_i^e\Delta c_i &= \underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{\gamma}_i^e\sum_{j\in\mathcal{I}_i^{\mathcal{C}}}\overline{mc}_{ij}\Delta x_j}_{\text{S: Average output growth}}+\underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{\gamma}_i^e\sum_{j\in\mathcal{I}_i^{\mathcal{C}}}\overline{mc}_{ij}(\Delta x_{ij}-\Delta x_j)}_{\text{R: Across Firms}} \qquad (20) \\
&\quad+\underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{\gamma}_i^e\sum_{j\in\mathcal{I}_i^{\mathcal{C}}}\bar{x}_{ij}\Delta mc_{ij}}_{\text{T: Efficiency}}+\underbrace{\frac{\bar{N}}{N^{\mathcal{C}}}\sum_{i\in\mathcal{C}}\bar{\tau}_i\bar{\gamma}_i^e[n_i^{\mathcal{E}}(c_{i5}^{\mathcal{E}}-c_{i5}^{\mathcal{C}})+n_i^{\mathcal{X}}(c_{i0}^{\mathcal{C}}-c_{i0}^{\mathcal{X}})]}_{\text{C: Product-Level Cost Churning}}
\end{aligned}
$$

B Augmented Translog Production Function

Let the variable $\tilde{v}_{it} = \ln(v_{it})$. The emissions augmented production function we estimate is

$$
\begin{aligned}
\tilde{x}_{it} &= \beta_l\tilde{l}_{it}+\beta_{ll}\tilde{l}_{it}^2+\beta_k\tilde{k}_{it}+\beta_{kk}\tilde{k}_{it}^2+\beta_m\tilde{m}_{it}+\beta_{mm}\tilde{m}_{it}^2+\beta_e\tilde{e}_{it}+\beta_{ee}\tilde{e}\tilde{e}_{it}^2+\beta_{lk}\tilde{l}_{it}\tilde{k}_{it}+\beta_{lm}\tilde{l}_{it}\tilde{m}_{it}+\beta_{le}\tilde{l}_{it}\tilde{e}_{it} \\
&\quad+\beta_{km}\tilde{k}_{it}\tilde{m}_{it}+\beta_{ke}\tilde{k}_{it}\tilde{e}_{it}+\beta_{me}\tilde{m}_{it}\tilde{e}_{it}+\beta_{klm}\tilde{k}_{it}\tilde{l}_{it}\tilde{m}_{it}+\beta_{kle}\tilde{k}_{it}\tilde{l}_{it}\tilde{e}_{it}+\beta_{kme}\tilde{k}_{it}\tilde{m}_{it}\tilde{e}_{it}+\beta_{lme}\tilde{l}_{it}\tilde{m}_{it}\tilde{e}_{it}+\omega_{it}
\end{aligned}
$$

where k_{it}, l_{it}, m_{it} and e_{it} are the capital, labor, materials and emissions among single-product firms.

C Summary Statistics

Table 9 documents summary statistics for key variables across our two primary data sources and the matched sample.

Table 9: Summary Statistics

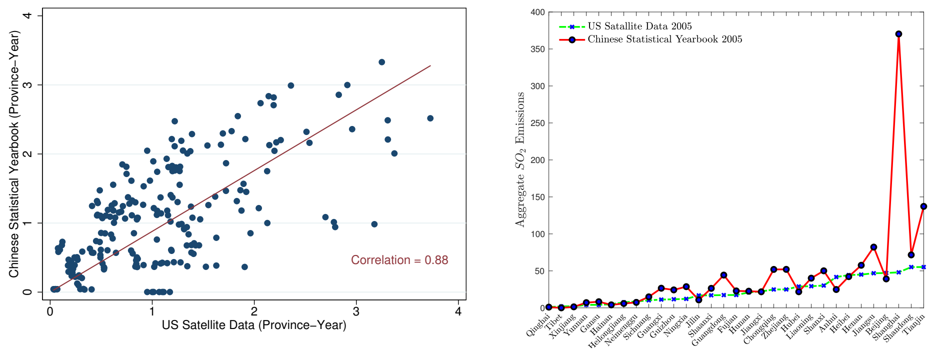
Sample	Environmental Survey			Manufacturing Survey			Matched Sample Survey		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean		
Revenue				73407.16	16748	651642.6	457797	41255	2553178
Export Rev.				13950.34	0	216466.1	43522.3	0	446968.5
Capital				38808.53	4397.178	577368	357577	20868,39	2499673
Labor				290.553	113	1293.149	1542.931	306	6726.919
Materials				54562.19	12350	481086.1	342659	30216	1906517
SO_2 Emis.	221975	7398	230851				252386.5	8000	2453999

Notes: The above table reports summary statistics for three samples. The leftmost panel reports summary statistics for the environmental survey collected by MEE, the middle panel reports summary statistics for the manufacturing survey collected by NBS, and the rightmost panel reports summary statistics for the matched sample (using the environmental, manufacturing and production surveys) used in our empirical exercises.

D Data Quality

We verify the external validity of the aggregate SO_2 data from the Ministry of Ecology and the Environment (MEE) with US Satellite Data (GMAO, 2015). We find that they exhibit similar patterns over time and space. Although independent estimates of SO_2 emissions have been previously found to be higher than those reported in official statistics (Streets and Waldhoff 2000; Streets et al. 2000; Ohara et al. 2007; Cao et al. 2009), we are interested in determining if there are systematic discrepancies across locations or over time. We do not find any significant evidence of systematic reporting bias.

Specifically, our first measure is the (aggregated) quantity of total SO_2 emissions produced in each province as reported in the Chinese yearbook. To get a normalized emissions level we divide each observation by the average amount of SO_2 emitted from given a province. The second measure of SO_2 emissions are US satellite reports of the average density of SO_2 emissions for each Chinese province. To construct a comparable measure of aggregate emissions, we multiply this density measure by the total area of each province and again normalize by average provincial emissions. In panel (a) of Figure 6 each data point represents a province-year combination. We observe very strong correlation across data sources; the correlation coefficient for each province-year combination is 0.88. In panel (b) we repeat this exercise for 2005 alone, but we normalize the total quantify of emissions by the province with the smallest amount of emissions (Qinghai). In panel (b) the red line with circles represents the value reported by MEE, while the blue line with squares represents the aggregated value constructed from US satellite data. Shanghai is a clear outlier in panel (b); one natural explanation for this discrepancy is a difference in the 'area' of Shanghai we use to compute our aggregate value from the US satellite data and the greater Shanghai area as classified in the firm-level survey.



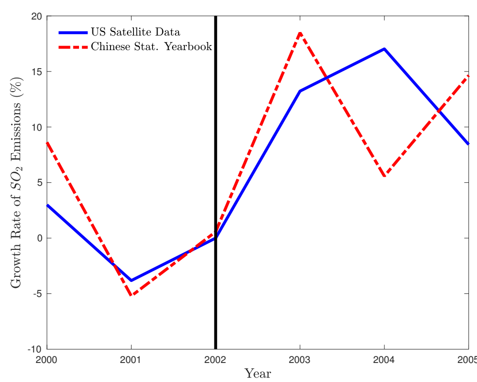
(a) All Years

(b) 2005

Figure 6: SO_2 Emissions Across Provinces, Chinese Data vs US Satellite Data

Notes: The above figures plot total SO_2 emissions from two different data sources. In panel (a) each data point represents a province-year combination of (normalized) SO_2 emissions from US satellite data and the Chinese annual reports. In panel (a) we normalize the data by average provincial emissions. In panel (b) we repeat this exercise for 2005 alone, but we normalize the total quantity of emissions by the province with the smallest amount of emissions (Qinghai). In panel (b) the red line with circles represents the value reported by MEE, while the blue line with squares represents the aggregated value constructed from US satellite data.

To provide a sense of intertemporal consistency we also aggregate both the US Satellite SO_2 data and the comparable data from Chinese Statistical Yearbook. We find that the two series follow each other very closely, though there is a somewhat larger discrepancy in 2004.



Notes: The above figure computes the aggregate annual growth rate of total SO_2 emissions from the Chinese Statistical Yearbook (red dashed line) and that computed from US Satellite data (solid blue line).

Figure 7: SO_2 Aggregate Growth Rates, Chinese Data vs US Satellite Data

E Measuring Firm-Level Emissions

The approach and formulue for calcuating emissions and generation were retrieved from technical documents produced by the Ministry of Ecology and Environment (2007a,b).

E.1 General description of SO_2 emissions

Industrial SO_2 emissions refer to the volume of sulphur dioxide emissions from fuel consumption and the production process on the premises of an enterprise during a given period of time. It is calculated using the following formula:

$$SO_2 \text{ emissions} = SO_2 \text{ emissions from fuel consumption} + SO_2 \text{ emissions from production}$$

E.2 Computation of Annual Emissions

Equation (21) is used to calculate the aggregate emitted kilograms of SO_2 during over a period of time when the enterprise is monitored:

$$P = C \times Q \times F^{-1} \times T \times G \times 10^{-6} \tag{21}$$

where

- P: the emitted kilograms of SO_2;
- C: the average density of the pollutant over each hour (milligrams/cubic metre);
- Q: the volume of wasted gas emissions (cubic metre/hour);
- F: the production load;
- T: the number of emission hours;
- G: the average production load of the monitored enterprise.

Annual SO_2 emissions in kilograms, P, are calculated as

$$E = \sum_{j=1}^{k} P_j \tag{22}$$

where k is the number of monitoring periods.

E.3 SO_2 Generation

The process to estimate SO_2 generation by the Ministry of Ecology and the Environment (MEE) was adopted directly from the US Environmental Protection agency. Specifically, equation (23) is used to calculate the aggregate pollution generated, G, by a particular firm:

$$G = \sum_{j=1} EF_{ij} \times m_j \tag{23}$$

where

- m_j: the aggregate volume/kilograms of the j^{th} input material;
- EF_{ij}: the emission factor for the particular pollutant from input j in industry i.

The emissions factors, EF_{ij}, varies along numerous dimensions. In particular, the EF_{ij} coefficients are specific to (1) a given pollutant (SO_2), (2) a given industry, (3) the materials used in production (e.g. cleaner energy sources are associated with smaller emissions factors).

F Additional Tables

F.1 Ownership Differences

Table 10: Differences Across Ownership and Emissions Output Elasticities (Multiple-Technology Approach)

	Domestic, Private				State-Owned				Foreign			
	Levels		Δ's 2000-5005		Levels		Δ's 2000-5005		Levels		Δ's 2000-5005	
Sector	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
mineral products	0.397	0.335	-0.438	-0.232	0.298	0.225	-0.534	-0.396	0.426	0.385	0.102	0.117
electricity generation	0.298	0.169	-0.051	-0.157	0.233	0.138	-0.095	-0.220	0.279	0.095	-0.067	-0.172
food products	0.189	0.132	0.052	-0.049	0.228	0.138	0.018	-0.109	0.277	0.132	0.198	-0.007
cloth	0.245	0.237	-0.343	-0.336	0.217	0.140	-0.349	-0.214	0.195	0.170	0.247	-0.116
clothing and apparel	0.245	0.178	0.060	-0.123	0.295	0.203	-0.078	-0.200	0.354	0.236	0.128	-0.041
wooden furniture	0.526	0.481	-0.086	-0.442	0.536	0.473	-0.193	-0.259	0.427	0.355	-0.212	-0.139
paper products	0.916	0.918	0.289	0.132	0.894	0.857	0.198	-0.164	0.721	0.691	-0.470	-0.354
fuel, diesel and gas	0.397	0.384	-0.282	-0.215	0.299	0.265	-0.068	-0.096	0.467	0.333	0.669	0.202
chemical products	0.618	0.721	-0.912	-0.716	0.610	0.621	0.370	0.138	0.675	0.625	0.034	0.124
rubber products	0.555	0.353	.	.	0.545	0.375	-0.647	-0.764	0.376	0.204	0.658	0.658
tires and conveyor belts	0.543	0.576	-0.121	-0.121	0.693	0.561	-0.071	-0.160	1.406	0.709	-0.202	-0.202
plastic products	0.137	0.121	0.338	0.173	0.131	0.108	0.347	0.206	0.138	0.102	0.172	0.033
glass and ceramic products	0.365	0.230	0.146	-0.102	0.476	0.288	-0.207	-0.260	0.467	0.322	0.089	0.061
crude steel	1.071	2.023	1.660	1.660	0.988	1.379	-0.116	0.086	1.953	1.705	.	.
high quality steel and steel plates	1.190	1.724	0.282	0.407	1.238	1.470	0.270	0.145	1.740	1.924	.	.
heavy metal products	0.390	0.356	0.192	0.274	0.425	0.323	0.980	0.527	0.489	0.425	0.310	0.056
light metal products	0.583	0.470	.	.	0.550	0.457	.	.	0.843	0.593	-0.006	0.066
auto parts	0.414	0.297	-0.423	-0.548	0.487	0.359	-0.430	-0.255	0.541	0.297	-0.151	-0.603
wheels, gears, and mining equipment	0.411	0.275	-0.413	-0.361	0.587	0.545	-0.136	-0.107	0.630	0.342	0.393	0.189
transportation equipment	0.930	2.116	.	.	1.067	2.257	-0.862	-0.795	0.664	0.618	3.182	3.182
abatement equip. & heavy mach.	1.295	2.728	0.079	0.079	1.057	2.374	0.170	-0.144	.	.	.	.
communication cables and electric wires	0.207	0.192	0.713	0.066	0.236	0.185	-0.038	0.074	0.206	0.181	-0.269	-0.281
measuring implements, printers, etc	0.588	0.584	.	.	0.646	0.598	-0.005	-0.166	1.057	1.102	-0.114	-0.114

Notes: Columns (1)-(4) report statistics for domestic, privately-held enterprises. Columns (5)-(8) and columns (9)-(12) report analogous statistics for state-owned and foreign-owned firms, respectively. Columns (1) and (2) report mean and median emissions output elasticities, while columns (3) and (4) report the mean and median change in emissions output elasticities over the 2000-2005 period for the multiple-technology approach. Each calculation is performed separately for 24 2-digit manufacturing sectors. There are insufficient observations to recover estimates for the alcoholic beverage industry when employing the multiple-technology approach.

Table 11: Differences Across Ownership and Marginal Costs (Multiple-Technology Approach)

	Domestic, Private				State-Owned				Foreign			
	Levels		Δ's 2000-5005		Levels		Δ's 2000-5005		Levels		Δ's 2000-5005	
Sector	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
mineral products	10.527	0.539	4.847	1.773	10.341	0.348	6.418	1.938	13.297	1.575	8.120	6.150
electricity generation	409.040	11.012	0.900	0.384	314.961	5.609	0.972	0.005	301.974	5.068	0.898	0.292
food products	18.906	6.917	0.337	0.036	25.428	7.976	2.751	0.033	23.190	5.876	0.240	-0.001
cloth	323.173	54.299	3.643	2.796	678.967	134.498	0.840	-0.257	361.462	74.732	0.652	0.027
clothing & apparel	489.681	109.782	1.424	0.128	1095.663	158.811	-2.143	0.162	685.427	102.779	0.727	0.129
wooden furniture	3.361	2.034	0.429	0.105	3.845	2.111	0.425	0.026	2.910	1.306	0.280	0.133
paper products	96.881	2.644	-0.125	-0.230	300.263	31.520	2.006	0.581	254.236	6.112	-0.590	-0.563
fuel, diesel & gas	6.643	1.505	2.400	0.421	16.208	4.863	1.446	0.533	18.814	1.417	2.078	0.204
chemical products	26.229	6.610	-0.196	-0.397	46.729	10.277	3.959	-0.412	44.435	16.999	-0.176	-0.233
rubber products	41.106	9.832	.	.	79.953	12.201	0.093	-0.247	18.359	4.886	0.146	0.146
tires & conveyor belts	149.291	1.379	-0.001	-0.001	684.928	128.769	0.401	0.401	139.224	9.768	0.794	0.794
plastic products	1198.518	665.582	-0.676	-0.999	1294.808	941.858	-0.339	-0.999	723.721	35.171	-0.044	-0.789
glass & ceramic products	34.223	1.387	0.863	-0.483	22.214	1.113	3.339	-0.156	22.782	0.641	0.230	-0.059
crude steel	1.077	0.489	0.683	-1.065	21.847	1.947	10.205	2.915	42.507	90.386	.	.
high quality steel & steel plates	0.482	2.731	-0.217	-1.004	4.272	0.342	0.505	-1.257	3.788	3.721	.	.
heavy metal products	51.258	10.808	0.169	-0.114	101.744	16.065	1.948	0.711	54.869	8.295	0.012	0.086
light metal products	30.523	4.370	.	.	59.074	5.957	.	.	93.137	9.575	1.470	2.269
auto parts	279.729	14.974	0.657	0.257	400.715	35.216	2.008	0.421	520.207	91.615	0.773	0.669
wheels, gears, & mining equipment	61.148	6.383	5.770	5.770	132.250	22.919	0.214	-0.153	82.236	7.225	-0.102	-0.098
transportation equipment	55.704	1.927	.	.	75.309	7.509	-5.645	-3.327	72.798	7.466	1.599	1.599
abatement equip. & heavy mach.	52.149	51.008	-0.326	-0.326	797.733	31.889	2.948	0.803	.	.	.	.
comm. cables & elec. wires	87.300	10.835	0.229	-0.109	88.419	8.935	1.090	0.540	114.218	10.714	1.000	0.204
measuring tech., printers, etc	18.664	4.604	.	.	24.270	1.348	0.322	0.054	46.067	0.181	7.022	7.022

Notes: Columns (1)-(4) report statistics for domestic, privately-held enterprises. Columns (5)-(8) and columns (9)-(12) report analogous statistics for state-owned and foreign-owned firms, respectively. Columns (1) and (2) report mean and median marginal costs, while columns (3) and (4) report the mean and median change in marginal costs over the 2000-2005 period for the multiple-technology approach. Each calculation is performed separately for 24 2-digit manufacturing sectors. There are insufficient observations to recover estimates for the alcoholic beverage industry when employing the multiple-technology approach.

Table 12: Differences Across Ownership and Markups (Multiple-Technology Approach)

	Domestic, Private				State-Owned				Foreign			
	Levels		Δ's 2000-5005		Levels		Δ's 2000-5005		Levels		Δ's 2000-5005	
Sector	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
mineral products	0.994	0.884	-0.037	-0.095	1.129	1.033	0.000	-0.023	1.098	0.903	0.331	0.325
electricity generation	1.230	1.131	0.025	-0.031	1.102	1.002	-0.073	-0.149	1.123	1.026	-0.059	-0.130
food products	1.244	1.143	0.209	0.149	1.083	0.961	0.247	0.221	1.385	1.300	0.190	0.077
cloth	1.004	0.921	-0.053	-0.180	1.397	1.331	-0.015	0.039	1.170	0.996	1.125	-0.093
clothing & apparel	1.715	1.247	0.065	-0.004	1.652	1.396	0.050	0.007	1.971	1.910	0.092	0.042
wooden furniture	1.241	1.191	0.057	-0.028	1.325	1.268	0.081	-0.011	1.435	1.432	-0.074	-0.065
paper products	1.376	1.264	0.074	0.072	1.661	1.553	0.055	-0.199	1.368	1.181	0.847	1.256
fuel, diesel & gas	0.733	0.603	-0.007	-0.113	0.944	0.745	-0.066	-0.169	0.773	0.609	-0.146	-0.050
chemical products	1.682	1.537	0.382	0.301	1.302	1.181	0.618	0.610	1.469	1.293	0.155	0.142
rubber products	1.395	1.241	.	.	1.746	1.528	0.334	0.368	1.972	1.903	0.140	0.140
tires & conveyor belts	1.497	1.112	0.004	0.004	1.395	1.020	0.012	0.012	2.204	1.652	2.162	2.162
plastic products	1.082	1.048	0.158	0.132	1.074	1.014	0.134	0.107	1.100	1.092	-0.013	-0.055
glass & ceramic products	1.437	1.332	0.031	0.092	1.555	1.384	0.059	-0.122	1.576	1.516	-0.063	-0.036
crude steel	1.902	1.522	0.179	0.179	1.636	1.520	0.060	-0.145	1.783	1.704	.	.
high quality steel & steel plates	1.266	0.999	.	-0.962	1.542	1.373	-0.552	-0.552	1.920	1.846	.	.
heavy metal products	2.055	1.978	0.249	0.190	2.059	1.845	0.247	-0.030	2.278	2.276	-0.017	-0.084
light metal products	1.372	1.133	.	.	1.821	1.579	.	.	1.414	1.405	0.345	0.311
auto parts	1.366	1.286	-0.082	-0.140	1.387	1.305	0.015	0.054	1.176	1.040	0.115	0.002
wheels, gears, & mining equipment	1.334	1.333	0.004	-0.172	1.641	1.592	0.142	0.074	2.233	2.053	0.399	0.169
transportation equipment	2.125	1.969	.	.	2.243	2.307	0.213	-0.034	1.479	1.480	-0.709	-0.709
abatement equip. & heavy mach.	3.340	3.223	0.616	0.616	2.175	1.999	0.354	-0.157	.	.	.	.
comm. cables & elec. wires	1.008	0.974	0.004	-0.060	1.295	1.189	-0.063	-0.140	1.667	1.078	-0.184	-0.217
measuring tech., printers, etc	1.096	1.141	.	.	1.566	1.537	-0.004	0.048	0.994	0.992	-0.771	-0.772

Notes: Columns (1)-(4) report statistics for domestic, privately-held enterprises. Columns (5)-(8) and columns (9)-(12) report analogous statistics for state-owned and foreign-owned firms, respectively. Columns (1) and (2) report mean and median markups, while columns (3) and (4) report the mean and median change in markups over the 2000-2005 period for the multiple-technology approach. Each calculation is performed separately for 24 2-digit manufacturing sectors. There are insufficient observations to recover estimates for the alcoholic beverage industry when employing the multiple-technology approach.

Table 13: Differences Across Ownership and Implied Emissions Taxes (Multiple-Technology Approach)

	Domestic, Private				State-Owned				Foreign			
	Levels		Δ's 2000-5005		Levels		Δ's 2000-5005		Levels		Δ's 2000-5005	
Sector	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
mineral products	0.300	0.046	1.594	-0.165	0.435	0.059	3.328	0.997	0.072	0.033	-0.105	-0.177
electricity generation	0.480	0.071	0.394	0.045	0.362	0.022	1.300	-0.020	0.406	0.017	1.018	0.183
food products	0.890	0.305	1.269	0.028	0.816	0.286	1.677	0.282	1.439	0.965	2.114	0.575
cloth	0.748	0.349	1.533	1.129	0.787	0.321	0.139	0.079	0.844	0.395	2.183	0.204
clothing & apparel	0.585	0.221	1.452	0.083	0.804	0.239	1.099	0.095	1.039	0.474	0.991	-0.207
wooden furniture	0.253	0.212	-0.033	-0.242	0.196	0.147	0.462	0.076	0.217	0.187	-0.128	-0.207
paper products	0.602	0.325	0.994	0.309	0.621	0.290	0.670	0.306	1.511	0.866	0.099	0.001
fuel, diesel & gas	0.403	0.245	0.944	0.568	0.426	0.232	1.538	0.739	0.633	0.271	1.392	1.184
chemical products	0.826	0.160	-0.915	-0.984	1.033	0.142	-0.140	-0.697	0.631	0.034	4.632	0.855
rubber products	1.855	1.221	.	.	0.792	0.306	1.441	-0.592	1.516	1.028	0.460	15.965
tires & conveyor belts	1.528	1.282	-0.060	-0.060	1.990	1.822	-0.887	-0.887	2.886	2.595	-0.866	-0.867
plastic products	0.070	0.031	1.595	0.718	0.080	0.026	1.287	0.401	0.179	0.050	1.787	0.275
glass & ceramic products	0.219	0.039	2.586	-0.118	0.297	0.058	0.430	0.548	0.401	0.122	1.720	0.150
crude steel	0.547	0.017	-0.020	-0.020	1.240	0.166	4.837	1.956	1.470	2.530	.	.
high quality steel & steel plates	1.338	0.704	-0.727	-0.863	1.297	0.199	-1.575	-2.178	0.966	1.653	.	.
heavy metal products	2.224	1.785	1.961	1.125	1.494	0.786	1.190	14.353	2.382	2.541	1.384	2.369
light metal products	1.261	2.924	.	.	1.823	1.590	.	.	2.024	2.427	0.092	0.535
auto parts	0.211	0.035	1.884	-0.785	0.192	0.010	2.956	0.361	0.490	0.047	0.556	0.234
wheels, gears, & mining equip.	1.554	0.646	0.141	-0.271	1.624	0.579	4.747	-0.294	2.890	6.005	4.000	-0.327
transportation equipment	1.926	5.225	.	.	2.374	6.567	-0.504	-0.628	0.055	0.073	.	.
abatement equip. & heavy mach.	1.404	16.984	2.885	2.885	4.050	9.086	0.913	-0.072	.	.	.	.
comm. cables & elec. wires	1.678	1.530	0.333	-0.003	1.217	0.595	2.439	0.354	1.528	1.907	3.138	0.687
measuring tech., printers, etc	2.734	2.552	.	.	1.419	1.171	1.682	-0.060	1.367	0.057	3.354	3.354

Notes: Columns (1)-(4) report statistics for domestic, privately-held enterprises. Columns (5)-(8) and columns (9)-(12) report analogous statistics for state-owned and foreign-owned firms, respectively. Columns (1) and (2) report the mean and median implied emissions taxes, while columns (3) and (4) report the mean and median change in the implied emissions taxes over the 2000-2005 period for the multiple-technology approach. Each calculation is performed separately for 24 2-digit manufacturing sectors. There are insufficient observations to recover estimates for the alcoholic beverage industry when employing the multiple-technology approach.

F.2 Decomposition Robustness

Tables 7 and 8 in the main text report decomposition results after trimming outliers. Starting with the full sample, we consistently trimmed one percentile from the top and bottom of the distribution of firm-level contributions of each subcomponent in Table 8. We then collected the remaining firms and recomputed the entire decomposition.

Table 14: Sources of Aggregate SO_2 Emissions Growth

	Percentage Contribution				
Approach	Scale	Policy	Technology	Reallocation	Churning
Single-Technology	87.58	-0.57	-21.24	34.19	0.02
Multiple-Technology	84.53	-0.48	-17.41	33.31	0.06

Notes: Table 7 documents the contribution from each source of emissions growth according to the decomposition equation (12).

The elimination of extreme firms inherently raises the question of the robustness of our main findings. Tables 14 and 15 report analogous decomposition results using the full sample without any trimming. In general, all of the same qualitative findings continue to hold: increases in economic scale explain almost all of the increase in emissions, resources reallocated towards dirty producers, while technology and policy change mitigated emissions growth. Relative to Tables 7 and 8, we observe that the reallocation and technology terms are somewhat larger in absolute magnitude, while scale is slightly smaller and the regulation term is close to zero.

Table 15: Subcomponents of SO_2 Emissions Growth

Approach	Component Share	Subcomponent Share		
		Scale		
		Number of firms	Number of Products	Average Output Growth
Single-Technology	87.58	0.001	-3.27	103.27
Multiple-Technology	84.53	0.002	-0.58	100.06
		Technology		
		EBTC	Efficiency	
Single-Technology	-21.24	0.47	99.53	
Multiple-Technology	-17.41	0.24	99.76	
		Reallocation		
		Across-Firm Reallocation	Across-Product (Within-Firm) Reallocation	
Single-Technology	34.19	99.58	0.42	
Multiple-Technology	33.31	100.12	-0.12	
		Churning		
		Firm-Level	Product-Level Emissions	Product-Level Cost
Single-Technology	0.02	-0.80	21.95	78.85
Multiple-Technology	0.06	3.96	63.96	32.07

Notes: Table 8 documents the contribution from each subcomponent of emissions growth in the decomposition equation (12).

Similarly, the subcomponents documented in Table 15 follow the same pattern as those reported in Table 8. Trimming the top and bottom one percent of firm-level contribution does not affect the inherent conclusions of the analysis though it does eliminate a number of extreme outliers.