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Why Is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade[†]

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Between 1990 and 2008, air pollution emissions from US manufacturing fell by 60 percent despite a substantial increase in manufacturing output. We show that these emissions reductions are primarily driven by within-product changes in emissions intensity rather than changes in output or in the composition of products produced. We then develop and estimate a quantitative model linking trade with the environment to better understand the economic forces driving these changes. Our estimates suggest that the implicit pollution tax that manufacturers face doubled between 1990 and 2008. These changes in environmental regulation, rather than changes in productivity and trade, account for most of the emissions reductions. (*JEL* F18, H23, L60, Q52, Q53, Q56, Q58)

Between 1990 and 2008, emissions of the most common air pollutants from US manufacturing fell by 60 percent, even as real US manufacturing output grew substantially. Figure 1 shows just how stark these environmental improvements have been. Between 1990 and 2000, the real value of US manufacturing output grew by one-third even as manufacturing's emissions of major regulated air pollutants like nitrogen oxides, particulate matter, sulfur dioxide, and volatile organic compounds fell on average by 35 percent. After 2000, growth in real manufacturing output slowed, even while manufacturing pollution emissions fell another 25 percentage points relative to 1990 levels.

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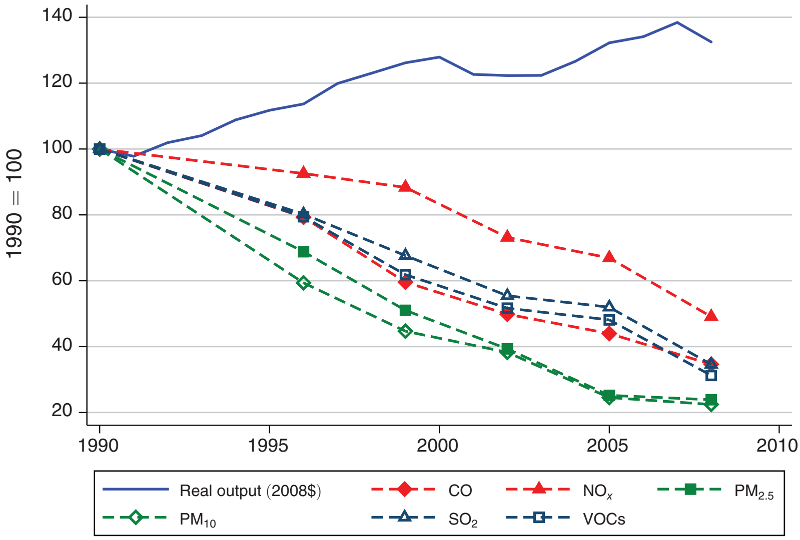

Figure 1. Trends in Manufacturing Pollution Emissions and Real Output

Notes: Real output is measured from the NBER-CES database, using its industry-specific output price deflators and expressed in US$(2008). Emissions come from the EPA's National Emissions Inventory in years 1990, 1996, 1999, 2002, 2005, and 2008. Values are normalized to 100 in 1990.

Research suggests at least three possible explanations for these substantial improvements in US air quality. First, US manufacturing trade has grown substantially (Autor, Dorn, and Hanson 2013; Pierce and Schott 2016). When polluting industries like steel or cement move abroad, total US pollution emissions may fall. Second, federal and state agencies require firms to install increasingly effective pollution abatement technologies. Some research directly attributes national changes in air quality to the Clean Air Act and to other environmental regulations (Henderson 1996; Chay and Greenstone 2005; Correia et al. 2013). Third, if manufacturers use fewer inputs each year to produce the same outputs and pollution is related to inputs, then annual productivity growth could improve air quality. In support of this third explanation, Figure 2 shows a clear negative relationship between plant-level pollution per unit of output and total factor productivity in US manufacturing; as total factor productivity rises, pollution per unit of output falls.[1]

The goal of this paper is to better understand the underlying forces that have caused changes in pollution emissions from US manufacturing. We do this in two complementary ways. We begin by decomposing changes in manufacturing emissions into changes due to the total scale of manufacturing output, the composition of products produced, and the pollution intensity of a given set of products. This data-driven exercise exploits newly available, administrative data on product-level emissions intensities that affords additional granularity relative to the existing literature. While the statistical decomposition delivers clear conclusions, it lacks the ability to uncover the primitive economic forces driving emissions reductions.

[1] This graph focuses on nitrogen oxides (NO$_x$) emissions, though graphs for other pollutants look similar.

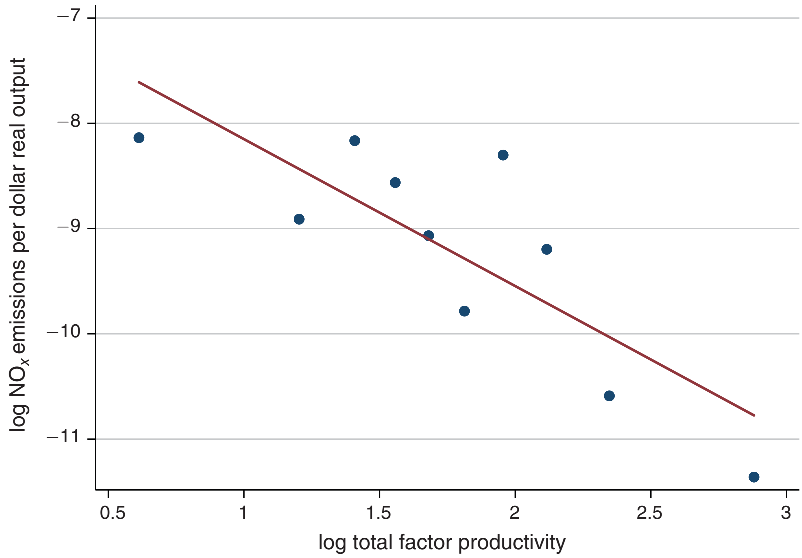

Figure 2. Plant-Level Pollution Intensity vs. Total Factor Productivity

Notes: This figure plots the relationship between plant-level total factor productivity and NO_x pollution per unit of output for US manufacturing in 1990. The plant-level productivity measure is constructed from the US Annual Survey of Manufacturers, using a total factor productivity index measure. We divide the sample into ten deciles based on this plant-level productivity measure. We then compute the mean values of log productivity and log pollution per unit of real output within each decile, weighting the decile mean by plant-level inventory-adjusted, real output. The plot is accompanied by a linear fit, relating plant-specific emissions intensities to total factor productivity at the same plant. The line is fit to the entire sample, not simply the decile means. See online Appendix III.H for additional details.

We complement this decomposition with a quantitative model of pollution emissions in US manufacturing. The model consists of firms endogenously choosing investments in pollution abatement to avoid a tax on pollution emissions. Production and pollution abatement choices depend on environmental regulation, productivity, and trade costs. The model weaves together elements of workhorse models from the international (Melitz 2003) and environmental (Copeland and Taylor 2003) literatures. While the model is highly stylized, it has several attractive features. It has explicit and simple theoretical microfoundations from which all the analysis is derived; it accounts for imperfect competition and can accommodate various market structures; it incorporates firm entry, exit, and cross-firm reallocation; it requires few parameters that can be estimated using reduced-form regressions; it can analyze a wide variety of counterfactuals; and it can account for many general equilibrium forces in settings where partial equilibrium, program evaluation methods may be able to deliver less insight.

We then combine the model with administrative plant-level data from the US Census Bureau and Environmental Protection Agency (EPA) with two main objectives. First, we use intermediate results from the model, combined with actual pollution abatement and emissions decisions, to back out the implicit tax per unit of pollution emissions that firms face. US federal, state, and local environmental regulations take many overlapping forms: command-and-control technology standards, cap-and-trade programs, and many others.[2] Our quantitative exercise yields a closed-form expression for the

[2] Berman and Bui (2001) describe the entire menu of local air quality regulations facing manufacturing firms around Los Angeles, finding 11 local air quality regulations for petroleum refining and 46 for manufacturing

overall regulatory burden from these disparate and overlapping environmental policies, allowing us to observe how this measure has changed over time. The second main objective of the quantitative exercise is to evaluate a range of counterfactuals, such as how pollution emissions would have evolved if air pollution regulation had remained unchanged after 1990. Many researchers in environmental economics and international trade use quantitative models to forecast the future: they study untested policies such as a global 10 percent decrease in all trade barriers or a national carbon tax. Unlike such work, this paper uses a model to interpret the past; it quantifies how different kinds of economic shocks (environmental regulation, productivity, and trade costs) led to observed changes in actual pollution emissions. Similar general equilibrium decompositions have been used to understand the causes of the collapse of trade around the Great Recession and the changes in between-group wage inequality (Burstein, Morales, and Vogel forthcoming; Eaton et al. 2016).

Our results suggest that changes in the scale of manufacturing output or changes to the composition of products produced cannot explain trends in pollution emissions from US manufacturing between 1990 and 2008. Instead, decreases in pollution per unit of output within narrowly defined product categories explain almost all of the changes in emissions over this time. We then show that the model-driven measure of the pollution tax rate that rationalizes observed pollution emissions and abatement decisions—a scalar measure of the stringency of environmental regulation—more than doubled for most pollutants between 1990 and 2008. We find broadly similar increases in regulation across all the main pollutants the Clean Air Act regulates (criteria pollutants), but we find no increases in an unregulated pollutant, CO_2, over this time period. Lastly, we find that this increasing stringency of environmental regulation accounts for most of the 1990-to-2008 decrease in pollution emissions from US manufacturing. Despite the plant-level relationship between pollution and productivity documented in Figure 2, and similar relationships found in related literature (Bloom et al. 2010, Martin 2011, Holladay 2016), we find that changes in US productivity have had smaller effects on US pollution emissions at the economy-wide level.

This paper departs from the literature in four primary ways. First, it provides new evidence on why pollution from US manufacturing is declining. Some research relates national changes in pollution emissions to three channels: changes in the aggregate level of manufacturing output, changes in the composition of output across manufacturing industries, and changes in the pollution emitted per unit output within an industry (Levinson 2009). Research describes these channels as scale, composition, and technique. The methodology behind our statistical decomposition resembles this work, but detailed administrative data allow us to extend previous analyses to look within physical products and not merely within industries.[3] This added granularity helps address previous concerns regarding the inability of industry-level data to distinguish between changes in the within-industry reallocation of production toward

(a count which excludes state and federal regulations). Most of the manufacturing policies apply to only a few industries each. The analysis includes the years 1979 to 1993. Los Angeles has among the most stringent air quality regulations in the country. We thank Eli Berman and Linda Bui for sharing details of these regulations.

[3] Throughout the paper, we use "product" to describe 1,440 five-digit Standard Industrial Classifications (SIC), "industry" to describe the 455 four-digit SIC codes, and "sector" to describe the 17 aggregations of two-digit International Standard Industrial Classification (ISIC) codes this paper's quantitative model analyzes.

cleaner products and industry-level reductions in emissions intensity (Koo 1974; Gamper-Rabindran 2006; Ederington, Levinson, and Minier 2008; Levinson 2009). More importantly, the conclusion of previous research that pollution per unit output within industries is falling (i.e., pollution is declining due to the "technique" effect) is silent on deeper economic causes. Pollution per unit output is an endogenous outcome of the global economy that numerous possible forces could explain. We use a quantitative model to relate changes in pollution to policy-relevant choices like trade costs and environmental regulation. Our analysis of this quantitative model suggests that environmental regulation accounts for much of the decline in pollution.

A second contribution of this study is to quantify the change in the overall regulatory burden, or shadow price of pollution, that manufacturing firms face due to local and national air pollution regulations. We find that this price more than doubled between 1990 and 2008 for most air pollutants we study, but we find no increase in the shadow price of CO_2. While analyzing the overall regulatory burden affecting firms does not prescribe a single law or policy lever, it does explain what all the hundreds of regulations have added up to, which is a question of central importance. Previous model-based attempts to measure regulatory stringency have required equating energy expenditures with pollution, then backing out regulatory costs from cost function estimates (van Soest, List, and Jeppesen 2006).

Third, this paper estimates, for the first time, a parameter that has played a central role in environmental economics models for at least 30 years: the elasticity governing a firm's trade-off between production and pollution abatement (Siebert et al. 1980, Copeland and Taylor 2003). This parameter has equivalent interpretations as the Cobb-Douglas cost share of pollution taxes in production or, alternatively, as the elasticity of pollution emissions with respect to productivity.

Lastly, this paper develops a flexible and tractable approach to analyzing economy-wide changes in pollution. Research studying changes in pollution typically uses quasi-experimental regressions, industrial organization models, or macro-trade models (Copeland and Taylor 1994; Fabra and Reguant 2014; Deschênes, Greenstone, and Shapiro 2017; Isen, Rossin-Slater, and Walker 2017; Keiser and Shapiro 2017).[4] Quasi-experimental studies can isolate the effect of individual policies one-at-a-time, but regulators have implemented dozens of overlapping pollution regulations over the last 20 years, many of which have not been analyzed with policy evaluation tools and have no natural comparison group. Industrial organization models have rich industry-specific detail but typically do not study an entire segment of the economy, like all of manufacturing, or account for general equilibrium forces. Theoretical, macro-trade models have provided considerable insight but have generally resisted estimation. Our methodology builds on tools from a recent trade literature sometimes described as "structural gravity" (Costinot and Rodríguez-Clare 2014, Hsieh and Ossa 2016), though the application to environmental questions has been limited (Shapiro 2016; Cherniwchan, Copeland, and Taylor 2017). A nascent literature explores the environmental implications of models of heterogeneous firms

[4] Some research describes a model of the environment and trade and then estimates linear regressions where the explanatory variables proxy for important variables in the theory (Antweiler, Copeland, and Taylor 2001). We take a literal interpretation of the model by estimating its primitive parameters and then solving for equilibrium outcomes given a vector of inputs.

(Bajona, Missios, and Pierce 2012; Andersen 2016), though does not analyze the models quantitatively. The analysis of firm heterogeneity reflects growing evidence that firms differ dramatically in their productivity and pollution levels, even within narrowly defined industries (Lyubich, Shapiro, and Walker 2018). We study the specific counterfactual of explaining historic changes in pollution. Our approach, however, is versatile enough to evaluate prospective environmental policies or design optimal environmental policy. One of our goals is to make clear how similar approaches could be used to study a range of environmental questions.

The rest of the paper proceeds as follows. Section I presents a statistical decomposition in order to break down aggregate emissions trends in our data, while also highlighting the frontier of what we are able to say with the data alone. Section II outlines our trade-environment model. Section III discusses the data, and Section IV discusses how we estimate the parameters. Section V presents the main results, and Section VI discusses alternative explanations and additional robustness concerns. Section VII concludes.

I. A Statistical Decomposition of US Emissions, 1990–2008

Much economic research interprets national changes in industrial air pollution via three pathways (Copeland and Taylor 1994; Grossman and Krueger 1995). One is a change in the scale of real output. The second is a change in the composition of production from products that require little pollution emissions to produce, like "household furniture," to products that require substantial pollution emissions to produce, like "carbon black." The third is a change in the production technique used to produce a single product, which could decrease a product's pollution emissions per unit of output.

We begin by presenting a statistical decomposition of manufacturing pollution emissions using newly developed administrative data on manufacturing plant-product-year output from 1990 to 2008. The Census of Manufacturers and the Annual Survey of Manufacturers collect sub-industry, product-level output data, at the plant-product-year level. We use this information to illustrate whether changes in the total scale of output or changes in the composition of products produced are able to explain the observed reductions in air pollution emissions. Our focus on products rather than industries is unique to the literature and is meant to capture the fact that even within a fairly narrow industry code (e.g., four-digit Standard Industrial Classification (SIC) code), many products differ significantly in their emissions intensities. Previous research has explored trends in manufacturing pollution emissions using industry-level data. The previous literature has acknowledged that a limitation of industry-level production data is the inability to distinguish changes in the reallocation of production toward cleaner products from industry-level "technique" based reductions in emissions intensity (Koo 1974; Gamper-Rabindran 2006; Ederington, Levinson, and Minier 2008; Levinson 2009). For example, while all of US manufacturing contains 455 four-digit SIC codes, the product trailer from the Census and Annual Survey of Manufacturers allows us to perform this decomposition using 1,440 products. This granularity allows us to quantify by how much the scale of output versus the types of products produced can explain the observed reductions in manufacturing air emissions.

Consider the following representation of total manufacturing pollution, denoted Z:

$$Z = \sum_s z_s = \sum_s x_s e_s = X \sum_s \kappa_s e_s. \tag{1}$$

Total manufacturing pollution Z equals the sum of pollution from each manufacturing product s, z_s. A manufacturing product in our setting can be thought of as a sub-industry classification, where for example, SIC 3312 (blast furnaces and steel mills) is subdivided into 24 different products ranging from steel wire (33125) to cold rolled sheets and strip (excluding metallic coated and electrical) (33127).[5] Alternatively, we can write manufacturing pollution as equal to the total output of a product x_s multiplied by a product-specific emissions factor e_s. We can also represent manufacturing pollution emissions as the total output shipped by all manufacturing industries, X, multiplied by the sum of each product's share of total output, $\kappa_s \equiv x_s/X$, times an emissions coefficient reflecting pollution per dollar of output shipped of that product ($e_s \equiv z_s/x_s$). In vector notation, we have

$$Z = X\kappa'\mathbf{e},$$

where κ and $\mathbf{e}$ are $S \times 1$ vectors containing the market shares of each of the S products and their pollution intensities, respectively. Totally differentiating then dividing through by Z yields three terms representing the scale, composition, and technique effects:

$$\frac{dZ}{Z} = \underbrace{\frac{dX}{X}}_{\text{scale}} + \underbrace{\frac{d\kappa}{\kappa}}_{\text{composition}} + \underbrace{\frac{de}{e}}_{\text{technique}}. \tag{2}$$

Taking the decomposition in equation (2) to the data requires annual data on total pollution, total output, each product's contribution to output, and each product's emissions intensity. Pollution and total output come from the EPA's National Emissions Inventory (NEI) and the Census of Manufacturing, respectively. We construct product-level output shares in each year using the product trailer from the Census and Annual Survey of Manufacturers. In order to construct product-level emissions factors, we match the National Emissions Inventory to the Annual Survey of Manufacturers in 1990 via name and address string matching. Online Appendix III.A describes the string matching process in more detail.

It is useful to distinguish plant- from product-level data. The NEI reports emissions for each plant while the Census reports output for each product within a plant. For single-product plants, the NEI reports emissions at the product level. For multi-product plans, we apportion plant-level emissions to products according to

[5] Output at the five-digit SIC level is the most disaggregate data available for all plants in the Census and Annual Survey of Manufacturers.

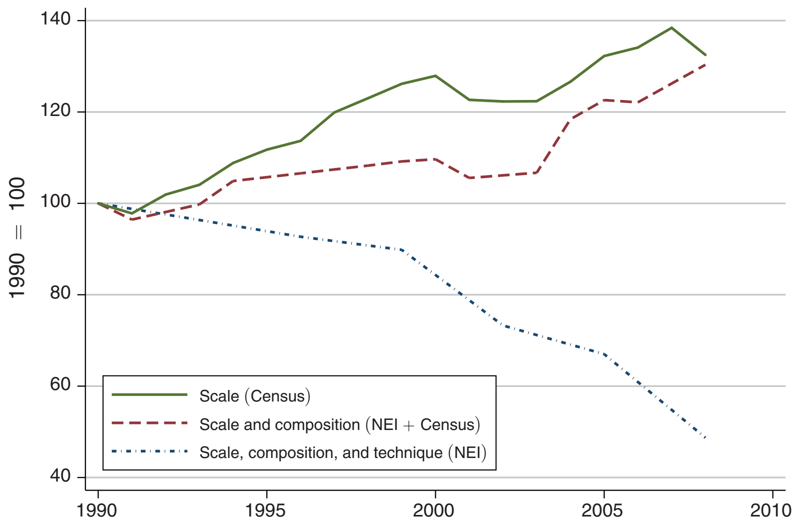

Figure 3. Nitrogen Oxides Emissions from United States Manufacturing

Notes: This figure plots observed and counterfactual trends in NO_x emissions based on the statistical decomposition from equation (2). The top line plots the counterfactual emissions with the same composition of goods and techniques as in 1990. The middle line represents emissions with the same emissions per unit of output as in 1990. The final line represents the actual observed emissions trends, which consists of changes to both the scale, composition, and techniques associated with production since 1990.

Sources: NBER-CES database, CMF, ASM, and NEI

those products' revenue shares within the plant, using year 1990 data.[6,7] We take the total emissions attributable to each product in 1990 and divide by the total product shipments in 1990 to construct emissions intensities.[8] We then use these 1990 product-level emissions intensities to project the scale and composition effects forward in time, holding technology (i.e., our emissions intensities) constant at 1990 emissions rates. The decomposition allows us to observe what emissions would have looked like in 2008 if firms still produced products with 1990 emissions intensities. Online Appendix III.B describes the underlying data.

Figure 3 illustrates the resulting statistical decomposition for nitrogen oxide emissions (NO_x). Online Appendix Figure 1 shows graphs for other pollutants, which have similar patterns, and panel A of online Appendix Table 1 shows numbers corresponding to these graphs. The top solid line in Figure 3 depicts the total real value of manufacturing shipments, where each industry's output is deflated by the NBER-CES industry-specific price index and then totaled. We scale total output so it equals 100 in 1990. This line summarizes what emissions would have

[6] Allocating inputs to products based on their revenue shares, an analogous approach, is standard in the productivity literature (Foster, Haltiwanger, and Syverson 2008; Collard-Wexler and De Loecker 2015). We discuss alternative approaches below.

[7] Previous research has used the World Bank's Industrial Pollution Projection System (IPPS) for emissions intensities. The IPPS data provide a list of emissions intensities by four-digit Standard Industrial Classification (SIC) codes (Hettige et al. 1995, Levinson 2009). Levinson (2015) constructs industry-level emissions intensities using the NBER-CES productivity database combined with raw NEI data.

[8] We deflated total product output by industry-year specific price indices, from the NBER-CES database, scaled so year 2008 = 1.

been if emissions rates and product composition had been fixed at their 1990 levels. The middle dashed line plots NO_x emissions that would have occurred if emissions intensities had remained fixed at 1990 levels but the composition of output across manufacturing products had equaled observed, historical values. The bottom dotted line plots actual NO_x emissions from manufacturing, as reported by the NEI. The bottom line implicitly summarizes the joint result of changing the scale, composition, and technique of manufacturing production over this time period.

The statistical decomposition leads to several conclusions. First, the dotted line shows that actual NO_x emissions fell by almost 50 percent. Second, the proximity of the solid and dashed lines shows that the composition between manufacturing products that emit high and low amounts of pollution has not changed much over time. Third, the solid and dashed lines each show that if the pollution intensity of industries had not changed, NO_x emissions would have risen by 20 to 30 percent. Finally, the gap between the solid line on top and dotted line at bottom shows that changes in the pollution intensity of individual products (i.e., technique) explains why NO_x emissions fell by 50 percent rather than rising by 30 percent.

Online Appendix Figure 2 compares the results from the product-level decomposition to those that stem from more aggregate, industry-level data of the sort used in Levinson (2009). Perhaps surprisingly, the additional granularity afforded by the product-level data provides little additional scope for compositional changes relative to the conclusions from the industry-level decomposition. Put another way, this analysis suggests that there was little or no change in the composition across products within industries that can account for the decrease in pollution.

As mentioned above, we do not observe plant-product-year emissions for plants that produce multiple products. Instead, we divide up a plant's emissions among products using product revenue shares. It is worth considering whether allocating plant-level emissions to product-level output using revenue shares can partly explain the similarity of the product and industry-level analyses. The best way to investigate the sensitivity of our product-level decomposition to this issue is to use the subset of plants that produce a single product, and for which apportionment of plant-level emissions to plant-product level output is no longer an issue. The results, listed in panel B of online Appendix Table 1, yield qualitatively similar conclusions to those from our preferred method.[9]

This relatively clear conclusion, that most reductions in emissions are driven by within-product changes in emissions intensity, echoes previous findings in the literature, albeit with more granular data. The data, however, are relatively silent on what might be causing these changes. The rest of the paper investigates the underlying economic forces driving these patterns in the data. If more productive plants emit less pollution per unit output, then product-level productivity growth could explain these patterns. Alternatively, changes in trade costs like the introduction of NAFTA or China's WTO ascension may have caused a reallocation of production away from unproductive and polluting firms toward more productive and perhaps less polluting

[9] As an alternative exercise, we used the full sample of plants, but apportioned plant-level emissions to plant-product level output equally for all products within a plant (e.g., for a three-product plant, one-third of plant-level emissions are assigned to each product). The results, listed in panel C of online Appendix Table 1, are also qualitatively similar to the main results.

firms that produce the same product. Lastly, increases in environmental regulatory stringency may also explain these reductions. The subsequent analysis focuses on interpreting the observed changes in the technique effect, rather than on assessing the lack of changes in composition effects. One possibility is that the most important drivers of changes in manufacturing composition are not strongly correlated with pollution intensity. This is an intriguing question we leave for future work.

The quantitative model, which fills the remainder of this paper, makes different and arguably stronger assumptions than this statistical decomposition. The advantage of these stronger assumptions is an ability to explore how environmental regulation, productivity, and trade contribute to the environmental improvements documented in Figures 1 and 3. The disadvantage is that these assumptions only roughly approximate reality. We discuss ways in which these assumptions can be relaxed in future research. The reader interested in additional detail on specific components of this model is referred to Copeland and Taylor (2003), Costinot and Rodríguez-Clare (2014), and Melitz and Redding (2014).

II. Model of Heterogeneous Firms with Endogenous Pollution Abatement

We describe a model of firm entry, production, trade, and pollution abatement, which is designed to reflect a stylized description of polluting industries. In the model, firms differ in their productivity levels, which leads these firms to differ in their pollution abatement investments and ultimately pollution emissions. The model accounts for endogenous changes in firm entry, exit, production, and export decisions in a tractable way that yields analytical solutions and allows us to analyze counterfactuals. Like all models, this approach seeks to reflect systematic patterns across firms while recognizing that some strict assumptions which enhance tractability, like monopolistic competition and constant elasticity of substitution (CES) utility, are not literally accurate descriptions of firms and consumers.

The model has a straightforward economic environment. We analyze a world of multiple countries, each with a representative agent. Each country has one productive factor (labor) which is inelastically supplied. The following three subsections explain the model's assumptions; present comparative statics for pollution intensity; and describe methodology for analyzing counterfactuals. Online Appendix B summarizes notation and shows more detailed derivations of results shown here.

A. *Model Assumptions*

1. Preferences: The representative agent in destination country d has the following utility function:

$$U_d = \prod_s \left(\left[\sum_o \int_{\omega \in \Omega_{o,s}} q_{od,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right]^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\beta_{d,s}}. \tag{3}$$

Equation (3) describes CES utility across product varieties within a sector and Cobb-Douglas preferences across sectors. The representative agent allocates expenditure across varieties of goods ω from the measure $\Omega_{o,s}$ of goods produced by sector s in origin county o. The parameter $\beta_{d,s}$ represents the share of country d's expenditure devoted to sector s, where $\sum_s \beta_{d,s} = 1$. The variable $q_{od,s}(\omega)$ represents the quantity of variety ω goods in sector s which are shipped from origin country o to destination country d. The country subscripts in $q_{od,s}(\omega)$ reflect the fact that the consumer price of a product, and thus its quantity consumed, depend on its production and trade costs, and hence on its country of origin; a given variety is produced in only one country. The sector-specific parameter $\sigma_s > 1$ represents the elasticity of substitution across varieties.

The assumption of CES utility, which is common in trade and macroeconomic research, implies that consumers experience decreasing marginal utility from consuming a given variety and increasing utility in the total measure of varieties. We assume this utility function because it provides a simple way to account for different varieties within a sector while leading to parsimonious aggregate descriptions of production and trade flows across countries and sectors.[10]

2. Firms and Market Structure: A competitive fringe of entrepreneurs may choose to pay the sunk entry cost $f^e_{o,s}$ to draw a productivity φ from some productivity distribution. After observing the productivity draw, an entrepreneur who decides to produce must pay a separate fixed cost. Firms engage in monopolistic competition so that conditional on choosing to operate, an entrepreneur chooses prices $p_{od,s}$ and abatement investments a to maximize profits:

$$\pi_{o,s}(\varphi) = \sum_d \pi_{od,s}(\varphi) - w_o f^e_{o,s}, \tag{4}$$

where

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

We assume the productivity distribution is Pareto, with cumulative distribution function

$$G(\varphi; b_{o,s}) = 1 - \left(\frac{\varphi}{b_{o,s}}\right)^{-\theta_s}. \tag{5}$$

The location parameter $b_{o,s}$ describes a country's productivity, while the shape parameter θ_s describes the dispersion of productivity draws within a sector s. For simplicity, we drop the variety notation ω and index a firm by its productivity φ. The firm sells the following number of units:

$$q_{od,s}(\varphi) = (1 - a(\varphi))\,\varphi l_{od,s}(\varphi). \tag{6}$$

[10] Research finds that non-CES utility functions, such as the linear demand system, translog utility, and certain generalizations which can allow for endogenous markups can be described as part of the same "gravity" family of models. While this implies that their measures of the gains from trade are closely related, these structures do not always obtain the kind of tractable closed-form relationships we use here (Melitz and Ottaviano 2008, Feenstra and Weinstein 2017, Arkolakis et al. forthcoming).

The profit function $\pi_{od,s}(\varphi)$ involves several terms. A consumer in destination d pays price $p_{od,s}(\varphi)$ for goods from firm φ. Each firm receives revenue $p_{od,s}(\varphi)q_{od,s}(\varphi)$ and requires $l_{od,s}(\varphi)$ units of productive labor at wage w_o to produce goods for sending to destination d. A fraction of this labor $1 - a$ is used to produce output and the remaining fraction a to abate pollution. We write the dependence of abatement on productivity $a(\varphi)$ to emphasize that the firm sees abatement as an endogenous choice that ultimately varies with a firm's productivity. Each firm pays the pollution tax $t_{o,s}$ per ton on $z_{od,s}(\varphi)$ tons of pollution emitted for producing goods shipped to destination d. Firms face iceberg trade costs, so $\tau_{od,s} \geq 1$ units must be shipped for one unit to arrive (hence, the firm produces $\tau_{od,s}(\varphi)q_{od,s}(\varphi)$ in order to sell $q_{od,s}(\varphi)$). A firm that chooses to enter the destination market d must pay the fixed cost $f_{od,s}$. Domestic trade costs are normalized so $\tau_{oo,s} = f_{oo,s} = 1$. We assume that pollution tax revenues are lost to rent-seeking. While this assumption is made for simplicity, the considerable sums that corporations spend to lobby on energy and environmental legislation give one basis for it.

We assume this market structure for several reasons. Many industries like cement and steel that have substantial pollution emissions are also concentrated and have barriers to entry (Ganapati, Shapiro, and Walker 2016). By accounting for fixed entry costs and sector-specific markups, our assumptions reflect a stylized version of polluting sectors. At the same time, this approach accounts for firm entry and exit and for reallocation of productive factors and output across firms. Finally, the Pareto technology distribution has plausible theoretical microfoundations (Gabaix 1999; Luttmer 2007) and provides a good fit to the empirical firm distribution, at least in the upper tail (Axtell 2001; Eaton, Kortum, and Kramarz 2011).[11]

It is useful to clarify the difference between firm-level and sector-level productivity in this model, and the relevance of environmental regulation to each. An entrepreneur may draw a productivity φ representing the number of units of output produced per worker involved in production. A sector in a country has a productivity level $b_{o,s}$ describing the location of the distribution of φ levels from which entrepreneurs draw. Our use of "productivity" generally refers to $b_{o,s}$, though our references to an individual firm's productivity refer to φ. One related concept that is commonly discussed and could respond to environmental regulation in this model is the number of workers per unit of output in a firm, $q_{od,s}(\varphi)/l_{od,s}(\varphi) = \varphi(1 - a(\varphi))$. This depends on environmental regulation since regulation increases the share of factors a allocated to abatement rather than to producing output.[12]

[11] Most of the literature following Melitz (2003) and using parametric distributions assumes that technology has a Pareto distribution. A few studies explore other productivity distributions, including the log-normal (Head, Mayer, and Thoenig 2014) and bounded Pareto (Feenstra 2018). Some research suggests that the Pareto distribution provides a more accurate fit to the distribution of US firms than the log-normal does (Axtell 2001).

[12] In principle, one could imagine that some firms comply with environmental regulation by increasing their overall productivity levels, which is a version of the Porter (1991) hypothesis. Empirical support for this idea has been mixed (Greenstone, List, and Syverson 2012; Ambec et al. 2013). Like much of the literature on heterogeneous firms, this static model rules out such channels: a firm's productivity level φ is its fixed attribute and cannot respond to economic forces, though the measure of entrepreneurs choosing to form firms can respond to such forces.

3. Pollution: Firms produce pollution emissions with the following technology:

$$z_{od,s}(\varphi) = \big(1 - a(\varphi)\big)^{1/\alpha_s} \varphi l_{od,s}(\varphi). \tag{7}$$

We assume pollution regulations are stringent enough that all firms engage in some abatement. We also assume that $\theta_s > (\sigma_s - 1)(1 - \alpha_s)$ so that entrants have finite expected profits; later we verify that this assumption actually holds for the parameter values we estimate. Equation (7) states that pollution is an increasing function of output and a decreasing function of abatement. It is essentially the pollution production technology adopted in Copeland and Taylor (2003), except that it incorporates the role of productivity φ and allows the pollution elasticity α_s to differ by sector. The extent to which a sector is "dirty" here depends on a primitive attribute of each industry (α), which can reflect the sector's production technology, its inputs, or other features.

Modeling emissions in this way is appealing because several sensible and seemingly different ways of describing pollution turn out to be equivalent to equation (7). As we show later, α represents the elasticity of pollution emissions intensity with respect to pollution abatement intensity. Pollution emissions intensity is measured as units of pollution emitted per unit of output, and pollution abatement intensity is measured as abatement expenditures divided by total factor costs. We also show that pollution emissions in this model can be described as another factor of production in a Cobb-Douglas production technology. Solving for $1 - a$, then substituting into equation (6) shows that we can write total output as a Cobb-Douglas function of pollution emissions and productive factors:

$$q_{od,s} = \big(z_{od,s}\big)^{\alpha_s} \big(\varphi \, l_{od,s}\big)^{1-\alpha_s}. \tag{8}$$

In this interpretation, α is the Cobb-Douglas share for pollution emissions. Copeland and Taylor (2003) discuss other equivalent interpretations of this model of abatement.

These points give conceptual reasons for equation (7), but we emphasize that it plays a critical role in our analysis. Our approach to recovering an important elasticity and our analysis of counterfactuals both rely on output being a Cobb-Douglas function of pollution and productive factors (see Section IV). Without this Cobb-Douglas relationship, which follows from Assumptions 2 and 3, it would be more difficult to analyze the model quantitatively.[13] While this kind of tractability is one reason why most of the relevant environmental literature has used this functional form, another is perhaps more important. Theory and evidence do not give clear guidance on how to think about pollution emissions in a firm's environmental

[13] This Cobb-Douglas assumption appears in the analysis through two channels. First, it directly leads to the first-order condition for abatement in equation (10). This first-order condition is what drives the role of the abatement elasticity α_s in subsequent results, including the free entry condition in equation (11), the equilibrium equations in changes in equations (12) and (13), and the expressions for competitiveness shocks in equations (19) and (21). This first-order condition also determines the expression for shocks to environmental regulation, in equation (23). The second channel by which this Cobb-Douglas assumption affects the analysis is through providing a simple regression equation to estimate the abatement elasticity, in equation (17).

decisions. Is pollution a second output, on which firms are taxed via environmental regulation? Or is pollution best thought of an input to production, which has a price due to environmental regulation? Or alternatively, should we think of firms as optimizing standard production decisions subject to a constraint on pollution emissions? An advantage of this Cobb-Douglas framework is that it does not require choosing one of these interpretations as correct and the others as incorrect, since in this framework these interpretations are equivalent.

Equation (7) shows that for an operating firm, pollution emissions decline when the firm reallocates productive factors to abatement investments. However, the model more broadly accounts for a variety of ways in which firm and consumer behavior affect pollution emissions: firm entry, exit, production, and trade in this model can all respond to environmental regulation, and all of these forces can interact to determine pollution emissions.[14]

4. Competitive Equilibrium: Consumers maximize utility, firms maximize profits; and in each country, labor supply equals labor demand:

$$L_o = L_o^e + L_o^p + L_o^t + L_o^m + L_o^{nx}. \tag{9}$$

A country's labor supply L_o is allocated to five uses: paying the fixed cost to draw a productivity (L_o^e); engaging in production, including pollution abatement (L_o^p); paying pollution taxes (L_o^t); paying market entry costs (L_o^m); and paying for net exports (L_o^{nx}). Pollution taxes require labor because we assume these are real resources lost to rent-seeking. Net exports (i.e., trade imbalances) require labor because they represent a transfer of real resources between countries.

This completes our description of the model, and we now turn to analyze its implications.

B. *Comparative Statics*

One motivation for the model is the conclusion of Section I that most of the change in pollution during the period 1990–2008 came from emitting less pollution per unit of output, i.e., from lower pollution intensity or the technique effect. We now show that in this model, each of the three main shocks we consider (pollution taxes, productivity, and trade liberalization) decreases pollution intensity within a sector. This implies that any of these three channels could explain the decrease in pollution intensity.

Additional notation helps explain this result. Let $i_{o,s}(\varphi) \equiv \sum_j z_{oj,s}(\varphi) / \sum_j q_{oj,s}(\varphi)$ denote the pollution intensity of a firm with productivity φ, defined as the physical units of pollution emitted per physical unit of output. Let $I_{o,s} \equiv Z_{o,s} P_{o,s} / R_{o,s}$ denote

[14] The pollution technology assumption implies constant returns to scale in pollution abatement. A model with increasing returns to scale in abatement would have different structure (see, e.g., Forslid, Okubo, and Ultveit-Moe 2011). We considered the implications of such a model but chose not to pursue it for two reasons. First, the importance of fixed costs for abatement technologies is empirically unknown. Scale economies could be positive for capital investments like scrubbers, zero for fuel-switching like low-sulfur coal, and negative due to principal-agent issues for management innovations. Second, prices in such a model depend directly on market size, and market size appears in the equilibrium conditions in ways that prevent us from backing out shocks and undertaking the decomposition this paper reports.

the pollution intensity of a sector, defined as the physical units of pollution emitted per real unit of output. The term $P_{o,s}$ represents the sectoral price index, $Z_{o,s}$ is total emissions, and $R_{o,s}$ is total revenue. Let $A_{o,s} \equiv E_{o,s}P_{o,s}^{\sigma_s-1}$ index market size, where $E_{o,s}$ is expenditure. Finally, let $\lambda_{od,s}$ denote the share of country d's expenditure in sector s which is purchased from country o, which also measures openness to trade. Online Appendix II.B and online Appendix II.C derive expressions for the price index and for sectoral expenditure shares.

PROPOSITION 1: *Pollution intensity of a firm is locally decreasing in productivity. Pollution intensity of a sector is locally decreasing in pollution taxes, in productivity, and in trade liberalization.*

PROOF:

For a firm with productivity φ, pollution intensity and its derivative are

$$i_{o,s}(\varphi) = \frac{\alpha_s}{\varphi^{1-\alpha_s}} \frac{(t_{o,s})^{\alpha_s-1}(w_o)^{1-\alpha_s}}{(\alpha_s)^{\alpha_s}(1-\alpha_s)^{1-\alpha_s}} \frac{\sum_j \tau_{oj,s}^{1-\sigma_s} A_{d,s}}{\sum_j \tau_{oj,s}^{-\sigma_s} A_{d,s}}, \quad \frac{\partial i_{o,s}(\varphi)}{\partial \varphi} = (\alpha_s - 1)\frac{i_{o,s}(\varphi)}{\varphi}.$$

Noting that $\alpha_s \in (0,1)$ and that $\varphi, i_{o,s}(\varphi) > 0$ implies the conclusion. Sector-level pollution intensity and its derivatives are

$$I_{o,s} = \frac{\alpha_s}{t_{o,s}}\frac{\sigma_s - 1}{\sigma_s}P_{o,s}, \quad \frac{\partial I_{o,s}}{\partial t_{o,s}} = \frac{I_{o,s}}{t_{o,s}}[\alpha_s \lambda_{oo,s} - 1],$$

$$\frac{\partial I_{o,s}}{\partial b_{o,s}} = -(1-\alpha_s)\frac{I_{o,s}}{b_{o,s}}\lambda_{oo,s}, \quad \frac{\partial I_{o,s}}{\partial \tau_{do,s}} = \frac{I_{o,s}}{\tau_{do,s}}\lambda_{do,s},$$

$$\frac{\partial I_{o,s}}{\partial f_{do,s}} = \frac{1-\alpha_s}{\theta_s}\left(\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)} - 1\right)\frac{I_{o,s}}{f_{do,s}}\lambda_{do,s}.$$

The facts that $\alpha_s \in (0,1)$, $\lambda_{oo,s} \in [0,1]$, and $I_{o,s}, t_{o,s} > 0$ imply the conclusion $\partial I_{o,s}/\partial t_{o,s} < 0$. We conclude $\partial I_{o,s}/\partial b_{o,s} < 0$ since all terms in that expression are positive except the leading minus sign, and we conclude $\partial I_{o,s}/\partial \tau_{do,s} > 0$ for any country pair with nonzero trade and trade costs since $I_{o,s}$, $\tau_{do,s}$, $\lambda_{do,s} > 0$. Finally, $\partial I_{o,s}/\partial f_{do,s} > 0$ since all terms in it are positive; we assume (and verify empirically) that $\theta_s > (\sigma_s - 1)(1-\alpha_s)$. ∎

The economics underlying Proposition 1 are informative. For an individual firm, productivity affects pollution intensity through abatement decisions. Solving the firm's profit-maximization problem for the optimal share a of factors invested in abatement gives the following first-order condition:

$$1 - a = \left(\frac{w_o}{\varphi t_{o,s}}\frac{\alpha_s}{1-\alpha_s}\right)^{\alpha_s}. \tag{10}$$

Productivity decreases a firm's pollution intensity in Proposition 1 because it increases abatement investments in this first-order condition. More productive firms charge lower prices, implying that the ratio of pollution taxes to output prices increases with productivity.[15] We focus on firm-level results only for productivity since this is the only term in $i_{o,s}(\varphi)$ (and the only primitive attribute in the model) which varies across firms within a sector.

For an entire sector, pollution taxes also decrease pollution intensity. This can be seen from the denominator of the expression for $I_{o,s}$ in the proof, and also in the first-order condition (10). Pollution taxes make firms redirect productive resources to abatement, which makes the sector's pollution intensity decline. Similarly, productivity growth increases the real output produced for a given level of pollution emitted, thereby decreasing pollution intensity.

At the sector-wide level, lower iceberg trade costs imply a smaller portion of a firm's output must be paid in order to export goods. Thus, lower iceberg trade costs let a sector emit less pollution in order to obtain the same total value. Decreasing fixed trade costs causes a reallocation of market share to firms that are more productive and have lower pollution intensity. This can be seen when setting $\theta_s = (1-\alpha_s)(\sigma_s - 1)$, which shuts off firm heterogeneity.

While productivity features prominently in the foregoing explanations, we emphasize that not all changes in pollution can be ascribed to it. The three terms in equation (7) show that emissions can change via several channels: the investment of productive factors in abatement a, the selection of which productivity levels φ entrepreneurs choose to form into firms, and the reallocation of productive factors across operating firms, $l_{od,s}$. The discussion above highlights the relevance of these channels to the various shocks.

What is the magnitude of trade liberalization's effect on pollution intensity? Proposition 1 shows that for both fixed and variable trade costs, this magnitude grows with baseline pollution intensity and with baseline openness, and decreases with baseline iceberg or fixed trade costs. Thus, a relatively closed country like the United States, where international trade accounts for a relatively small share of expenditure, will have relatively limited effects of trade liberalization on pollution.

Proposition 1 describes the sign of local, partial equilibrium changes. Discrete changes in pollution taxes, productivity, and trade costs might lead to different patterns, and they provide one reason to analyze the model quantitatively. One general conclusion which arises from this model even without quantification is that a sector's pollution intensity can fall due to productivity, trade, and environmental regulation.

C. *Methodology for Analyzing Counterfactuals*

We now describe how we use this model to analyze counterfactuals. We combine the model's assumptions into two conditions that summarize firm behavior. In a competitive equilibrium, these conditions must be satisfied at a given point in time. We then use these conditions to analyze how counterfactuals affect welfare.

[15] The prediction that more productive firms charge lower prices comes from the assumption of monopolistic competition but would also result from many other market structures and has empirical support (Foster, Haltiwanger, and Syverson 2008). Certainly some specific innovations do increase pollution intensity. The use of pesticides in agriculture, for example, probably increased both productivity and pollution intensity. This model envisions a broad set of factor-neutral productivity changes which allow producers to use fewer inputs for obtaining the same output, and such broad factor-neutral productivity improvements are likely to decrease pollution emitted to produce a given output.

The first condition for a competitive equilibrium, shown earlier in equation (9), is that labor demand must equal labor supply in each country. The second condition for a competitive equilibrium says that the expected profit that an entrepreneur obtains from drawing a productivity must equal the fixed cost of drawing a productivity:

$$(11) \qquad \frac{1-\alpha_s}{\theta_s}\frac{\sigma_s - 1}{\sigma_s} R_{o,s} \;=\; w_o f^e_{o,s} M^e_{o,s}.$$

(See derivation in online Appendix II.D.) This is also known as a free entry condition. The left-hand side describes the profit entrepreneurs expect from drawing a productivity. This expected profit equals total revenues divided by markups, and scaled by the Pareto shape parameter and the pollution elasticity. On the right-hand side, the term $f^e_{o,s}$ represents the fixed cost of forming a firm, which is paid in local wages and multiplied by the mass of firms entering.

To analyze counterfactual changes in environmental regulation, productivity, and trade costs, we rewrite each variable as a proportional change from a base year, which is a methodology developed in Dekle, Eaton, and Kortum (2008). The benefit of this methodology is that many variables which are difficult to measure do not appear in changes.

Formally, we use this methodology as follows. Let x denote any variable from the model, let x' denote the value of this variable under a counterfactual scenario, and let $\hat{x} \equiv x'/x$ denote the proportional change in this variable due to the counterfactual. Written in changes, the two equilibrium equations (9) and (11) become the following:

$$(12) \qquad 1 \;=\; \psi_o \left(\frac{\sum_s \hat{M}^e_{o,s} R_{o,s} \dfrac{(\sigma_s - 1)(\theta_s - \alpha_s + 1)}{\sigma_s \theta_s} + \eta'_o}{\sum_s R_{o,s} \dfrac{(\sigma_s - 1)(\theta_s - \alpha_s + 1)}{\sigma_s \theta_s} + \eta_o} \right),$$

$$(13) \qquad \hat{w}_o \;=\; \sum_d \frac{\zeta_{od,s}\left(\dfrac{\hat{w}_o}{\hat{b}_{o,s}}\right)^{-\theta_s} (\hat{\tau}_{od,s})^{-\frac{\theta_s}{1-\alpha_s}} (\hat{f}_{od,s})^{1-\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)}} (\hat{t}_{o,s})^{-\frac{\alpha_s\theta_s}{1-\alpha_s}}}{\sum_i \lambda_{id,s} \hat{M}^e_{i,s}\left(\dfrac{\hat{w}_o}{\hat{b}_{o,s}}\right)^{-\theta_s} (\hat{\tau}_{od,s})^{-\frac{\theta_s}{1-\alpha_s}} (\hat{f}_{od,s})^{1-\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)}} (\hat{t}_{o,s})^{-\frac{\alpha_s\theta_s}{1-\alpha_s}}} \hat{\beta}_{d,s} \frac{R'_d - NX'_d}{R_d - NX_d}.$$

(See derivations in online Appendix II.E and online Appendix II.F.) We assume for simplicity that the fixed cost of drawing a productivity is constant over time. In these equilibrium conditions, we have defined the parameter combinations η_o and ψ_o, and export shares $\zeta_{od,s} \equiv X_{od,s}/\sum_d X_{od,s}$, where $X_{od,s}$ is the value of trade from country o to country d of goods from sector s.[16] Equation (12) says that in any counterfactual, labor demand must equal labor supply in each country. Equation (13) says that in any counterfactual, the expected profit from drawing a productivity must equal

[16] Specifically, $\eta_{o,s} \equiv \sum_s \left[-\frac{\theta_s - (\sigma_s - 1)(1-\alpha_s) - \sigma_s\theta_s}{\sigma_s\theta_s} \beta_{o,s} NX_o - NX_{o,s} \frac{(\sigma_s - 1)(\theta_s - \alpha_s + 1)}{\sigma_s\theta_s} \right]$ and $\psi_o \equiv \left[1 - \sum_s \frac{\theta_s - (\sigma_s - 1)(1-\alpha_s)}{\sigma_s\theta_s} \beta_{o,s} \right] / \left[1 - \sum_s \frac{\theta_s - (\sigma_s - 1)(1-\alpha_s)}{\sigma_s\theta_s} \beta'_{o,s} \right]$, where $NX_{o,s}$ are net exports (exports minus imports) in sector s.

the fixed cost of drawing a productivity. We use equations (12) and (13) to find the wages and firm entry decisions that characterize each counterfactual.

To measure pollution emissions associated with a counterfactual, we integrate pollution emissions from (7) over the measure of operating firms. The change in country o's pollution emissions between a baseline year and a counterfactual is

$$\hat{Z}_o = \frac{\sum_s \frac{\hat{M}^e_{o,s}\hat{w}_o}{\hat{t}_{o,s}} Z_{o,s}}{\sum_s Z_{o,s}}. \tag{14}$$

(See derivation in online Appendix II.G.) The denominator of equation (14) describes the sum over sectors of baseline pollution. The numerator shows the same sum, but each sector's pollution is multiplied by the proportional change in that sector's pollution due to a counterfactual,

$$\hat{Z}_{o,s} = \frac{\hat{M}^e_{o,s}\hat{w}_o}{\hat{t}_{o,s}}. \tag{15}$$

A sector's change in pollution emissions increases proportionally with firm entry $\hat{M}^e_{o,s}$ and wages $\hat{w}_o$, and decreases with regulation $\hat{t}_{o,s}$.

III. Data

The data for this paper fall into two categories: plant-level microdata for estimating the model's parameters, and country-by-sector aggregates used to analyze counterfactuals. We use a few additional data sources for sensitivity analyses described in Section VI.

We use plant-level microdata to estimate three parameters of the model, calculated separately for each sector: the elasticity of substitution across product varieties; the shape parameter of the Pareto distribution of firm productivities; and a pollution elasticity. Estimating the elasticity of substitution requires input costs and the value of total sales for each sector. We obtain these data from the US Census Bureau's Annual Survey of Manufactures (ASM) in the first year of our sample, 1990. The ASM is a probabilistic sample of approximately 60,000 establishments per year.[17] All our calculations with the ASM use sampling weights provided by the Census Bureau so the calculations are representative of the sector as a whole. We also use the ASM data to estimate the Pareto shape parameter; details are described below.

Estimating the pollution elasticity requires two additional pieces of information: pollution abatement expenditures and pollution emissions. Pollution abatement expenditures come from the Pollution Abatement Costs and Expenditures (PACE) survey, which was developed jointly by the US Environmental Protection Agency

[17] Between 1990 and 1996, firms with at least 250 employees or $500 million in sales were sampled with certainty. Beginning in 1998, firms with at least 500 employees or $1 billion in sales were sampled with certainty. Below these thresholds, the probability of appearing in the sample increases with a firm's size.

and the US Census Bureau.[18] We also use data on air pollution emissions from the US Environmental Protection Agency's National Emissions Inventory (NEI), which provides a comprehensive and detailed report of air pollution emissions from all sources above a low minimum reporting threshold. The NEI was created to provide EPA, federal and state decision-makers, the US public, and foreign countries with accurate measures of US pollution emissions.[19]

We compile aggregate data for the US and foreign countries separately for each sector and for each of the years 1990–2008. In particular, we need production and trade data from each country, and we need a measure of pollution emissions in the United States. For production in years 1990–1995, we use data from the Structural Analysis Database of the Organization for Economic Co-operation and Development (OECD). For trade in years 1990–1995, we use data from the OECD's Structural Analysis Database. For production and trade in years 1995–2008, we use data from the World Input-Output Dataset (WIOD). We adjust the WIOD values to exactly match the OECD data in the year 1995. These datasets are reported in two-digit International Standard Industrial Classification codes, third revision. We convert trade data, which are reported in foreign currencies, to nominal US dollars using annual exchange rates from the OECD Statistics dataset (see online Appendix Section III.C for more details). We aggregate these data to two countries (the US and Foreign) and to 17 manufacturing sectors defined in online Appendix Table 2. We abstract from non-manufacturing activity. Although almost no countries report intranational trade (goods produced in the same country where they are consumed), we measure it as total production minus total exports.

We measure US pollution emissions with the same National Emissions Inventory (NEI) data used to measure pollution parameters. The NEI is conducted roughly triennially, and we use years 1990, 1996, 1999, 2002, 2005, 2008. The year 1993 had no inventory. We focus on sector-level emissions of six of the main air pollutants regulated under the Clean Air Act: carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter less than 10 micrometers (PM_{10}), particulate matter less than 2.5 micrometers ($PM_{2.5}$), sulfur dioxide (SO_2), and volatile organic compounds (VOCs).

[18] Empirical research has used the PACE survey to show that pollution abatement expenditures respond to Clean Air Act county-specific regulations; other work has shown that PACE expenditures are correlated with state-specific foreign direct investment (Keller and Levinson 2002; Becker 2005). The 1990 and 2005 PACE data that we use have similar structure and are broadly comparable. The 1999 PACE data, which we do not use, was not comparable with these surveys (Becker and Shadbegian 2005).

[19] Our measures of particulate matter pollution in the NEI include only filterable particulate matter. This category includes particulates that can be captured on a filter during sampling. It excludes condensible particulate matter, which are gaseous particles that condense to small particles after they cool. It also excludes "secondary" particulate matter, which is formed in the atmosphere through reactions involving other gases like NO_x and SO_2. Filterable particulate matter is the only type of particulate matter reported in all NEI years 1990–2008. Several recent studies have used NEI microdata to explore temporal and spatial patterns in emissions trends and to incorporate air pollution into national accounts (Levinson 2009; Muller and Mendelsohn 2009; Muller, Mendelsohn, and Nordhaus 2011). The classification of "polluting" industries in other studies (Greenstone 2002; Greenstone, List, and Syverson 2012) relies on an EPA study that used pollution emissions data from the AIRS dataset, which were later integrated into the NEI.

IV. Estimation and Results: Parameters and Shocks

A. *Estimating Parameters*

We first describe estimation of pollution parameters, then trade and macro parameters. To estimate the pollution parameters, we divide $z_{od,s}(\varphi) = (1 - a(\varphi))^{1/\alpha_s}\varphi l_{od,s}(\varphi)$ from Assumption 3 by equation (6) from Assumption 2 to show that pollution intensity is a function of abatement investments:

$$(16) \qquad \frac{z}{q} = \left(1 - a\right)^{(1-\alpha)/\alpha}.$$

Taking logs of equation (16), taking first differences Δ over time, and allowing for national trends η_t in emissions intensity and idiosyncratic disturbances $\epsilon_{i,t}$ to pollution intensity gives

$$(17) \qquad \Delta \ln\left(\frac{z_{i,t}}{q_{i,t}}\right) = \frac{1-\alpha}{\alpha}\Delta \ln\left(1 - a_{i,t}\right) + \eta_t + \epsilon_{i,t}.$$

Since a is the abatement cost share, we expect $(1-\alpha)/\alpha$ to be positive (i.e., pollution intensity increases with 1 minus the abatement expenditure share). Online Appendix III.C describes the data extract used in these regressions, which combines emissions from NEI, value of shipments and costs from ASM, and pollution abatement costs from PACE. Pollution abatement costs may be endogenous here, leading to biased estimates of α. If regulators require the dirtiest plants to spend more on pollution abatement, then reverse causality will bias estimates of $(1-\alpha)/\alpha$ downward. Moreover, our measures of abatement costs and total factor costs are based on PACE and ASM surveys, both of which may contain measurement error. An additional possibility is that abatement costs decrease precisely because regulation causes exit of the dirtiest firms (Levinson and Taylor 2008).

To address all three of these possible endogeneity concerns, we instrument for changes in the abatement cost share $\ln(1 - a_{i,t})$ in equation (17) using changes in local environmental regulatory stringency. The EPA requires polluting firms in areas that exceed air quality standards ("nonattainment" counties) to install pollution abatement technologies. These instruments directly address the reverse causality and measurement error concerns described in the previous paragraph. We aggregate data to the county-sector-year level so it helps address the third concern about endogenous plant exit.

We estimate a single α using this regression approach, and we use an additional implication from the model to scale this estimate for each sector.[20] We use the fact that α_s represents pollution tax payments as a share of production costs. As equation (8) implies, under Cobb-Douglas production with constant returns to scale, the output elasticity α_s is equal to the share of firm costs which represent pollution taxes.

[20] In principle, we could use our instrumental variables regression approach to estimate α for each of the 17 sectors in our analysis. In practice, we have a limited sample of plants that we observe in all three of the NEI, PACE, and ASM datasets. When dividing these plants into 17 sectors, the samples are too small to estimate equation (17) separately for each sector.

Since the United States does not have pollution taxes, we cannot directly observe the share of firm costs that represent pollution taxes. If the pollution tax rate is constant across sectors, however, then the relative value of α_s across sectors is proportional to the tons of pollution emitted per dollar of input costs in each sector. For example, if the basic metals sector emitted twice as much pollution per dollar of input costs as the textiles sector did, then we would have $\alpha_{\text{basic-metals}} = 2\alpha_{\text{textiles}}$. We use this approach to measure relative differences in α across sectors. We then scale these values so the mean across all sectors equals the economy-wide elasticity of pollution emissions intensity with respect to abatement costs from our equation (17) regression estimate.

As discussed earlier, this approach to recovering pollution elasticities relies heavily on Assumptions 2 and 3, which together imply this Cobb-Douglas result. Without this Cobb-Douglas relationship, regardless of whether it is assumed directly or derived from microfoundations like (17) and (8), it would be much less straightforward to recover estimates of the pollution elasticity α or to use the model to study counterfactuals.

Table 1 reports the first-stage, reduced-form, and instrumental variable regressions of equation (17) for the five pollutants in the NEI for which we have an instrumental variable for abatement expenditures. It analyzes each pollutant in a separate regression, where county-level nonattainment designations imposed under the Clean Air Act serve as instrumental variables for the abatement cost shares in panel C.[21] Columns 1–5 analyze each pollutant separately, and column 6 uses total emissions of all pollutants in tons as a summary measure of emissions. All regressions report standard errors in parentheses, clustered by commuting zone.

Panel A of Table 1 presents the first-stage regressions which show that designating a county as nonattainment increases the proportion of firm costs devoted to pollution abatement in sectors that account for a larger share of pollutant p emissions. All of these first-stage regressions have negative signs, implying that regulated firms increase the share of costs devoted to pollution abatement by 6 percent relative to the baseline share. For the pooled regression in column 6, the first-stage F-statistic of 42 (equal to the square of the t-statistic) suggests this instrument is quite strong. For the pollutant-specific regressions, estimates for CO, NO_x, and VOCs have strong instruments (F-statistics ranging from 14 to 49), though the first-stage F-statistics for particulate matter are fairly small (1.4 and 3.4).

[21] Technically, the instrumental variable we use for changes in abatement expenditures is an interaction between a variable indicating the pollution intensity of pollutant p of a sector in 1990 (i.e., $\text{PolluterShare}_{jp} = \frac{\text{IndustryEmissions}_{jp}}{\text{TotalEmissions}_p}$) and whether the county switches into nonattainment for any pollutant between 1990 and 1993 (i.e., $\mathbf{1}[\text{Nonattain}_c] = 1$). Thus, the instrumental variable is $\text{PolluterShare}_{jp} \times \mathbf{1}[\text{Nonattain}_c]$. We allow for a county to be in nonattainment if it violates the EPA standards for any of the pollutants regulated under the Clean Air Act. In practice, nonattainment is pollutant specific. We model nonattainment in this way in order to capture cross-pollutant regulatory spillovers and to ameliorate the fact that many pollutants have little variation over this time period (e.g., CO). The focus on counties that switched into nonattainment between 1990 and 1993 is meant to capture all the counties that became newly regulated under the 1990 Clean Air Act Amendments. We include the lower order interaction terms in all regression models to facilitate identification of the difference-in-differences interaction term.

TABLE 1—POLLUTION ELASTICITY: INSTRUMENTAL VARIABLES REGRESSIONS, BY POLLUTANT

	CO (1)	NO_x (O_3) (2)	PM_{10} (3)	$PM_{2.5}$ (4)	VOC (O_3) (5)	Total (any) (6)
Panel A. First-stage						
$\text{Nonattain}_{cp} \times \text{Polluter}_p$	−0.057	−0.061	−0.101	−0.126	−0.063	−0.058
	(0.015)	(0.011)	(0.085)	(0.068)	(0.009)	(0.009)
Panel B. Reduced-form						
$\text{Nonattain}_{cp} \times \text{Polluter}_p$	−7.386	−5.985	−9.474	−7.399	−7.812	−5.346
	(5.244)	(4.782)	(6.860)	(4.427)	(1.214)	(1.979)
Panel C. Instrumental variables						
Abatement expenditure ratio	130.030	98.592	94.118	58.551	124.907	91.604
	(64.278)	(72.412)	(78.483)	(46.795)	(36.827)	(25.373)
Observations	≈3,500	≈3,500	≈3,500	≈3,500	≈3,500	≈3,500
First-stage *F*-stat	14	30	1.4	3.4	52	42
Panel D. Pollution elasticity parameter						
Pollution elasticity(α)	0.008	0.010	0.011	0.017	0.008	0.011
	(0.004)	(0.007)	(0.009)	(0.013)	(0.002)	(0.003)
County-NAICS FE	X	X	X	X	X	X

Notes: This table presents a series of regression coefficients from 18 separate regressions, one for each column of each panel A through C. An observation is a county × industry × year, where industry is a six-digit NAICS code. The dependent variable in panel A is the same in each column and represents the log of 1 minus the abatement cost share of county × industry × year production. The regressor of interest is an interaction between two indicator variables that denote whether the industry is in a county that was newly regulated (i.e., $\text{Nonattain}_{cp} = 1$) and whether the industry is a polluting industry (i.e., $\text{Polluter}_p = 1$). The variable, Nonattain, changes across columns, reflecting different pollutant-specific nonattainment designations as indicated in the column headings. Parentheses in the column headings describe the type of nonattainment used as the regressor. The dependent variable in panels B and C represent the log emissions intensity, defined as pollution emissions per dollar of real output. The dependent variable in panels B and C changes in each column, where the pollution emissions are indicated in the column headings. Panel C presents the instrumental variable estimates of log pollution intensity regressed on log abatement cost shares, which in practice represents the ratio of the estimates presented in panel A and panel B. Lastly, panel D transforms the regression estimates in panel C to back out a measure of α for each pollutant, where the standard errors are calculated using the delta method. Robust standard errors are in parentheses, clustering by commuting zone.

Sources: ASM, NEI, PACE

Panel B presents evidence from reduced-form regressions of pollution emissions intensity on the regulation instrument.[22] The regression estimates show that polluting sectors in newly regulated counties decrease their pollution per unit of output after the regulations go into place. The relationship between nonattainment and pollution emission rates is negative for all pollutants, imprecise for most pollutants, but precise for VOC emissions and for total pollution emissions. Panel C, which presents our instrumental variable regression estimates, shows that changes in pollution abatement cost shares, instrumented with changes in Clean Air Act regulations, predict changes in pollution intensity. Panel D presents our estimates of α that come from a nonlinear transformation of the regression coefficient $(1-\alpha)/\alpha$. The estimates of α range from 0.008 to 0.017. When we aggregate over pollutants in column 6, we obtain the value $\alpha = 0.011$, which is statistically significant at the 1 percent level.

[22]The dependent variable in panels B and C is $\log((\text{pollution}+1)/\text{output})$ in order to prevent attrition for non-polluting county × sector × year cells in the sample.

Table 2—Parameter Estimates

Sector	Tons pollution per dollar costs (1)	Pollution elasticity (α) (2)	Input share (3)	Elasticity of substitution (σ) (4)	Pareto shape parameter (θ) (5)	Shape parameter standard error (6)
Food, beverages, tobacco	2.60	0.0040	0.74	3.79	3.89	(0.13)
Textiles, apparel, fur, leather	1.44	0.0022	0.79	4.87	4.80	(0.10)
Wood products	6.75	0.0103	0.83	5.94	6.20	(0.17)
Paper and publishing	14.61	0.0223	0.79	4.80	5.21	(0.10)
Coke, refined petroleum, fuels	13.88	0.0212	0.88	8.18	9.91	(1.67)
Chemicals	13.42	0.0205	0.70	3.28	3.50	(0.08)
Rubber and plastics	3.13	0.0048	0.78	4.59	4.62	(0.08)
Other non-metallic minerals	19.91	0.0303	0.73	3.66	4.05	(0.11)
Basic metals	36.57	0.0557	0.85	6.66	10.01	(0.50)
Fabricated metals	1.24	0.0019	0.79	4.77	4.80	(0.06)
Machinery and equipment	1.00	0.0015	0.76	4.25	4.19	(0.14)
Office, computing, electrical	1.52	0.0023	0.81	5.24	5.32	(0.15)
Radio, television, communication	0.32	0.0005	0.79	4.66	4.77	(0.23)
Medical, precision, and optical	0.94	0.0014	0.65	2.89	2.86	(0.06)
Motor vehicles, trailers	1.03	0.0016	0.82	5.62	5.60	(0.18)
Other transport equipment	1.26	0.0019	0.74	3.88	3.87	(0.13)
Furniture, other, recycling	3.06	0.0047	0.73	3.77	3.75	(0.03)
Mean across industries	7.22	0.011	0.77	4.76	5.14	(0.23)

Notes: This table presents summary means and regression estimates for 17 separate industries, one per row, using data from a single year, 1990. Column 1 presents the total tons of pollution per dollar input costs for each sector, where pollution data comes from the NEI and data on input costs come from the ASM. Column 2 presents the sector-specific pollution elasticity, which is calculated using the economy-wide estimate of 0.011 from Table 1, scaled across industries by the tons pollution per dollar costs from column 1. Column 3 presents the input share that is defined as the ratio of costs to revenues using data from the ASM. We deflate revenues and input expenditures using industry-specific price output and input price deflators, respectively. Column 4 displays the sector-specific elasticity of substitution, which is calculated from equation (38). Columns 5 and 6 present regression estimates and standard errors for the Pareto shape parameter, derived from equation (39). The actual parameter is a nonlinear transformation of the regression coefficient, where the reported standard errors are calculated using the delta method, clustering by four-digit NAICS code.

Table 2 shows estimates separately for each sector; the various pollutants have similar patterns (online Appendix Table 3). The resulting pollution elasticities, estimated using the pooled sample of all pollutants in Table 2, range from 0.001 to 0.048. The dirtiest sectors are basic metals and other non-metallic minerals.

The overall estimate of 0.011 implies that firms are behaving as if they pay one percent of their total production costs to pollution taxes. We lack a method to test this number independently, but we can compare it to two related statistics. First, the PACE data report that manufacturing pollution abatement costs are about one-half of a percent of total manufacturing sales (US Census Bureau 2008). Second, Greenstone, List, and Syverson (2012) find that nonattainment designations decrease the total factor productivity of regulated firms by 2.6 percent. Because these numbers all characterize the economic costs of environmental regulation, it is notable that are of the same order of magnitude.

We also estimate the elasticity of substitution and shape parameter of the Pareto distribution separately for each sector, by building on the approach used in Hsieh and Ossa (2016) and Antràs, Fort, and Tintelnot (2017) (Table 2). Since these parameters have been estimated elsewhere with similar methodology, methodological details are described in online Appendix III.D. We estimate the Pareto shape parameter θ_s by regressing the log of a firm's sales rank on the log of its sales using the microdata from the 1990 Annual Survey of Manufactures. The regression estimates of the Pareto shape parameter are extremely precise, which reflects the fact that power law distributions describe firm size well, at least in the upper tail (Gabaix 2009). We estimate the elasticity of substitution σ_s by taking the ratio of the value of shipments to production costs.[23] The estimates support our assumption that $\theta_s > (\sigma_s - 1)(1 - \alpha_s)$.

B. *Recovering Historic Values of Shocks*

This paper's research question of why pollution followed its historical path requires studying counterfactuals where some shocks take on their actual, historical values, and other shocks do not. Analyzing such counterfactuals requires measuring the historic values of each shock for each year in 1990–2008. We now explain how we use implications of the model together with country $\times$ sector aggregate data to recover historic values of the paper's four main shocks: foreign competitiveness; domestic competitiveness; expenditure shares; and environmental regulation.

Foreign Competitiveness.—Informally, "competitiveness" in the model measures the ability of a country to sell a wide variety of products at relatively low prices. We describe a single "foreign competitiveness" shock because analyzing the causes of changes in US pollution does not require distinguishing which underlying forces change foreign competitiveness.[24] Formally, foreign competitiveness combines foreign productivity, foreign environmental regulation, and foreign exporting trade costs:

$$(18)\quad \hat{\Gamma}^*_{od,s} \equiv (1/\hat{b}_{o,s})^{-\theta_s}(\hat{\tau}_{od,s})^{-\theta_s/(1-\alpha_s)}(\hat{f}_{od,s})^{1-\theta_s/(\sigma_s-1)(1-\alpha_s)}(\hat{t}_{o,s})^{-\alpha_s\theta_s/(1-\alpha_s)}, \quad o \neq U.S.,$$

$$(19)\quad = \frac{\hat{\lambda}_{od,s}}{\hat{M}^e_{o,s}\hat{w}_o^{-\theta_s}}(\hat{P}_{d,s})^{-\frac{\theta_s}{1-\alpha_s}}\left(\frac{\hat{\beta}_{d,s}}{\hat{w}_d}\frac{R'_d - \widehat{NX}_d NX_d}{R_d - NX_d}\right)^{1-\frac{\theta s}{(\sigma_s-1)(1-\alpha_s)}}.$$

[23] These methods are literally consistent with the model, but it is worth emphasizing that they do not extrapolate well to other models. Our methodology for estimating the trade elasticity relies on the assumption that productivity has a Pareto distribution. Our methodology for estimating the elasticity of substitution relies on the assumption that firms engage in monopolistic competition. It is feasible in principle to use other features of the model to estimate these parameters, such as gravity equations for bilateral trade, which are more robust to model misspecification and which extrapolate more easily to other models. With our data on the total value of bilateral trade flows, however, it is difficult to implement such methods. We are not aware of other papers that estimate both of these two parameters separately for a variety of sectors using such other methods, though it is noteworthy that the mean values we obtain for these parameters are similar to economy-wide estimates of these parameters from other studies.

[24] We also lack the data to measure each component of foreign competitiveness separately. Separately measuring productivity and trade costs would require foreign producer price index data, which are not available for most countries, sectors, and years. Separately measuring the effect of foreign environmental regulation requires data on air pollution emissions for each country $\times$ sector, which are not available.

(For derivation, see online Appendix II.H.) The first equation defines this shock, and the second shows how we measure it. One can see where this shock contributes to the analysis of counterfactuals by observing that the right-hand side of equation (18) appears in both the numerator and denominator of the second equilibrium condition in changes, which is equation (13). An asterisk (*) denotes the actual, historic value of a shock. The right-hand side of equation (19) shows that the change in foreign competitiveness can be measured by the change in the share of US expenditure on goods from a foreign country, divided by the change in nominal income times firm entry.

US Competitiveness.—Shocks to US competitiveness represent changes in US productivity and trade costs for exports, which are allowed to vary across sectors and over time. These have similar definition and measurement:

$$\hat{\Gamma}^*_{od,s} \equiv (1/\hat{b}_{o,s})^{-\theta_s} (\hat{\tau}_{od,s})^{-\theta_s/(1-\alpha_s)} (\hat{f}_{od,s})^{1-\theta_s/(\sigma_s-1)(1-\alpha_s)}, \quad o = U.S., \tag{20}$$

$$= \hat{t}_{o,s}^{\frac{\alpha_s\theta_s}{1-\alpha_s}} \frac{\hat{\lambda}_{od,s}}{\hat{M}^e_{o,s}\hat{w}_o^{-\theta_s}} \hat{P}_{d,s}^{-\frac{\theta_s}{1-\alpha_s}} \left(\frac{\hat{\beta}_{d,s}}{\hat{w}_d}\frac{R'_d - \widehat{NX}_d NX_d}{R_d - NX_d}\right)^{1-\frac{\theta s}{(\sigma_s-1)(1-\alpha_s)}}. \tag{21}$$

(For derivation, see online Appendix II.H.) Again the first equation defines the shock and the second shows how we measure it. Because we have pollution emissions data for the US but not foreign countries, we separate the environmental regulation term $\hat{t}_{o,s}$ from other components of US competitiveness.

We recover a separate foreign competitiveness shock for each sector and year and also a separate domestic competitiveness shock for each sector and year. For example, we recover one foreign competitiveness shock for the basic metals sector, a separate foreign competitiveness shock for the chemicals sector, etc. If some force has increased foreign competitiveness only in dirty industries, these shocks are designed to capture that force. For example, foreign countries might have improved their productivity in dirty industries, might have begun facing lower trade costs for exports in dirty industries, or might have decreased the stringency of environmental regulation for dirty industries.[25]

Expenditure Shares.—We measure shocks to sectoral expenditure shares as the share of a country's expenditure on sector s in a counterfactual, divided by the share of the country's expenditure on sector s in a baseline year:[26]

$$\hat{\beta}^*_{d,s} = \frac{\sum_o X'_{od,s}/\sum_{o,s} X'_{od,s}}{\sum_o X_{od,s}/\sum_{o,s} X_{od,s}}. \tag{22}$$

[25] Because sector is the finest unit of analysis in our model, these shocks do not separately distinguish within-sector changes. Suppose China became less competitive at producing dirty structural steel from blast furnace plants, but became more competitive at producing cleaner rebar steel from mini-mill plants. Our sector-level analysis might interpret this as no aggregate change in foreign competitiveness for the basic metals sector, whereas competitiveness actually grew in the dirty products within this sector but decreased in the clean products within this sector. The finding of the statistical decomposition that composition effects are similarly small both across industries and products provides suggestive evidence that this is not a first-order channel for studying pollution intensity.

[26] Our specification of CES preferences implies that we abstract from consumer tastes changing among varieties within a sector.

We include this shock in our analysis because with it, when all shocks are set to exactly match their historic levels, the model can recreate historic paths of emissions, production, and trade.[27]

Environmental Regulation.—Finally, we measure shocks to environmental regulation by rearranging equation (14):

$$\hat{t}_{o,s} = \frac{\hat{M}^{e}_{o,s}\,\hat{w}_{o}}{\hat{Z}_{o,s}}. \tag{23}$$

The change in environmental regulation equals the change in the mass of entering firms times the change in factor prices, divided by the change in pollution emissions.

This result helps contrast the technique effect from the statistical decomposition with the environmental regulation shock analyzed in this model. The technique effect for a specific sector is defined as the change in pollution per real unit of output within a sector, or $\hat{Z}_{o,s}/(\hat{R}_{o,s}/\hat{P}_{o,s})$. Combining the previous expressions for changes in pollution $\hat{Z}_{o,s}$, changes in factor prices $\hat{w}_o$, and changes in firm entry $\hat{M}_{o,s}$ shows that environmental regulation in this model can be written as $\hat{t}_{o,s} = \hat{Z}_{o,s}/\hat{R}_{o,s}$ (see derivation in online Appendix II.I). In other words, all three forces we study—trade costs, productivity, and environmental regulation—determine the technique effect in the statistical decomposition, but trade costs and productivity do so through changes in the price index $\hat{P}_{o,s}$.

C. *Description of Environmental Regulation Shocks*

The previous subsection described how we calculate historic values of each of the shocks in the model. We calculate these shocks primarily to use them in decomposing historic changes in pollution emissions into the share accounted for by changes in environmental regulation, productivity, and trade costs. The levels of some of these shocks, however, are interesting in their own right. We focus on the environmental regulation shock here; shocks to expenditure shares, wages, and firm entry are less directly relevant to the question of why pollution emissions have declined so we discuss these in online Appendix III.E.[28]

[27] Exactly matching historic data requires a fifth shock, to trade imbalances; see online Appendix III.E. Consumer expenditure in this model involves two stages of budgeting: expenditure is first allocated to each sector, with expenditure shares equal to Cobb-Douglas exponents; and then across varieties within a sector. The model can therefore only match historic changes in expenditure shares across sectors if it allows changes in the Cobb-Douglas exponents over time. In the absence of changes in the Cobb-Douglas exponents, the model could match all historic changes in the data except changes in expenditure shares across sectors. One could therefore think of this expenditure share shock as a residual. This shock will primarily affect the composition of production and consumption across sectors, rather than the emissions intensity within a given sector. Given the conclusion of Section II that most historic decreases in emissions intensity have been within rather than across products, this shock to expenditure shares is unlikely to play a large role in explaining decreases in emissions.

[28] We focus on results for NO_x regulation, both since NO_x emissions are measured with higher-quality methods than most other pollutants are, and because we have detailed data on one major regulation, the NO_x Budget Trading Program. According to the 2008 NEI, which reports monitoring method for almost all plants, over half of manufacturing NO_x emissions are reported based on continuous emissions monitoring systems or other direct measures. We considered focusing on SO_2, but according to plant-level data we obtained from the EPA Clean Air Markets Division, the Acid Rain Program which created a cap-and-trade system for SO_2 in most years included only one or two manufacturing plants.

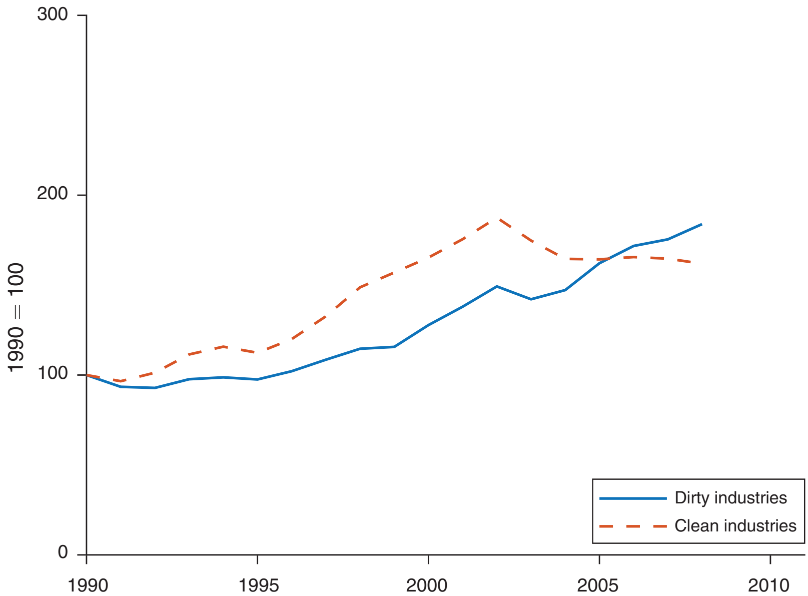

Figure 4. Shocks to Implicit NO_x Pollution Tax, 1990–2008

Notes: This figure plots the time path of the shock to environmental regulation for NO_x that we recover from the model outlined in Section II and derived using equation (23). The model delivers the value of the indicated shock for each of the 17 industries in our sample in each year. Here, we summarize the results by plotting the mean separately for both dirty industries (solid line) and clean industries (dotted line), weighted by baseline revenue in each industry. As described in the main text, dirty industries are defined as those with a value of the pollution elasticity α_s above the economy-wide mean of 0.011, and clean industries are defined as those with a value of this pollution elasticity below 0.011.

Figure 4 suggests that the implied pollution tax for NO_x for US manufacturing nearly doubled between 1990 and 2008. As Section VIB describes, the rate of increase in implicit taxes for other pollutants was if anything more rapid. While the level of pollution taxes for dirty industries may have been much greater in 1990, the rate of increase in the stringency of implicit taxes on dirty industries between 1990 and 2008 generally resembled the rate of increase of taxes for clean industries over this period.

Is this a realistic change in the stringency of environmental regulation? We emphasize that the US does not actually have a pollution tax on NO_x. A way to think about the meaning of this tax is as follows: if all US environmental regulation relevant to NO_x emissions from manufacturing were replaced with a pollution tax, what change in that tax rate would lead to the changes in firm behavior that we actually observe? Given dramatic expansion of NO_x regulation over these 18 years, a doubling in the implicit tax on pollution seems plausible. A very incomplete list of actual changes in NO_x regulations includes: a nearly doubling of the number of counties in ozone nonattainment between 2003 and 2004, which may be the largest expansion of nonattainment areas since the Clean Air Act began; the 1990 Clean Air Act Amendments, which required large NO_x emitters in ozone nonattainment areas to install stringent pollution controls by 1995; the RECLAIM cap-and-trade for Los Angeles, which began in 1993; the Ozone Transport Commission cap-and-trade for

New England, which began in 1999; and the NO_x Budget Trading Program for the Eastern US, which began in 2003.[29]

V. Counterfactuals

Methodology.—To analyze counterfactuals, we choose a counterfactual scenario (e.g., what if US environmental regulation had evolved as we observe in the years 1990–2008, but other shocks had remained fixed at their 1990 levels?). For each year 1990–2008, we then find the firm decisions, including pollution emissions, which would have prevailed in that counterfactual. Finally, we compare those counterfactual emissions against the actual emissions that occurred. Online Appendix III.F describes this procedure in more detail. We show some results separately for "dirty" and "clean" sectors; these results define dirty sectors as sectors with values of the pollution elasticity (α) above the national mean of 0.011, and clean sectors as all others.[30]

Each counterfactual creates direct and indirect effects. For example, a shock to environmental regulation will affect pollution directly. Environmental regulation may also affect average output per worker, and this change in output per worker may create indirect effects on pollution. In this example, we attribute both the direct and indirect effects to environmental regulation, and not to productivity. More broadly, when we add a shock to a specific counterfactual (e.g., changing environmental regulation), we attribute all resulting changes in pollution to that shock, regardless of whether these changes in pollution occur directly or indirectly. This is a general equilibrium decomposition in which all prices and quantities can change in response to a single exogenous shock.

Results.—Figure 5 plots the time paths of pollution emissions under four separate counterfactuals, indicated in the legend; online Appendix Table 1 summarizes some numbers corresponding to these graphs. The solid line shows actual historic pollution emissions. Each dashed line shows the model's counterfactual prediction of what would have happened if the indicated shock had followed its historic path and other shocks had remained fixed at their 1990 levels. For example, the line with stars shows the pollution which the US would have emitted in a counterfactual where foreign competitiveness followed its historic path but other shocks remained fixed at their 1990 levels. Each line is normalized to 100 in the year 1990. The markers on the dashed lines show the years when pollution emissions are observed in the NEI rather than linearly interpolated.

[29] Ozone nonattainment regulations target NO_x and VOC emissions since ozone pollution forms through photochemical reactions involving NO_x, VOCs, heat, and sunlight. The 1990 Clean Air Act Amendments began requiring plants in ozone nonattainment areas to install Reasonably Available Control Technology (RACT). Some of these policies focus more on electricity generating units than on manufacturing. However, the relevant statistic here is the share of manufacturing pollution to which these policies applied.

[30] The dirty sectors are: paper and publishing; coke, refined petroleum, and fuels; chemicals; other non-metallic minerals; and basic metals. The clean sectors are: food, beverages, and tobacco; textiles, apparel, fur, and leather; wood products; rubber and plastics; fabricated metals; machinery and equipment; office, computing, and electrical; radio, television, and communication; medical, precision, and optical; motor vehicles and trailers; other transport equipment; and furniture, other, and recycling.

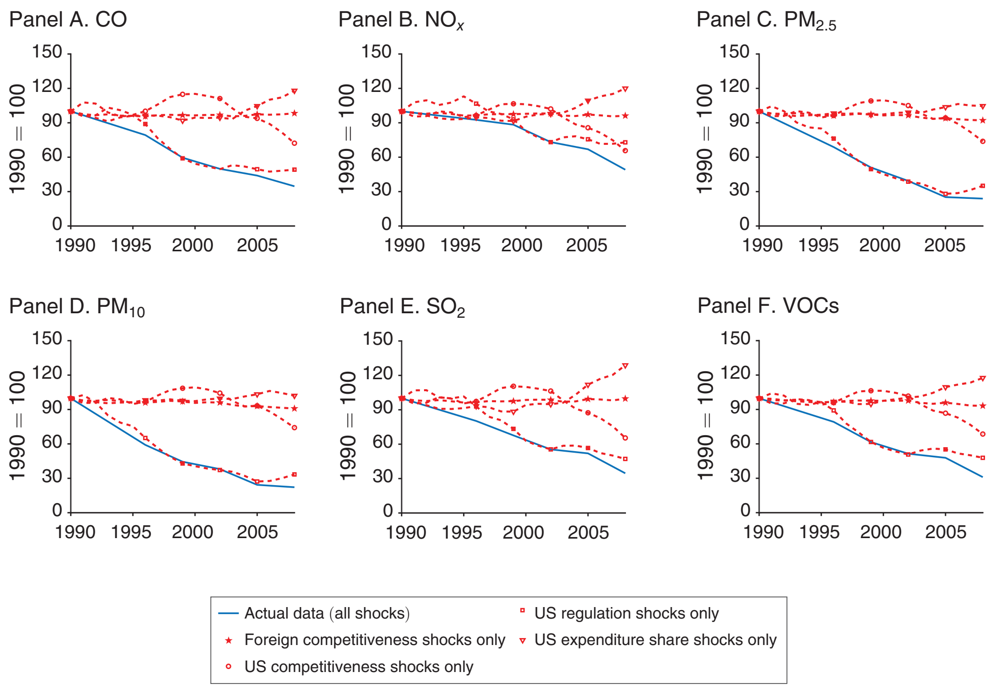

Figure 5. Counterfactual US Manufacturing Pollution Emissions under Subsets of Shocks, 1990–2008

Notes: This figure plots a separate counterfactual exercise for each pollutant and shock. Each subfigure plots the actual and counterfactual time path of the indicated pollutant emissions in US manufacturing. The solid line displays the actual time path of emissions, and the dotted lines show the counterfactual emissions in a scenario where only a single explanatory factor is allowed to take on its actual historical values. The scenario for each explanatory factor, or "shock," is indicated in the legend. For each counterfactual, all other explanatory factors are constrained to take their base year, 1990, values. The year 1990 values have been normalized to 100 in all figures. The star, circle, triangle, and square markers on the dashed lines show the years 1990, 1996, 1999, 2002, 2005, and 2008, when pollution data from NEI are observed rather than linearly interpolated.

Figure 5 suggests that foreign competitiveness had a limited effect on US manufacturing pollution emissions. Between 1990 and 2000, in a counterfactual where foreign competitiveness followed its actual historic path and other shocks remained unchanged at their 1990 values, pollution would have increased by a few percentage points. After 2000, when China's growth accelerated, foreign competitiveness led to modest decreases in US pollution of a few percentage points. By 2008, in this counterfactual, US pollution emissions were a few percent below their 1990 value. Ultimately, shocks to foreign competitiveness account for little of the total decline in US pollution.

Given the large effects of China's economic growth over this time on US manufacturing employment (Autor, Dorn, and Hanson 2013), or the scope of NAFTA for Mexico's access to US markets (Caliendo and Parro 2015), one might have expected foreign competitiveness to cause large decreases in pollution. Figure 5 suggests that this was not the case. Why didn't Chinese or other foreign competition more substantially affect US pollution over this time period? A few ideas help explain. Although China's exports are concentrated in low-skilled sectors, they were not especially concentrated in dirty sectors. Moreover, aggregate data on US manufacturing show that the effect of China's growth on manufacturing output or on value added was much smaller than its effect on employment (Pierce and Schott 2016). Finally, one effect of foreign competition would be to shift the composition of US production to cleaner or dirtier types of products, and the statistical decomposition from Section I provided little evidence that such a shift occurred.

Figure 5 suggests that changes to US competitiveness do not explain most of the change in US manufacturing NO_x emissions. Between 1997 and 2003, the effect of US competitiveness alone caused US pollution emissions to increase by about 10 percent. After 2003, the effect of this shock was to decrease pollution, but for most pollutants by much less than the observed decrease. How can we make sense of this finding that US competitiveness does not explain most of the change in pollution? Figure 2 and plant-level regressions from papers discussed in the introduction suggest that more productive firms emit less pollution per unit of output. The model reflects this fact, since at the plant level, more productive firms in the model emit less pollution per unit of output. However, at the economy-wide level, while productivity growth may diminish factor demand per unit of output, factors are used for other output in the same or other plants. Unless productivity growth is much larger in dirty industries, productivity growth may have limited scope to affect pollution.[31]

Figure 5 also quantifies how changing consumer expenditure shares across sectors affected pollution emissions, and it suggests they play little role in explaining the historic trends in pollution emissions. Between the years 1990 and 2000, expenditure shares on clean sectors decreased slightly, and this decreased US pollution emissions. After 2000, by contrast, increasing expenditure on pollution-intensive sectors leads to an increase in US pollution emissions of 10 to 20 percent.

The first three counterfactuals suggest that foreign competitiveness, domestic competitiveness, and US expenditure shares do not account for a majority of the decrease in pollution emissions. By contrast, Figure 5 suggests that changes in environmental regulation over this time period account for much of the decrease in pollution emissions. In the early years of this analysis, regulation by itself would have caused about 10 percent less pollution reduction than actually occurred. By the year 2008, regulation explains most of the change in pollution. The pattern is similar across pollutants and years.

The findings of this section that regulation explains most of the observed changes in emissions across pollutants and that most pollutants had similar magnitude declines in emissions together imply that environmental regulation had similar effects over this time period for the pollutants we study. It is difficult to assess this conclusion independently, but cursory reflection suggests it is plausible. Most pollutants experienced increased regulatory stringency over this time period. We have discussed in previous sections the many NO_x regulations that took place over this time period. The pollutants PM and VOC also experienced large expansions in Clean Air Act county nonattainment designations (and increasingly stringent nonattainment

[31] Another way to think about these patterns is in terms of scale and technique effects. Proposition 1 shows that increasing a sector's productivity decreases its emissions intensity, which corresponds to the technique effect decreasing total emissions. But given inelastic factor supply, the increased productivity leads to increased total output, which corresponds to the scale effect increasing total emissions. The offsetting signs of the technique and scale effects here may help explain why even large productivity growth may have limited effects on total pollution emissions.

standards within these designations). The 1990 Clean Air Act Amendments also established new guidelines for CO that depend on the degree of local air quality violations. Areas in "moderate" or "serious" violation were required to implement programs introducing oxygenated fuels and/or enhanced emission inspection programs, among other measures. The 1990 Clean Air Act Amendments established the Acid Rain Program, which was designed to control SO_2 emissions over this time period. As mentioned above, there are additional air pollution programs at local, state, and regional levels, but the relative importance of these regulations compared to federal regulations is empirically unknown. In addition, firms and industries which emit large amounts of one pollutant often emit large amounts of other pollutants. This suggests that some types of abatement for one pollutant may affect other pollutants at the plant.

VI. Alternative Explanations

This analysis finds that the stringency of environmental regulation for criteria air pollutants more than doubled between 1990 and 2008, and this change explains much of the observed national decrease in pollution emissions. We now consider alternative explanations for the decrease in pollution emissions.

A. *Do Shocks Besides Environmental Regulation Affect Pollution Intensity?*

Proposition 1 provided analytical evidence that marginal increases in pollution taxes, productivity, and trade liberalization each decrease sector-specific pollution intensity. We now provide some quantitative evidence as to how other channels, aside from pollution taxes, affect pollution intensity.

We consider a series of counterfactuals which each take data for 1990, increase or decrease the level of foreign competitiveness in a sector, then calculate the resulting change in US pollution intensity for that sector. Online Appendix Figure 5 plots the result.[32] The x-axis describes the change in foreign competitiveness and the y-axis records the resulting change in US sector-specific emissions intensity. The value 1 on the x-axis describes a counterfactual where a shock does not change, and the value 100 on the y-axis describes an outcome where pollution intensity for the sector does not change. We plot results separately for each of the 17 sectors (thin gray lines), and also show the mean change in pollution intensity across all sectors (thick blue line).

Online Appendix Figure 5 shows that increasing foreign competitiveness in a sector decreases US pollution intensity in that sector. This shows that the analytical results of Proposition 1 hold quantitatively for nonmarginal changes. This also implies that the conclusions of the model-based decomposition are not predestined given the findings of Section I (i.e., foreign competitiveness in this model can affect pollution intensity). This figure also shows that the magnitude of this effect is not

[32] For brevity, we present this sensitivity analysis for NO_x emissions only. To create these graphs, we consider shocks ranging from 0.50 to 2.0 in increments of 0.25. For example, a shock of 0.50 in online Appendix Figure 5 represents a counterfactual where foreign competitiveness falls to half of its 1990 value but US competitiveness and US environmental regulation remain at their 1990 values. For each counterfactual, we measure the resulting change in pollution. We then plot these results for the entire range of shocks from 0.50 to 2.0.

large. Doubling foreign competitiveness only decreases pollution intensity by a few percentage points for most sectors.

Two reasons help explain why these magnitudes are not large. First, the US is among the world's most closed countries, with an import penetration ratio below 10 percent. Proposition 1 shows that the effect of trade liberalization on pollution intensity is larger for relatively open countries and sectors, and so increasing foreign competitiveness may have limited effects on pollution intensity for a closed country like the US.

Second, models with similar trade assumptions to ours find that trade liberalization does not have large magnitude effects on real income. Even extreme trade policies like a 40 percent uniform global tariff (whereas mean current US and EU tariffs are around 2 percent) would only decrease US GDP by less than 1 percent (Costinot and Rodríguez-Clare 2014). The key potential channels for those effects—reallocation and selection, and associated price index changes—are similar in that setting and ours. In monopolistic competition models with heterogeneous firms like we study, part of the benefit of trade liberalization comes through reallocation of output to more productive firms. The correlation of productivity and firm-level pollution intensity is around minus one (see Figure 2), so the magnitude of the increase in productivity and real income due to trade liberalization may be broadly similar to the decrease in pollution intensity due to trade liberalization.

In order for trade liberalization to account for more than a small share of the decreases in emissions documented in Figure 1, trade must have very different effects on pollution emissions than trade does on real income. One way to interpret our results is that in our model, which reflects a set of leading frameworks from the international and environmental literatures, trade's effects on emissions are not vastly larger than trade's effects on real income.

As discussed earlier, one important caveat in this analysis deals with the ability of the model to account for composition changes within a sector. Because sector is the finest unit of analysis in the model, a decrease in foreign competitiveness for dirty products within a sector and an increase in foreign competitiveness for clean products within that sector could offset each other and appear in the model as no net change in foreign competitiveness for that sector. If such changes were widespread, they could represent a channel which is not captured in this model and through which trade decreases emissions intensities. The conclusion of Section I that product-level patterns in emissions intensities are very similar to industry-level patterns in emissions intensities provides some evidence that this is not a first-order issue in reality, though it remains an issue the model is not designed to accommodate.

B. *Does the Model Describe Environmental Regulation?*

We now provide two tests of whether the shock we call "environmental regulation" corresponds to true regulation. We first compare our model-based measure of regulation to one well-known change in environmental regulation, the NO_x Budget Trading Program (NBP). We then calculate model-based measures of regulation for carbon dioxide, a pollutant which largely has not been regulated.

NO_x Budget Trading Program.—The NBP was a cap-and-trade program for NO_x emissions from power plants and large industrial plants in the Eastern US. The EPA

distributed permits to each source and allowed trading of permits. Most sources were electricity generating units but many oil refineries, chemical plants, and other manufacturing plants faced NBP regulation.[33] We obtain data from the EPA's Air Markets Program Data (AMPD) on facilities regulated under the NBP. We link the AMPD data to the NEI data by requiring an exact match on county and industry and a non-exact match on facility name, longitude, and latitude.[34] About 13 percent of manufacturing emissions of NO_x came from manufacturing plants that were subject to the NBP.

We explore how our model-driven measure of pollution taxes corresponds with the NBP by using the following difference-in-difference-in-differences regression model:

$$\ln(t_{rst}) = \beta_1\big(\mathbf{1}[NBP_r] \times \mathbf{1}[NBPIndustry_s] \times \mathbf{1}[Year > 2002]\big) + \eta_{rt} + \gamma_{st} + \psi_{rs} + \epsilon_{rst}. \tag{24}$$

We regress our measure of implied pollution taxes, t, as defined in equation (23), in sector s of NBP region r and year t, on a three-way interaction term describing the effect of being in an NBP-regulated sector in an NBP state in the years after the regulation went into place. We aggregate the data to the sector $\times$ region $\times$ year level, where a region is defined as inside/outside the NBP region, and sectors are defined by the 17 manufacturing sectors defined in Table 2.[35] We control for region $\times$ year fixed effects η_{rt}, sector $\times$ year fixed effects γ_{st}, and region $\times$ sector fixed effects ψ_{rs}. With these sets of fixed effects, the model effectively controls for time-invariant observed or unobserved determinants of pollution taxes by sector $\times$ region, common transitory shocks to sectors across regions, and transitory shocks within a region that affect all sectors similarly. The identifying assumption of the model is that there exist no transitory shocks specific to regulated sectors in the NBP region in the years after the NBP went into place. While this assumption is inherently untestable, the data permit some indirect tests. For example, data from years prior to the change in regulations permit the analysis of pretrends across treatment and control groups prior to the change in policy. The coefficient of interest, β_1, describes how the NBP affected pollution taxes in polluting sectors of regulated states.

Online Appendix Table 4 presents results from several versions of equation (24). Each column represents a separate regression, and parentheses show standard errors robust to clustering at the sector $\times$ region level. The first column represents the baseline specification and suggests that polluting manufacturing firms in the NBP region in the years after the NBP went into place experienced a 1.195 log point increase

[33] Economic research has studied the NBP, including difference-in-difference-in-differences research designs to measure effects on pollution, health, and employment (Fowlie 2010; Curtis 2018; Deschênes, Greenstone, and Shapiro 2017).

[34] The NPB data's only measure of industry is a facility's "source category." We exclude NBP participants with cogeneration, electric utility, or small power producer as source category, since these are typically not manufacturing.

[35] States in the NBP region include Alabama, Connecticut, Delaware, Illinois, Indiana, Kentucky, Maryland, Massachusetts, Michigan, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Rhode Island, South Carolina, Tennessee, Virginia, Washington DC, and West Virginia. All other states are defined as outside the NBP region.

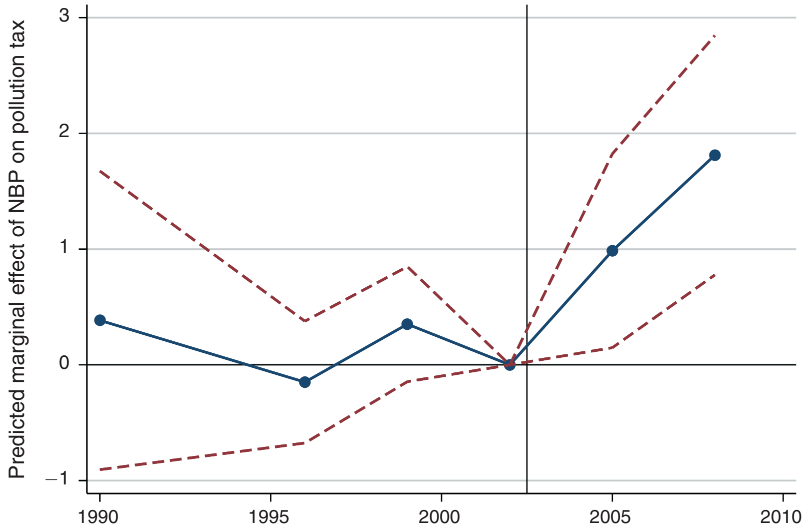

Figure 6. NO_x Pollution Tax Changes as a Function of NO_x Budget Trading Program Status

Notes: This figure reports regression coefficients from an event-study version of equation (24) in the text. The coefficients are plotted on a solid line and represent the time path of pollution taxes in polluting industries of NBP regions in the years just before and just after the NBP rollout, measured relative to a counterfactual. The dashed lines represent 95 percent confidence intervals. The dependent variable is the model-driven measure of pollution taxes for a region × sector × year. The regression model includes region × year fixed effects, sector × year fixed effects, and region × sector fixed effects. Standard errors are clustered by sector × region.

in pollution taxes, or approximately 2.3× increase relative to the counterfactual.[36] Column 2 adds sector × year fixed effects, and the results are nearly identical. Columns 3 and 4 add region × year fixed effects which slightly attenuate results, but the results remain statistically significant across all 4 specifications.

Figure 6 shows an event study version of equation (24), including leads and lags in event time.[37] The figure suggests two main findings: First, in the years leading up to the policy, the implied taxes in the treatment and control groups are relatively similar and are not statistically different. This lends some reassurance that the research design is capturing a sharp event that affects NBP-regulated plants in the NBP region in the years after the NBP rather than some underlying trend in the data. Second, the years after the policy reveal a sharp and statistically significant increase in the implied pollution taxes for the NO_x polluting sectors in the NBP region. The magnitudes of these estimates correspond closely to those from online Appendix Table 4.

[36] 2.3× is calculated as $\exp(1.195) - 1 = 2.303$.

[37] Specifically, we estimate models of the following form

$$\ln(\hat{t}_{rst}) = \sum_{\tau=1990}^{2008} \beta_k \big(\mathbf{1}[NBP_r] \times \mathbf{1}[NBPRegulated_s] \times \mathbf{1}[Year = \tau]\big) + \eta_{rt} + \gamma_{st} + \psi_{rs} + \epsilon_{rst}.$$

We normalize the event-time coefficient in the year prior to the policy to 0.

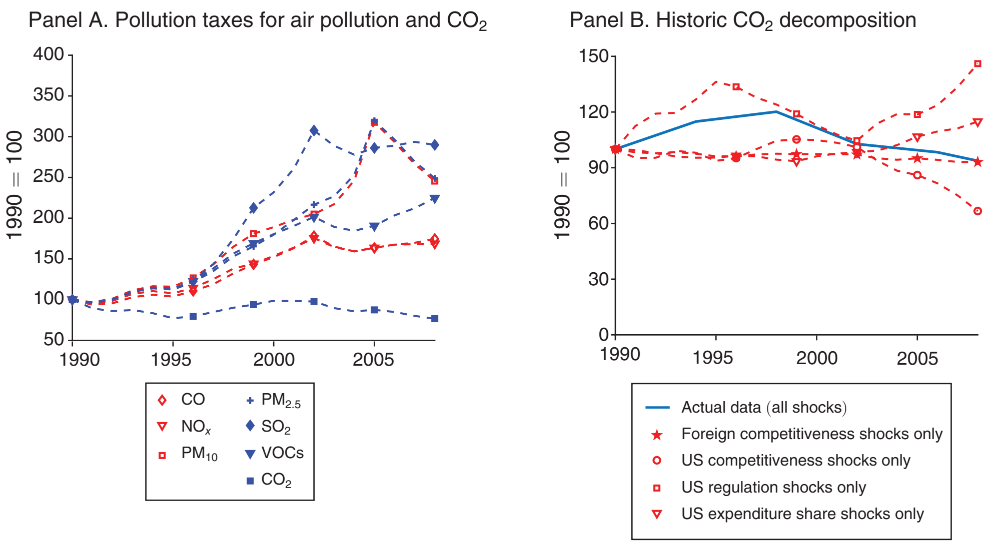

Figure 7. Analysis of Carbon Dioxide Emissions

Notes: Panel A plots implicit pollution taxes recovered for each pollutant and year, including CO_2. Panel B shows the same decomposition as Figure 5, except for CO_2 rather than for a criteria pollutant. The star, circle, triangle, and square markers on the dashed lines show the years when pollution data from NEI or MECS are observed rather than linearly interpolated.

Carbon Dioxide.—This paper focuses on six "criteria" air pollutants which have been a focus of US environmental regulations, in part because they have available data. This section analyzes a pollutant that has not experienced much regulation over this period, CO_2.[38] CO_2 emissions also contribute to climate change, so it is important to understand the underlying forces driving changes in manufacturing CO_2 emissions.[39] Online Appendix III.C provides additional details on the CO_2 data.

Panel A of Figure 7 shows our inferred measure of the stringency of environmental regulation for each of the pollutants in this study, including CO_2. The dashed lines in that figure show that between 1990 and 2008, the stringency of regulation for most air pollutants increased by 75 to 250 percent. However, the solid line suggests the stringency of CO_2 regulation was more flat over this entire time period, and if anything actually decreased modestly.[40] Although criteria air pollution regulation became much more stringent over this time period, CO_2 regulation hardly changed.

[38] The Northeast states began a cap-and-trade system for CO_2 emissions, the Regional Greenhouse Gas Initiative (RGGI), in 2008. Boulder, Colorado, and San Francisco implemented small carbon taxes in 2006 and 2008, respectively. States and the federal governments operate other taxes on various fuels which emit CO_2.

[39] Local pollution regulation may have limited effects on CO_2 emissions because end-of-pipe abatement technologies for local pollution (e.g., scrubbers) do not decrease CO_2. For example, the NO_x Budget Trading Program discussed above caused 35–40 percent decreases in NO_x emissions from regulated power plants but essentially no change in CO_2 emissions (Deschênes, Greenstone, and Shapiro 2017). Although local pollution regulation might have small effects on CO_2 emissions, CO_2 regulation could substantially decrease local pollution emissions because there is no economically viable end-of-pipe abatement technology for CO_2, so fuel switching from coal to gas due to a CO_2 tax would decrease local pollutants (Parry, Veung, and Heine 2015).

[40] For all pollutants, panel A of Figure 7 shows the mean across sectors. For each pollutant, some sectors have inferred pollution taxes above and others below this mean value across sectors.

The fact that we find such large increases in the implicit tax rate for air pollution emissions and smaller changes in the implicit tax rate for CO_2 emissions provides an additional piece of evidence that the model-driven measures of pollution taxes capture realistic features of the regulatory environment rather than changes in other associated economic variables.

Panel B of Figure 7 shows the counterfactual decomposition for CO_2 emissions. The graph is the same as online Appendix Figure 5, except that it shows results for CO_2 rather than for criteria air pollutants. The solid line shows that CO_2 emissions from manufacturing initially increased then decreased, but overall changed little relative to 1990. The dashed lines show counterfactual CO_2 emissions under different sets of shocks. Overall, no one set of shocks completely explains the modest changes in CO_2 emissions, and regulation plays a limited role.

C. *Other Technical Aspects of the Model*

We now briefly discuss the extent to which the model accounts for several other important issues, and we consider the possible importance of each.[41] We first consider the importance of reallocation and selection effects. Formally, we shut off selection and reallocation by analyzing how a model with monopolistic competition but homogeneous firms affects the decomposition. Mathematically, we shut off firm heterogeneity by setting $\sigma_s - 1 = \theta_s/(1-\alpha_s)$.

Online Appendix Table 1 shows that shutting off firm heterogeneity has small effects on the decomposition results; when we shut off firm heterogeneity, environmental regulation alone accounts for a nearly equivalent decrease in pollution emissions. For the other shocks, shutting off firm heterogeneity has quantitatively larger effects on the decomposition, but the qualitative conclusions are unchanged.

Why does firm heterogeneity have small effects on our estimates, particularly given the strong relationship between plant-level pollution intensity and plant-level productivity documented in Figure 2? We emphasize two explanations. First, as discussed earlier, more productive firms may have lower pollution intensity at the plant level, but increasing plant-level productivity for a given level of output may free up productive factors which can be used in other factories to make widgets and pollution elsewhere. Second, in some settings, the effects of firm heterogeneity on the magnitude from gains from trade are not large.[42] Our environmental setting differs from this literature's focus, but the intuition persists that adding more margins by which policy can affect welfare need not mean policy has larger effects on welfare.

[41] Online Appendix III.G describes additional sensitivity analyses that we explore and which leave the main conclusions unchanged, including alternative values of the Pareto shape parameter and the pollution elasticity and adding a non-manufacturing sector to the quantitative exercise.

[42] Costinot and Rodríguez-Clare (2014) find that in a model with multiple sectors but no intermediate goods, a 40 percent global tariff would create a 1.2 percent global decrease in welfare (measured as the average across regions) in a world with monopolistic competition and heterogeneous firms and a 1.4 percent decrease in welfare in a world with monopolistic competition and homogeneous firms. More broadly, Arkolakis, Costinot, and Rodríguez-Clare (2012) show that the gains from trade are equivalent in these two frameworks for a model with one sector, no intermediate goods, and the same trade elasticity. Melitz and Redding (2014) argue that the gains from trade are strictly larger in a model with firm heterogeneity because given primitive parameters, the trade elasticity differs across models.

As highlighted earlier, multiple channels in this model transmit a change in a given shock to pollution. Here we discuss a partial equilibrium version of the model which assumes no change in factor prices or firm entry: $\hat{w}_o = \hat{M}^e_{o,s} = 0$. We then calculate the change in pollution from a given shock merely from the change in pollution taxes: $\hat{Z}_{o,s} = 1/\hat{t}_{o,s}$. One could think of this as including the "direct" channel discussed at the beginning of this section, but turning off "indirect" channels. Row 8 of online Appendix Table 1 shows the results. By definition, because shocks to foreign competitiveness, US competitiveness, US expenditure shares, and trade deficits do not change pollution taxes in this model, these shocks lead to no change in pollution in this partial equilibrium scenario. In contrast, shocks to environmental regulation still substantially decrease pollution in this setting. Put another way, the general and partial equilibrium results are more similar for the counterfactual where only environmental regulation changes, and are less similar for the other counterfactuals. One interpretation of this is finding that the general equilibrium price, wage, and firm entry adjustments in the model are relatively less important for our conclusions about the effects of environmental regulation on pollution, and relatively more important for our conclusions about the effects of the other shocks.

Another abstraction is aggregation. If firms have changed their focuses of production within one of our 17 sectors from more- to less-dirty sectors and products, then our analysis may confound regulation with product substitution. Additionally, if firms offshore particularly dirty parts of their production processes, then trade might affect pollution through the exchange of intermediate goods. The statistical decomposition presented in Section I at the product level suggests that compositional changes in the type of goods produced within narrow product categories are not able to explain a significant fraction of the observed emissions reductions. If US manufacturing had disproportionately increased offshoring of dirty products, then one would expect the offshoring of these dirty products to change the composition of US production to cleaner goods. Our statistical decomposition, however, provides very little role for composition effects, and looking at product rather than industry level delivers similar results. This evidence suggests that fragmenting production or offshoring is not likely to account for a large share of the reductions in emissions intensities.

Another important issue is technical change which decreases pollution emissions or pollution intensity. A few findings in our analysis suggest that such technical change is not a predominant source of bias. Secular technical change decreases the demand for all productive inputs. The productivity shock in our model is designed to account for such technical change, and we find that it does not account for the majority of changes in pollution emissions. This suggests that for any such technical change to explain the observed decrease in pollution, it must be biased toward increasing the use of relatively cleaner inputs. The inputs which produce the local air pollutants we study, however, generally also produce CO_2. Thus, it is likely that if biased technical change explained the observed decrease in local air pollutants, then that technical change would also reduce CO_2. We showed that CO_2 from manufacturing changed very little, and local air pollutants from manufacturing fell considerably. It seems relatively unlikely that technical change would decrease demand for inputs which are intensive in the six pollutants that have been heavily regulated, but would leave unchanged the demand for inputs intensive in CO_2.

Finally, we consider the assumption that pollution is proportional to a firm's outputs rather than to its inputs, which is implicit in equation (7). This paper's model implies that more productive firms emit less pollution only because they invest more in pollution abatement. One could imagine a different model in which more productive firms emit less pollution because they use fewer factor inputs to produce a unit of output. We investigated this alternative by removing the productivity term φ from equation (7), giving an expression for pollution which is proportional to inputs rather than outputs. We then re-derived expressions for a firm's chosen pollution emissions under that modified assumption. This modification produces identical expressions for firm-level and economy-level pollution emissions both in observed data and in counterfactuals. This modification does produce a different mechanism by which productivity affects pollution, by decreasing factor inputs rather than increasing abatement investments. However, the magnitude of the effect of productivity on pollution in the two models is numerically equivalent.

Every model is an abstraction, and the goal of our model-based analysis is to analyze several prominent explanations for pollution's decline. While we have emphasized advantages of our approach, one disadvantage is that one can always come up with additional hypotheses to explain an observed change in pollution.

VII. Conclusions

Public observers once worried that US economic growth would lead to increasingly dangerous levels of pollution. Instead, US air quality has improved dramatically. This paper focuses on US manufacturing and assesses three candidate explanations for why pollution emissions have fallen since 1990.

The first explanation is that increasing production of pollution-intensive goods in China, Mexico, and other foreign countries has decreased US pollution. Second, environmental regulation may have led to adoption of increasingly effective abatement technologies. Third, if productivity decreases pollution intensity, then rising productivity may have decreased pollution emissions.

We begin with a statistical decomposition which shows that almost all of the change in pollution emissions from US manufacturing is due to changes in pollution intensity within narrowly defined product-categories. To quantify the importance of environmental regulation, productivity, and trade, we build on recent trade and environmental research to develop a model of heterogeneous firms that choose optimal investments in pollution abatement in response to environmental regulation. Although the methods we use are typically applied to research questions in international trade, we use them to address an open question in environmental economics: why are pollution emissions from US manufacturing declining? While many quantitative models are used to forecast how untested future policies like carbon taxes or tariff reductions would affect pollution and welfare, we use our model to analyze the past: to recover the implied changes in environmental regulation and other shocks that firms actually faced in each year 1990–2008. We then use the implied changes to quantify how pollution would have changed under scenarios other than those that actually occurred.

The paper obtains three main conclusions. First, the fall in pollution emissions is due to decreasing pollution per unit output in narrowly defined manufacturing product categories, rather than reallocation across products or changes in the scale of real manufacturing output. Second, environmental regulation has grown increasingly stringent, and the pollution tax that explains US data roughly doubled between 1990 and 2008. Third, environmental regulation accounts for most of the observed reduction in pollution emissions from manufacturing. Productivity improvements and trade costs play relatively smaller roles.

We believe there are a number of worthwhile extensions to the work presented here. First, like most models of monopolistic competition, our model assumes that prices are a constant markup over marginal cost. While theory makes predictions about how markups should respond to various competitive forces, the empirical evidence on the relationship between environmental policy and markups is limited. Second, the decomposition methodology developed in the paper could be applied to other settings. For example, why has energy efficiency improved across the United States? Has this been driven by efficiency standards? Rising energy prices? Population migration? One could adapt the tools from this paper to address this important policy question. We leave these extensions and questions for future work.

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