Why is U.S. Air Quality Improving?
The Roles of Trade, Regulation, Productivity, and Preferences*

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Abstract

Between 1990 and 2008, emissions of the most common air pollutants from U.S. manufacturing fell by 60 percent, even as real U.S. manufacturing output grew substantially. This paper develops a quantitative model to explain how changes in trade, environmental regulation, productivity, and consumer preferences have contributed to these reductions in pollution emissions. The model’s key parameters are estimated with regressions using restricted-access data on plant-level production decisions which we link to pollution emissions data. We combine these parameter estimates with detailed historical data to decompose the causes of the observed change in pollution. Finally, we compare the model-driven decomposition to a statistical decomposition. The model and data suggest three findings. First, the fall in pollution emissions is due to decreasing pollution per unit output within narrowly defined industries, rather than to reallocation across industries or to change in the scale of total manufacturing output. Second, the implicit pollution tax which rationalizes firm production and abatement behavior increased several-fold between 1990 and 2008. Third, environmental regulation explains 75 percent or more of the observed reduction in pollution emissions from manufacturing.

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1 Introduction

Between 1990 and 2008, emissions of the most common air pollutants from U.S. manufacturing fell by 60 percent, even as real U.S. manufacturing output grew substantially. Figure 1 shows just how stark these environmental improvements have been. Between 1990 and 2000, the real value of U.S. manufacturing output grew by a 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.

Research suggests at least four possible explanations of these substantial improvements in U.S. air quality. First, U.S. manufacturing imports have risen substantially (Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2012; Fowlie, Reguant, and Ryan, Forthcoming). When dirty industries like steel or cement move abroad, total U.S. pollution emissions may fall. Second, federal and state agencies require firms to install increasingly stringent pollution abatement technologies. Some research, for example, directly attributes national changes in air quality to the Clean Air Act and to other environmental regulations (Henderson, 1996; Chay and Greenstone, 2005; Correia, III, Dockery, Wang, Ezzati, and Dominici, 2013). Third, research finds that more productive plants emit less pollution per unit of output (Bloom, Genakos, Martin, and Sadun, 2010; Holladay, 2011; Martin, 2011). If manufacturers use fewer inputs each year to produce the same outputs, then annual productivity growth could improve air quality. Finally, due to non-homothetic tastes or secular change, Americans may gradually choose to spend less on heavy manufactured goods and more on services and cleaner goods (Levinson and O’Brien, 2013).

In order to explain the observed reduction in manufacturing pollution emissions, this paper develops a quantitative model of firms endogenously choosing investments in pollution abatement. Production and pollution abatement choices in the model depend on trade costs, pollution taxes, productivity, and consumer preferences. We take this model to data with two main objectives. First, we use 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. U.S. federal and state environmental regulations take many overlapping forms: command-and-control technology standards, cap-and-trade programs, and many others. Summarizing all of these policies as an implicit tax on pollution lets us quantify aggregate changes in the stringency of all air pollution regulation for U.S. manufacturing. The paper’s second objective is to decompose the underlying forces which have caused changes in pollution emissions from U.S. manufacturing. We begin with a statistical decomposition that describes emissions counterfactuals while holding constant either the scale of production or the composition of total manufacturing output. We then use the model to explore how shocks to trade costs, environmental regulation, productivity, and preferences have each contributed to changes in air pollution emissions from U.S. manufacturing between 1990 and 2008. We 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 analyze 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 such a model to interpret the past—we quantify how different kinds of economic shocks led to observed historic changes in pollution.
The paper obtains three main results. First, trends in pollution emissions from U.S. manufacturing between 1990 and 2008 cannot be explained either by the scale of manufacturing output or by changes to the composition of polluting industries within the manufacturing sector over this time period. Second, using the quantitative model, we find that the pollution tax rate which rationalizes actual pollution emissions—a scalar measure of the stringency of environmental regulation—increased dramatically between 1990 and 2008. We find similar patterns in regulation across all the main pollutants the Clean Air Act regulates (“criteria pollutants”). Third, we find that the increasing stringency of environmental regulation explains 75 percent or more of the 1990 to 2008 decrease in pollution emissions from U.S. manufacturing. Changes in trade costs, productivity, and preferences play comparatively smaller roles.

The model weaves together elements of workhorse models from the trade and environment literatures. In the model we describe, consumers have constant elasticity of substitution preferences across varieties of goods. As in Melitz (2003), entrepreneurs draw productivities from a Pareto distribution and may pay a fixed cost to produce goods and a separate fixed cost to export goods. As in Copeland and Taylor (2003), operating firms face pollution taxes and allocate a share of productive factors to abating pollution. Together, these assumptions let us quantify pollution emissions that would have occurred in counterfactuals—for example, we measure the path of pollution emissions if air pollution regulation for manufacturing had remained unchanged after 1990.

To take this model to the data, we rely upon a rich set of administrative plant-level information from the United States Census Bureau, which we link to plant level data from the EPA. These data report pollution emissions, value of shipments, and production costs for each plant in the U.S. manufacturing sector. These data allow us to estimate the key parameters of our model. We first estimate the elasticity of pollution emissions with respect to a measure of pollution abatement. We also estimate industry-level elasticities of substitution and the parameters governing the distribution of productivity, both of which play central roles in trade research.

The model imposes strong functional form assumptions which only approximate reality. To appreciate the potential insight such strong assumptions can provide, consider an example of how simpler approaches could give misleading results. Plant-level evidence finds that firms’ heterogeneous productivities or quality of management are strongly correlated with firms’ heterogeneous pollution emissions rates (Bloom, Genakos, Martin, and Sadun, 2010; Holladay, 2011; Martin, 2011). This stylized fact motivates our assumptions about firm heterogeneity. However, the idea that improving productivity is likely to decrease pollution, which holds true in plant-level regressions, may be misleading at the economy-wide level. Suppose that a one percent increase in a firm’s productivity causes a one percent decrease in pollution-per-unit-of-output. However, increasing national productivity also increases national income. Because consumers may spend the additional income on pollution-emitting goods, this productivity shock may decrease pollution intensity but increase total output. In this simple example, partial equilibrium analysis may suggest that productivity growth benefits the environment, but in general equilibrium, productivity growth has ambiguous environmental effects. Similarly, while some research finds that opening markets to international trade reallocates market share to more productive firms, it would be premature from just these plant-level regressions to conclude
that opening markets to trade decreases aggregate pollution emissions.

This paper builds on three strands of literature. First, research at the intersection of trade and the environment has used statistical decompositions and reduced-form regressions to explain changes in a country’s pollution emissions (Koo, 1974; Grossman and Krueger, 1995; Antweiler, Copeland, and Taylor, 2001; Gamper-Rabindran, 2006; Ederington, Levinson, and Minier, 2008; Levinson, 2009). Most of this work relates pollution to economic objects that are endogenous outcomes of the global economy, such as trade flows or GDP. We extend some of this work, showing with new data and more recent time periods, whether scale and composition of U.S. manufacturing between 1990 and 2008 explain the observed reductions in manufacturing emissions. In contrast with this literature, we also develop a model-driven decomposition that allows us to uncover how fundamental shocks such as trade costs, regulation, productivity, and preferences affect pollution emissions. In doing so, we provide the first structural estimates of a model with heterogeneous firms and endogenous pollution abatement.

A second body of research measures the stringency and consequences of air pollution regulation. Many papers focus on a single regulation (Greenstone, 2002; Becker, 2005; Walker, 2013; Deschenes, Greenstone, and Shapiro, 2013). This focus on single regulations is due to parsimony, and because researchers can form credible empirical comparison groups for a subset of environmental policies. However, the EPA, state, and local regulators have implemented dozens of overlapping air pollution regulations over the last 20 years, many of which have not been analyzed with policy evaluation tools. For example, while much research has compared attainment and non-attainment counties, large polluters in attainment counties are still regulated, albeit with weaker stringency than in nonattainment counties. Berman and Bui (2001a,b) describe the entire menu of local air quality regulations facing manufacturing firms around Los Angeles, and find 11 local air quality regulations for petroleum refining and 46 for manufacturing, a count which excludes state and federal regulations.\footnote{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.} We believe this is the first paper to estimate how the overall regulatory burden, or “shadow tax,” that manufacturing firms face due to local and national air pollution regulations has affected pollution emissions.

Third, this paper contributes to a recent literature applying firm-level microfounded models of international trade to policy questions (Eaton and Kortum, 2002; Dekle, Eaton, and Kortum, 2008; Donaldson, Forthcoming). Like Shapiro (2013), we use these models to analyze environmental regulation. Unlike existing literature, we analyze a setting of monopolistic competition where profit-maximizing heterogeneous firms endogenously choose investments in pollution abatement. Our model builds on several papers in the trade literature (Copeland and Taylor, 2003; Melitz, 2003; Chaney, 2008; Hsieh and Ossa, 2011; Eaton, Kortum, Neiman, and Romalis, 2011; Arkolakis, Costinot, and Rodriguez-Clare, 2012). We know of few general equilibrium decompositions like we provide, though Eaton, Kortum, Neiman, and Romalis (2011) and Burstein, Morales, and Vogel (2013) provide related decompositions for trade and for wage inequality, respectively. Also, a nascent literature explores the environmental implications of models of heterogeneous firms (Forslid, Okubo, and Ultveit-Moe, 2011; Bajona, Missios, and Pierce, 2012), but does not develop or
estimate quantitative models.²

The rest of the paper proceeds as follows. Section 2 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 3 outlines our trade-environment model. Section 4 discusses the data, and Section 5 discusses how the parameters are estimated. Section 6 presents the main results, and Section 7 discusses alternative explanations. Section 8 concludes.

2 A Statistical Decomposition of U.S. 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 composition from relatively clean industries like furniture assembly to relatively dirty industries like steel. The third is a change in the production technique of a given industry, which decreases an industry’s pollution emissions per unit of output.

We begin by presenting a statistical decomposition of manufacturing pollution emissions into three effects: scale, composition, and technique. While existing research has performed similar exercises (Koo, 1974; Gamper-Rabindran, 2006; Ederington, Levinson, and Minier, 2008; Levinson, 2009), we update this work with more recent data. In addition, this decomposition provides a useful summary of pollution trends while also clarifying what the stronger assumptions of the model can illuminate.

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

$$Z = \sum_s z_s = \sum_s x_s e_s = X \sum_s \kappa_s e_s$$

Here total manufacturing pollution $Z$ equals the sum of pollution from each manufacturing industry, $z_s$. Alternatively, we can write manufacturing pollution as equal to the total output in an industry $x_s$ multiplied by an industry specific emissions factor $e_s$. We can also represent manufacturing pollution emissions as the total value shipped by all manufacturing industries, $X$, multiplied by the sum of each industry’s share of total output, $\kappa_s \equiv x_s / X$, times an emissions coefficient reflecting pollution per dollar of value shipped in that industry ($e_s \equiv z_s / x_s$). In vector notation, we have

$$Z = X \kappa' e$$

where $\kappa$ and $e$ are $S \times 1$ vectors containing the market shares of each of the $S$ industries and their pollution intensities, respectively. Totally differentiating yields three terms representing the scale, composition, and

²An older literature uses computable general models to examine the role of intermediates in local air pollution (Jorgenson and Wilcoxen, 1990; Hazilla and Kopp, 1990; Ballard and Medema, 1993). However, these papers treat an industry’s pollution emissions as fixed per unit of output or as determined entirely by end-of-pipe abatement. A related literature has examined the tradeoff between scrubbers and low-sulfur coal in the context of the Acid Rain program (Gollop and Roberts, 1985; Carlson, Burtraw, Cropper, and Palmer, 2000). A literature on climate change analyzes how energy inputs affect CO₂ emissions (Babiker, 2005; Biringer, Carbone, and Rutherford, 2013; Shapiro, 2013), but CO₂ emissions depend only on inputs and not on abatement decisions because no economically viable abatement technology exists for CO₂.
technique effects:

\[ dZ = \kappa e'dX + Xe'd\kappa + Xe'de \]  

(2)

Taking the decomposition in equation (2) to the data requires annual data on total pollution, total output, each industry’s contribution to output, and each industry’s emissions intensity. Pollution and output come from the EPA’s National Emissions Inventory (NEI) and the NBER-CES Manufacturing Industry Database, respectively. We use the World Bank’s Industrial Pollution Projection System (IPPS) for emissions intensities, which was created to match 1987 emissions intensities and is time-invariant. The IPPS data provides a list of emissions intensities by four-digit Standard Industrial Classification (SIC) codes (Hettige, Martin, Singh, Wheeler, and Mundial, 1995). We use the 1987 emissions intensities to project the scale and composition effects forward in time, while holding technology or “technique” constant at 1987 emissions rates (i.e. what would emission have looked like in 2005 if firms still produced with 1987 emissions intensities?).

Figure 2 illustrates the resulting statistical decomposition for nitrogen oxide emissions (NO\(_x\)). Other pollutants generate similar patterns. The top solid line 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 that to equal 100 in 1990. This line summarizes what emissions would have been if we had kept the same emissions rates and the same industry composition as in 1990. The middle dashed line plots NO\(_x\) emissions that would have occurred if emissions intensities had remained fixed at baseline levels but the composition of output across manufacturing sub-industries 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 40 percent. Second, the proximity of the solid and dashed lines shows that the composition between clean and dirty manufacturing sub-industries has not changed much over time, although between 1990-2007, manufacturing had shifted to slightly cleaner sub-industries. 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 about 20 percent. Finally, the gap between the solid line on top and dotted line at bottom shows that changes in the pollution intensity of individual manufacturing sub-industries explains why NO\(_x\) emissions fell by 40 percent rather than rising by 20 percent.

The rest of the paper investigates the causes of these observed emissions changes. The decomposition shows that almost the entire decline in NO\(_x\) emissions is due to less pollution emitted per unit of output within a narrowly-defined industry. But it does not explain why pollution intensity fell. Several hypotheses could explain this result. If more productive plants emit less pollution per unit output, then industry-wide productivity growth could explain these patterns. Alternatively, the introduction of NAFTA or China’s WTO ascension may have caused a reallocation of production away from unproductive and dirty firms toward more productive and perhaps cleaner firms within an industry. Lastly, increases in environmental regulatory stringency may also explain these reductions.
The quantitative model, which fills the remainder of this paper, makes much stronger assumptions than this statistical decomposition. The benefit of these stronger assumptions is an ability to explain how trade, regulation, productivity, and preferences contribute to the environmental improvements documented in Figures 1 and 2.

3 Model of Heterogeneous Firms with Endogenous Pollution Abatement

The model has a straightforward economic environment. We analyze a world of two countries (US and Foreign), each with a representative agent. Each country has a single productive factor, which we call labor, and which is inelastically supplied. We present the model’s main results here and intermediate derivations in Appendix B. This section explains the model’s four assumptions, shows how we use the model to analyze counterfactuals, and then discusses how we obtain empirical counterparts to the key economic objects in the model.

3.1 Model Assumptions

A1. Preferences. The representative agent in destination country \(d\) has the following utility function:

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

Equation (3) describes constant elasticity of substitution utility across product varieties within a sector, Cobb-Douglas preferences across sectors, and multiplicative damages from pollution. The representative agent allocates expenditure across varieties of goods \(\omega\) from the measure \(\Omega_{o,s}\) of goods produced by industry \(s\) in origin county \(o\). The parameter \(\beta_{d,s}\) represents the share of country \(d\)’s expenditure devoted to industry \(s\), where \(\sum_s \beta_{d,s} = 1\). We refer to \(\beta_{d,s}\) as consumer preferences. The variable \(q_{od,s}(\omega)\) represents the quantity of variety \(\omega\) goods in industry \(s\) which are exported from origin country \(o\) to destination country \(d\). The industry-specific parameter \(\sigma_s > 1\) represents the elasticity of substitution across varieties. The parameter \(\delta\) governs the disutility of pollution \(Z_d\). We assume that pollution is a pure externality, so the representative agent ignores the term \(Z_d^{-\delta}\) in making expenditure choices.

A2. Firms and Market Structure. An entrepreneur may choose to pay the cost \(f_{o,s}^e\) to draw a productivity \(\varphi\) from a Pareto distribution with shape parameter \(\theta_s\) and location parameter \(b_{o,s}\). After observing the productivity draw, an entrepreneur who decides to produce will maximize profits. Firms engage in monopolistic competition so that conditional on choosing to operate, an entrepreneur chooses prices \(p_{od,s}\) and abatement investments \(\xi\) to maximize profits:

\[
\pi_{od,s}(\varphi) = \sum_d \pi_{od,s}(\varphi) - w_{o}f_{o,s}^e,
\]  
(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}l_{od,s}

Output is given by \(q_{od,s} = (1 - \xi)l_{od,s}\varphi\). The profit function involves several terms. For simplicity, we drop
the variety notation $\omega$ and index a firm by its productivity $\varphi$. A consumer in destination $d$ pays price $p_{od,s}(\varphi)$ for goods from firm $\varphi$. Each firm receives revenue $p_{od,s}(\varphi)q_{od,s}(\varphi)$ and hires $l_{od,s}(\varphi)$ units of productive labor at wage $w_o$ to produce goods for sending to destination $d$. A fraction of this labor $1 - \xi$ is used to produce output, and a fraction $\xi$ to abating pollution. Each firm pays the pollution tax rate $t_{o,s}$ on $z_{od,s}(\varphi)$ units of pollution emitted for producing goods shipped to destination $d$. Firms face iceberg, per-unit trade costs, so $\tau_{od,s} \geq 1$ units must be shipped for one unit to arrive. A firm that chooses to enter the destination market $d$ must pay the fixed cost $f_{od,s}$.\(^3\) Domestic trade costs are normalized so $\tau_{oo,s} = f_{oo,s} = 1$. Pollution tax revenues are lost to rent-seeking. Here $b_{o,s}$ describes a country’s productivity while $\theta_s$ describes the dispersion of productivity draws within an industry $s$.

We assume this market structure for several reasons. Many dirty industries like cement and steel are concentrated and have barriers to entry. By accounting for fixed entry costs and industry-specific markups, our assumptions reflect a stylized version of polluting industries. At the same time, this formulation lets us account for firm entry and exit, and for reallocation of production 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).

**A3. Pollution.** Pollution emissions are produced with the following technology:

$$z_{od,s} = (1 - \xi)^{1/\alpha_s} \varphi l_{od,s}$$  \((5)\)

Equation (5) says that pollution is an increasing function of output, and a decreasing function of pollution abatement expenditures. In addition, this formulation also implies that more productive firms emit less pollution per unit output produced.\(^4\) We assume pollution regulations are stringent enough that all firms engage in some abatement. The parameter $\alpha$ has two interpretations. First, $\alpha$ 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. Second, we show that pollution emissions in this model can be described as another factor of production in a Cobb-Douglas production technology, and in this interpretation $\alpha$ is the Cobb-Douglas share for pollution emissions. The parameter $\alpha$, and variants thereof, play central roles in many models of pollution abatement (Copeland and Taylor, 2003; Levinson and Taylor, 2008; Forslid, Okubo, and Ultveit-Moe, 2011; Kreickemeier and Richter, 2014), but, to the best of our knowledge, has never been estimated empirically.

**A4. Competitive Equilibrium.** Consumers maximize utility; firms maximize profits; and in each

\(^3\)The assumption that this fixed cost is paid in destination- and not origin-country labor simplifies counterfactual analysis. Related work makes the same assumption that fixed market entry costs are paid in destination labor (Hsieh and Ossa, 2011; Eaton, Kortum, and Kramarz, 2011). The equivalence between welfare calculations in some perfect and monopolistic competition models in Arkolakis, Costinot, and Rodriguez-Clare (2012) requires fixed exporting costs to be paid in destination country labor.

\(^4\)Equation (5) is essentially the pollution production technology adopted in Copeland and Taylor (2003). Modeling emissions in this way is appealing because many sensible and seemingly different ways of modeling pollution turn out to be equivalent to equation (5). We describe and formally show two additional interpretations below.
country, labor supply equals labor demand:

$$L_o = L_o^c + L_o^m + L_o^p$$  \hspace{1cm} (6)$$

A country’s labor supply $L_o$ is allocated among three activities: paying the fixed entry cost $f_{o,s}$ for firms to produce ($L_o^c$); paying international entry costs $f_{od,s}$, which can be interpreted as marketing costs ($L_o^m$); and engaging in production, including pollution abatement ($L_o^p$).

Utility maximization implies that the share $\lambda_{od,s}$ of country $d$’s expenditure on goods from industry $s$ in country $o$ has the following “gravity” structure:\footnote{The “gravity” description reflects the fact that bilateral trade in this and many other models is proportional to two countries’ incomes (in an analogy to gravity in physics, their mass) and inversely proportional to their trade cost (analogously to physics, their distance). Most trade models with constant elasticity of substitution preferences and iceberg trade costs produce a gravity equation. This relationship also has empirical support—Leamer and Levinsohn (1995, p. 1384), for example, describe empirical estimates of gravity equations as “some of the clearest and most robust empirical findings in economics.”}

$$\lambda_{od,s} = \frac{M_{o,s}^e \left( \frac{u_{od,s}}{b_{o,s}} \right)^{-\frac{\theta_s}{1-\alpha_s}} (\tau_{od,s})^{-\frac{\theta_s}{1-\alpha_s}} (f_{od,s})^{1-\frac{\theta_s}{(1-\alpha_s)(1-\alpha_s)}} (t_{o,s})^{-\frac{\alpha_s \theta_s}{1-\alpha_s}}}{\sum_i M_{i,s}^e \left( \frac{u_{id,s}}{b_{i,s}} \right)^{-\frac{\theta_s}{1-\alpha_s}} (\tau_{id,s})^{-\frac{\theta_s}{1-\alpha_s}} (f_{id,s})^{1-\frac{\theta_s}{(1-\alpha_s)(1-\alpha_s)}} (t_{i,s})^{-\frac{\alpha_s \theta_s}{1-\alpha_s}} + \alpha s \theta s (1-\alpha s)(\sigma s - 1)(1-\alpha s)}$$  \hspace{1cm} (7)$$

where $M_{o,s}$ represents the mass of entrepreneurs who attempt entry into production in country $o$ and sector $s$. Ignoring some terms which cancel, the numerator of equation (7) represents the value of imports and the denominator represents total expenditure, so the denominator is the sum over countries $i$ of total imports from each country.

The gravity equation (7) is an intermediate result of the model, but it summarizes nicely how environmental regulation affects economic activity. It shows that a country with a high pollution tax $t_{o,s}$ will have lower exports and less production, particularly in dirty industries with high values of the pollution parameter $\alpha_s$. An empirical literature measures how environmental regulation affects plant openings, employment, shipments, and other outcomes (see discussion of literature in Walker (2013)). A voluminous trade literature derives gravity equations expressing trade flows in a way that approximate actual bilateral trade patterns (see discussion of literature in Anderson and van Wincoop (2003)). Equation (7) provides an appealing link between these two literatures. In addition, equation (7) allows empirical tests of the hypothesis that industry reallocates production to countries with weaker environmental regulation (known as the “pollution havens hypothesis”; see Levinson and Taylor (2008)).

### 3.2 Equilibrium in Changes

By combining assumptions A1 through A4 in specific ways, we can use this model to analyze counterfactuals. We first combine the model’s assumptions into two equilibrium conditions that summarize firm behavior. One equilibrium condition is the labor market clearing assumption (6). This condition says that in any counterfactual, it must be that total labor demanded equals total labor supplied in each country.

The other equilibrium condition combines two facts. First, the expected profit from operating a firm must equal the fixed cost of forming a firm. Second, a cutoff productivity for each destination market determines
whether the expected profit from entering that market exceeds the fixed marketing cost required to sell there (i.e., a free entry condition and zero cutoff profit). Equation (22) of Appendix B formally describes the second equilibrium condition. These are equilibrium conditions because if a set of data satisfies these conditions, then those data represent a competitive equilibrium in the sense of Assumption A4. We use these conditions to analyze how counterfactuals affect welfare.

The two equilibrium conditions include numerous variables which are difficult to measure. Rather than attempt to measure these variables, we rewrite each variable as a proportional change from a base year, as in Dekle, Eaton, and Kortum (2008). The benefit of writing the model in changes is that we do not need data on difficult-to-observe variables because many of them do not appear in changes. For example, constructing an empirical analogue to the model’s equilibrium conditions in levels (6) and (22) would require data on productivity levels for each country and industry, the fixed costs of entering each market, the fixed cost of beginning production, and the measure of firms operating in each country and industry. But in changes these variables do not appear in the equilibrium conditions, and so we do not need to measure them.

We analyze the model as follows. Let $x$ denote some variable from the model, let $x'$ denote the value under a counterfactual scenario, and let $\hat{x} = x'/x$ denote the proportional change in $x$ due to the counterfactual. Written in changes, the two equilibrium conditions (6) and (22) become the following:

$$1 = \psi_o \sum_s \eta_o \hat{M}^e_{o,s}$$

$$\hat{w}_o = \sum_d \left( \frac{\zeta_{od,s}}{\sum_d X_{od,s}} \right) \left( \hat{\tau}_{od,s} \right) \left( \hat{\tau}_{od,s} \right) \left( \hat{f}_{od,s} \right) \left( \hat{f}_{od,s} \right) \left( \hat{t}_{od,s} \right) \left( \hat{t}_{od,s} \right) \left( \hat{\beta}_{d,s} \hat{w}_d \right)$$

To express these equilibrium conditions succinctly, we have defined export shares $\zeta_{od,s} \equiv X_{od,s}/\sum_d X_{od,s}$ and the parameter combinations $\eta_o$ and $\psi_o$. Intuitively, equation (8) says that the change in labor demand from each industry must equal the change in a country’s labor supply. Equation (9) summarizes two ideas: given a set of shocks, changes to wages and firm entry must be such that entrepreneurs earn zero expected profit from drawing a productivity; and firms with positive expected profits from exporting choose to export.

For each counterfactual, we use these equilibrium conditions to solve for the values of wages and firm entry decisions that characterize that counterfactual. In order to measure pollution emissions associated with the counterfactual, we integrate pollution emissions in (5). The change in country $o$’s pollution emissions between a baseline year and counterfactual is then given by

$$\hat{Z}_o = \sum_{s} \frac{\hat{M}^e_{o,s} \hat{Z}_{o,s}}{\sum_{s} \hat{Z}_{o,s}}$$

An industry’s pollution emissions increase proportionally with firm entry and decrease with regulation and wages. Equation (10) says that the proportional change in pollution emissions is the sum over industries of
pollution in a counterfactual scenario all divided by observed baseline pollution.

3.3 Taking the Model to the Data

A goal of this paper is to construct empirical analogues to key terms in the model and then to use the resulting framework to analyze counterfactuals. To clarify how we pursue this goal, it may help to distinguish between three classes of variables in the equilibrium conditions (8) and (9): data and parameters; shocks; and endogenous variables. Data and parameters represent quantities that we assume are fixed in counterfactuals. The data in this model include baseline country expenditure shares and baseline export shares ($\lambda_{od,s}$ and $\zeta_{od,s}$). The parameters in the model consist of the elasticity of substitution across product varieties, the shape parameter of the Pareto distribution of firm productivities, and the pollution elasticity ($\sigma_s$, $\theta_s$, and $\alpha_s$). Each parameter differs by industry $s$. We estimate elasticities of substitution and shape parameters using methods similar to those used by Hsieh and Ossa (2011). As far as we know, there are no existing empirical estimates of the pollution elasticity.

Shocks represent changes to the global economy’s primitive attributes. The shocks in this model include changes to variable and fixed trade costs, regulation, productivity, and preferences ($\hat{\tau}_{od,s}$ and $\hat{f}_{od,s}$; $\hat{t}_{o,s}$; $\hat{b}_{o,s}$; and $\hat{\beta}_{o,s}$). We measure these shocks but do not explain why they occurred. Endogenous variables represent values which are determined by the equilibrium interaction between supply and demand in each counterfactual so as to achieve a competitive equilibrium. The endogenous variables in this model include changes in nominal wages in each country and changes to the mass of entrepreneurs who attempt entry into production in each country and sector ($\hat{w}_o$ and $\hat{M}_{o,s}$).

We now turn to putting this model to work—we first explain the data we compile to analyze the model, and then we present our results.

4 Data

We combine several datasets to apply this model empirically. The text below provides a brief overview, while Appendix C provides additional detail. The data for this paper fall into three categories: plant-level microdata for estimating the model’s parameters; country by industry aggregates used to analyze counterfactuals; and ancillary data for sensitivity analysis.

4.1 Plant-Level Data for Estimating Parameters

We use plant-level microdata to estimate three parameters of the model, calculated separately for each industry: 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 industry. We obtain these data from the U.S. 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. All our calculations with the ASM use sampling weights

---

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
provided by the Census Bureau so the calculations are representative of the industry as a whole. We also use the ASM data to estimate the Pareto shape parameter, the details of which are described below.

To estimate the pollution elasticity, we require 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 Environmental Protection Agency and the Census Bureau.\(^8\) We also use data on air pollution emissions from the U.S. Environmental Protection Agency’s National Emissions Inventory (NEI), which provides a comprehensive and detailed report of air pollution emissions from all sources. The NEI was created to provide EPA, federal and state decision makers, the U.S. public, and foreign countries with authoritative estimates of U.S. pollution emissions.\(^9\)

### 4.2 Country×Industry Data for Analyzing Counterfactuals

We compile aggregate data for the U.S. and foreign countries separately for each industry and for each of the years 1990-2008. In particular, we need production and trade data from each country, and we need to a measure of pollution emissions in the United States.

For production, we use data from the Structural Analysis Database of the Organization for Economic Co-operation and Development (OECD). For trade, we use data from the OECD’s Structural Analysis Database. Both 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 U.S. dollars using annual exchange rates from the OECD Statistics dataset.\(^10\) We aggregate these data to two countries (the U.S. and Foreign) and to 17 manufacturing industries defined in Table A1. 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 U.S. pollution emissions with the same National Emissions Inventory (NEI) data used to measure pollution parameters. The NEI is not conducted annually, and we use all available years: 1990, 1996, 1999, 2002, 2005, 2008 (1993 had no inventory). We focus on industry-level emissions of six of the of appearing in the sample increases with a firm’s size.

\(^8\)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).

\(^9\)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 condensable 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 which used pollution emissions data from the AIRS dataset, which was later integrated into the NEI.

\(^10\)The OECD only reports production data in these years for 32 countries. To extrapolate to other countries, we take the ratio of GDP to gross output in these countries, which is 0.310. Dekle, Eaton, and Kortum (2008) report an extremely similar value for this ratio of 0.312. We impute gross output for other countries by dividing their GDP, observed in the World Development Indicators data, by 0.310. We allocate this gross output to sectors according to the share of exports in non-U.S. countries from each sector in the OECD data.
main air pollutants regulated under the Clean Air Act: carbon monoxide (CO), nitrogen oxides (NO\textsubscript{x}), particulate matter less than 10 micrometers (PM\textsubscript{10}), particulate matter less than 2.5 micrometers (PM\textsubscript{2.5}), sulfur dioxide (SO\textsubscript{2}), and volatile organic compounds (VOCs).

We use two concordances to link SIC and NAICS data with the ISIC trade and output data. We concord SIC to NAICS codes using a crosswalk table from the U.S. Census. We then concord NAICS to the ISIC Rev. 3 codes used in the bilateral trade data by using a crosswalk table from Statistics Canada.

5 Estimation and Results

5.1 Pollution Parameters

We use a simple interpretation of \(\alpha\) to estimate it. Although the model literally describes pollution as a second output which is taxed, Assumptions A2 and A3 of the model imply that pollution intensity is a function of abatement investments:

\[
\frac{z}{q} = (1 - \xi)^{(1-\alpha)/\alpha}
\]

where, as before, \(\xi\) represents the share of factors used for pollution abatement rather than for production. Taking logs of equation (11), taking first differences over time, and allowing for national trends \(\eta_t\) in emissions intensity and idiosyncratic disturbances \(\epsilon_{i,t}\) to pollution intensity gives

\[
\Delta \ln \left( \frac{z_{i,t}}{q_{i,t}} \right) = \frac{1 - \alpha}{\alpha} \Delta \ln (1 - \xi_{i,t}) + \eta_t + \epsilon_{i,t}
\]

where \(\Delta\) represents the first-difference operator. Since \(\xi\) is the abatement cost share, the less firms spend on abatement the larger \(z/q\) will be. So we expect \((1 - \alpha)/\alpha\) to be positive.

To estimate equation (12), we construct a balanced county×industry panel for the years 1990 and 2005.\textsuperscript{11} We use data on pollution emissions from NEI, the value of shipments and value of production costs from ASM, and pollution abatement costs from PACE (\(z\), \(q\), and \(\xi\), respectively).\textsuperscript{12} Equation (12) is designed to measure the effect of pollution abatement on pollution emissions intensity. There are several reasons to be concerned that changes in pollution abatement costs are endogenous, and hence estimates of \(\alpha\) are biased. For example, if regulators require the dirtiest plants to spend large shares of their costs on pollution abatement, then reverse causality will create downward bias in estimates of \((1 - \alpha)/\alpha\). Moreover, our measures of abatement costs and total factor costs are based on survey responses from PACE and the ASM, both of which may contain measurement error in reported expenditures.

To address possible endogeneity concerns, we instrument for changes in the abatement cost share \(\ln(1 - \xi_{i,t})\) using changes in local environmental regulatory stringency. The Environmental Protection

\textsuperscript{11} The years 1990 and 2005 are the only years of data for which the PACE survey overlaps with the NEI. In future work, we hope to match the NEI to the PACE using name and address matching algorithms to facilitate within plant comparisons over time.

\textsuperscript{12} We proxy for measures of physical output \(q_{i,t}\) using plant revenue, deflated by industry-specific output price deflators from the NBER-CES database. While the NEI provides plant-level emissions data, the plant-level regression requires matching the NEI to plant-level Census data using name and address matching algorithms. We are currently exploring the accuracy of these matches, and we present results using industry aggregates.
Agency sets National Ambient Air Quality Standards which describe the minimum air quality needed to protect human health. The EPA requires polluting firms in areas that exceed the EPA’s air quality standards (“nonattainment” counties) to install pollution abatement technologies. Existing research has found that changes to county nonattainment status increase pollution abatement expenditures for polluting firms (Becker, 2005). We revisit this work by examining how county-level nonattainment designation influences abatement expenditures and ultimately, pollution intensity per unit of output.

In principle, we could use our instrumental variables regression approach to estimate \( \alpha \) 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 industries, the samples are too small to estimate equation (12) separately for each industry. Instead, we estimate a single \( \alpha \) using this regression approach, and we use an additional implication from the model to obtain values of \( \alpha \) for each sector. We use the fact that \( \alpha_s \) represents pollution tax payments as a share of production costs. We can write total output as a Cobb-Douglas function of pollution emissions and productive factors:

\[
q = (z)^{\alpha_s} (l\varphi)^{1-\alpha_s}
\]

Under Cobb-Douglas production, with constant returns to scale and perfect competition, the output elasticity \( \alpha_s \) is equal to the input share of pollution, i.e., the share of firm costs which represent pollution taxes. Since the U.S. does not have pollution taxes, we cannot directly observe the share of firm costs which represent pollution taxes. However, if the per-unit pollution tax is constant across industries, then the relative value of \( \alpha_s \) across industries is proportional to the tons of pollution emitted per dollar of input costs in each industry. For example, if the basic metals industry emitted twice as much pollution per dollar of input costs as the textiles industry did, then we would have \( \alpha_{\text{basic-metals}} = 2\alpha_{\text{textiles}} \). We use this approach to measure relative differences in \( \alpha \) across industries. We then scale these values so the mean across sectors equals the economy-wide elasticity of pollution emissions intensity with respect to abatement costs from our equation (12) regression estimate, \( \hat{\alpha} \).

Table 1 reports the first-stage, reduced-form, and instrumental variable analogues of equation (12) for the five pollutants in the NEI for which we have an instrumental variable for abatement expenditures.\(^\text{13}\) We analyze 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.\(^\text{14}\) Columns (1) through (5) analyze each pollutant separately, and Column (6) uses total emissions of all pollutants in tons as a summary measure of emissions.

Panel A of Table 1 present the “first-stage” regressions which show that designating a county as nonattainment for pollutant \( p \) increases the proportion of firm costs devoted to pollution abatement in industries that emit the pollutant \( p \). All of these first-stage regressions have negative signs, implying that regulated

\(^\text{13}\)There are no changes in county-level SO\(_2\) nonattainment in our sample, and thus we do not report results for SO\(_2\).

\(^\text{14}\)Technically, the instrumental variable we use for changes in abatement expenditures is an interaction between an indicator for whether the county\(\times\)industry has non-zero emissions of pollutant \( p \) in 1990 (i.e. \( 1[\text{Polluter}_{ip}=1] \)) and whether the county switches into nonattainment for pollutant \( p \) between 1990 and 2005 (i.e. \( 1[\text{Nonattain}_{cp}]=1 \)). Thus, the instrumental variable is \( 1[\text{Polluter}_{ip}]\times 1[\text{Nonattain}_{cp}] \). We include the lower order interaction terms in all regression models to facilitate identification of difference-in-differences interaction term.
firms increase the share of costs devoted to pollution abatement by 6 percent relative to the baseline share. Panel B presents evidence from the “reduced form” regressions of pollution emissions intensity on the regulation instrument. The regression estimates show that polluting industries 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 presents our instrumental variable regression estimates, showing that changes in pollution abatement cost shares, instrumented with changes in Clean Air Act regulations, predict changes in pollution intensity. Two of five pollutants are individually statistically significant and the overall regression in column (6) is precise. Panel D presents our estimates of $\alpha$ that come from a nonlinear transformation of the regression coefficient $(1 - \alpha)/\alpha$. Although the exact value differs slightly across pollutants, the estimates of $\alpha$ 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 one percent level.

This value of $\alpha$ applies to the manufacturing industry as a whole. As described above, we obtain values of $\alpha_s$ for each sector by using information on pollution emissions per dollar of input costs in each sector. We rescale emissions per dollar of input cost in each sector so that the overall average across all sectors is equal to 0.011 from Table 1. Appendix Table A2 reports these rescaled values of $\alpha$ separately for each pollutant and industry. The resulting pollution elasticities range from 0.001 to 0.048. Perhaps unsurprisingly, the cleanest industries are Radio, Television, Communication; and Motor Vehicles, Trailers. The dirtiest industries are Basic Metals, and Other Non-Metallic Minerals.

Are these estimates of $\alpha$ reasonable? The pollution parameter $\alpha$ represents the share of costs which firms devote to paying pollution taxes. Thus, the overall estimate of 0.011 implies that firms are implicitly paying 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. Taken at face value, the PACE data report that manufacturing pollution abatement costs are about half a percent of total manufacturing sales (U.S. Census Bureau, 2008). Greenstone, List, and Syverson (2012) find that nonattainment designations decrease the total factor productivity of regulated firms by 2.6 percent. None of these numbers need to be identical, but because they all characterize the economic costs of environmental regulation, it is encouraging that they have the same order of magnitude.

### 5.2 Macroeconomic Parameters

In addition to the pollution elasticity, we must estimate the elasticity of substitution and shape parameter of the Pareto distribution separately for each sector. We do so by building on the approach in Hsieh and Ossa (2011). To estimate the elasticity of substitution across product varieties, we use the implication of the model that an industry’s expenditures on labor for production are proportional to the industry’s revenue:

$$w_o l_{o,s}^p = (1 - \alpha_s) \frac{\sigma_s - 1}{\sigma_s} X_{o,s}$$

(13)
Here $L_{o,s}^0$ represents labor used in production and $X_{o,s}$ represents revenue.\footnote{In the model, this prediction reflects only wage payments used for production. In applying this prediction empirically, we measure all factor payments in the data (not merely wages), and we treat all factor payments in the data as productive (since the data do not separately measure fixed entry and marketing costs). Firm revenues are “inventory-adjusted” total value of shipments for a plant in 1990, and firm costs consist of expenditures on labor, parts and materials, energy, and capital.} We use the 1990 Annual Survey of Manufactures to calculate these elasticities separately for each of the 17 aggregated ISIC sectors.

Column 4 of Table 2 presents our estimates of $\sigma_s$ for each sector.\footnote{The reported elasticity is calculated as $\sigma_s = (1 - \alpha_s)/(1 - \alpha_s - wL_o/X_s)$, where $\alpha_s$ is the pollution elasticity estimated above and $wL_o/X_s$ is factor costs divided by the value of shipments. Columns 1-3 of Table 2 present these intermediate inputs into $\sigma_s$.} The elasticity of substitution ranges from 2.89 to 8.18 across industries, with a cross-industry mean of 4.76. We expect a smaller elasticity of substitution for industries with more differentiated products. The pattern across sectors generally follows this expectation. The largest elasticity of 8.18 in absolute value is for the Coke, Refined Petroleum, and Nuclear Fuels sector, which have fairly homogeneous products. The smallest elasticity of 2.89 is for the Medical, Precision, and Optical Products sector, which has fairly differentiated products. The economy-wide mean of 4.76 is similar to estimates of the trade elasticity of 4 to 10 (Arkolakis, Costinot, and Rodriguez-Clare, 2012), with more recent estimates closer to 4 (Simonovska and Waugh, 2014).

Next, we estimate the shape parameter of the Pareto distribution of firm productivities. We rely on the fact that if the distribution of firm productivities is Pareto with shape parameter $\theta_s$, then the distribution of firm sales is Pareto with shape parameter $\theta_s/(\sigma_s - 1)$. The Pareto tail cumulative distribution function is $\Pr\{x > X_{i,s}\} = (b_{i,s}/X_{i,s})^{\theta_s/\sigma_s - 1}$ for $X_{i,s} \geq b_{i,s}$. Taking logs gives

$$\ln(\Pr\{x > X_{i,s}\}) = \gamma_{0,s} + \gamma_{1,s} \ln(X_{i,s}) + \epsilon_{i,s}$$

(14)

We estimate equation (14) separately for each industry $s$, and the coefficient $\gamma_{1,s}$ in each regression is generally close to negative one. The Pareto shape parameter is then given by $\theta_s = \gamma_{1,s}(1 - \sigma_s)$.

We use a subset of the firm-level data to estimate equation (14). Because selection into exporting can bias these estimates (di Giovanni, Levchenko, and Ranciere, 2011), we estimate this regression using only domestic sales. Additionally, since the Pareto distribution best fits the right tail of the firm distribution, we estimate these regressions using firms above the 75th percentile of sales within each industry.\footnote{In the census microdata, we measure domestic sales as inventory-adjusted total value of shipments minus the value of export shipments. Estimating the regression using only the upper tail of firm sizes follows the literature by taking a set of firms for which the relationship between firm rank and size is approximately linear (Gabaix, 2009; di Giovanni, Levchenko, and Ranciere, 2011). To determine the percentile cutoff for these regressions, we bin the data into values of firm size that are equidistant from each other on the log scale, then collapse the rank/size data to the bin level for 10 bins. We examine the scatter plot of these points overlaid by the linear fit to these points. In general, the upper 75th percentile of the sales distribution is strongly linear with respect to firm rank.}

Columns 5 and 6 of Table 2 present our estimates of the Pareto shape parameter $\theta_s$ for each industry. For each row of the table, we estimate the Pareto shape parameters $\theta_s$ 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). The shape parameter estimates are close to the elasticity of substitution estimates for the corresponding industry. This relationship stems from the fact that regression estimates of equation (14) obtain coefficients $\gamma_{i,s}$ near minus one, and...
the Pareto shape parameter is calculated as \( \theta_s = \gamma_{1,s}(1 - \sigma_s) \).

### 5.3 Recovering Historic Values of Shocks

The previous section explained how we use plant-level microdata to estimate the model’s key parameters. Given these parameters, this section explains how we use country \( \times \) industry aggregate data to recover historic values of the paper’s four shocks: foreign competitiveness (a measure of trade); environmental regulation; domestic competitiveness (a measure of productivity); and consumer preferences.

Why do we need to measure historic values of these shocks? The model and estimated parameters are all we need to analyze counterfactuals. But this paper’s research question of why pollution followed its historical path requires us to look at a specific counterfactual where some shocks take on their historical values and other shocks do not. Analyzing that kind of counterfactual requires measuring the actual, historic values of each shock for each year in 1990-2008.

Historic values of shocks to competitiveness, regulation, and preferences could in principle be measured from data on tariffs and shipping costs, announcements of new environmental regulation, total factor productivity, and consumer surveys. But while such data may be proxies that are correlated with the shocks described in the model, they do not actually measure the shocks. For example, the unit pollution tax variable \( t \) in the model is meant to encompass the full set of air pollution regulations facing firms, whereas changes in regulation like Clean Air Act nonattainment designations or the implementation of cap-and-trade programs represent only partial changes in environmental regulation.

Hence we use insights from the model to infer historic values of each shock from country \( \times \) industry data on production, trade, and pollution. Our general approach is to take four equations describing a competitive equilibrium: gravity (7), labor market clearing, (8), the aggregated equilibrium condition (9), and the equation describing changes in pollution emissions (10). We then manipulate these equations to express each shock as a unique function of things we observe: data and parameters. For each shock described below, we use observed data (on the right-hand-side) to construct empirical analogues to the theoretical shocks (on the left-hand side). We let an asterisk \( (x^*) \) denote the historical value of shock \( x \).

We define the shock to foreign competitiveness as

\[
\hat{\Gamma}_{od,s}^{*} = \frac{1}{\hat{b}_{o,s}} - \theta_s(\hat{\tau}_{od,s})^{-\theta_s/(1-\alpha_s)}(\hat{f}_{od,s})^{1-\theta_s/(\sigma_s-1)(1-\alpha_s)}(\hat{t}_{o,s})^{-\alpha_s\theta_s/(1-\alpha_s)} \quad \text{for } o \neq U.S.
\]

Foreign competitiveness combines foreign productivity, variable and fixed trade costs for foreign exports, and foreign environmental regulation \( (\hat{b}_{o,s}, \hat{\tau}_{od,s}, \hat{f}_{od,s}, \text{and } \hat{t}_{o,s}) \). We combine these variables into a single “foreign competitiveness” shock because these variables all decrease the ability of foreign firms to sell a wide variety of products to U.S. consumers at low prices, and because we lack the data to measure each component of this foreign shock separately.\(^{18}\) By manipulating equation (9), we can write the shock to

\(^{18}\)Separately measuring productivity and trade costs would require foreign producer price index data, which are not available for most countries, sectors, and years. We have tried using OECD STAT and Thompson Reuters Datastream to obtain these price data. Analyzing counterfactuals with those data suggests that the effects of productivity and trade costs separately are similar to the effects of the foreign shocks we describe here. However, in some cases it is computationally difficult to separately analyze trade costs and productivity in counterfactuals. Separately measuring the effect of foreign environmental regulation requires data on global pollution emissions, which are not available.
foreign competitiveness as equal to the share of output growth from that sector:

\[
\hat{\Gamma}_{od,s}^{*} = \frac{\hat{\lambda}_{od,s}}{M_{o,s}(\hat{\tilde{w}}_o)^{-\theta_s}} \left( \hat{P}_{d,s} \right)^{-\frac{\theta_s}{1-\alpha_s}} \left( \hat{\beta}_{d,s} \right)^{-\frac{\theta_s}{1-\alpha_s}} \left( \hat{\tilde{w}}_d \hat{w}_d \hat{L}_d - \hat{N}X_d \hat{N}X_d \right)^{\frac{1}{2} - \frac{\theta_s}{(\sigma_s - 1)(1 - \alpha_s)}}
\]  

(15)

The right-hand-side of equation (15) shows that the change in foreign competitiveness equals the change in the share of U.S. expenditure on goods from a foreign country, divided by the change in nominal income times firm entry. The first term in parentheses summarizes changes to the destination price index, and the second term in parentheses accounts for the effects of changing preferences and changing trade imbalances \(NX_d\) on sector composition. We do not need to measure the terms in parentheses on the right-hand side of equation (15) because they are specific to destination \(d\), and so they cancel between the numerator and denominator in the gravity equation (7) and in the second equilibrium condition (9), which are the only places the shocks appear in analyzing counterfactuals. Because labor is the only factor of production, the change in nominal wages equals \(\hat{\tilde{w}}_o = \sum_{d,s} X'_{od,s} / \sum_{d,s} X_{od,s} \). Combining equations (7) and (9) shows that the change in the mass of firm entry in a sector equals the share of output growth from that sector:

\[
\hat{M}_{e,o,s} = \left( \hat{\tilde{w}}_o^{-1} \right) \sum_d X'_{od,s} / \sum_d X_{od,s} \]

We measure shocks to environmental regulation by integrating pollution emissions in equation (5) over individual firms, and then dividing the result by baseline pollution, giving

\[
\hat{t}_{o,s} = \frac{\hat{M}_{e,o,s}}{\hat{\tilde{w}}_o \hat{Z}_{o,s}}
\]  

(16)

The change in environmental regulation equals the change in the mass of firms, divided by the change in pollution emissions, scaled by the change in aggregate output.

We define shocks to U.S. competitiveness as

\[
\hat{\Gamma}_{od,s}^{*} \equiv \left( \hat{\tilde{w}}_o^{-1} \right) \left( \hat{\tilde{w}}_o^{-1} \right)^{\theta_s / (1 - \alpha_s)} \left( \hat{f}_{od,s} \right)^{1 - \theta_s / (\sigma_s - 1)(1 - \alpha_s)} \text{ for } o = \text{U.S.}
\]

We measure this shock as

\[
\hat{\Gamma}_{od,s}^{*} = \left( \hat{t}_{o,s} \right)^{\frac{\alpha_s}{1 - \alpha_s}} \frac{\hat{\lambda}_{od,s}}{M_{e,o,s}(\hat{\tilde{w}}_o)^{-\theta_s}} \left( \hat{P}_{d,s} \right)^{-\frac{\theta_s}{1-\alpha_s}} \left( \hat{\beta}_{d,s} \right)^{-\frac{\theta_s}{1-\alpha_s}} \left( \hat{\tilde{w}}_d \hat{w}_d \hat{L}_d - \hat{N}X_d \hat{N}X_d \right)^{\frac{1}{2} - \frac{\theta_s}{(\sigma_s - 1)(1 - \alpha_s)}}
\]  

(17)

We measure the change to U.S. competitiveness almost exactly as we measure the change to foreign competitiveness. However, because we have pollution emissions data for the U.S. but not foreign countries, we can separate the environmental regulation term \(\hat{t}_{o,s}\) from other components of U.S. competitiveness.

We measure shocks to consumer preferences as changes in the share of expenditure allocated to each sector:

\[
\hat{\beta}_{d,s}^{*} = \frac{\sum_o X'_{od,s} / \sum_{o,s} X'_{od,s}}{\sum_o X_{od,s} / \sum_{o,s} X_{od,s}}
\]  

(18)

The numerator in this equation describes the share of a country’s expenditure on sector \(s\) in some year,
while the denominator describes the share of the country’s expenditure on sector $s$ in 1990.

To exactly reconstruct historic economic variables, we also need to account for a fifth shock, namely shocks to trade imbalances. We show this in counterfactual results but do not emphasize it. We need to incorporate this shock because the goal of the decomposition is to exactly recreate historic values of pollution emissions when all shocks take their historic values, allowing us to investigate how pollution emissions differ when some shocks do not take their historic values. In a dynamic model, trade imbalances would represent intertemporal concerns like saving or consumption smoothing, but in the comparative statics we examine here, trade imbalances appear as transfers from one country to another. In the full decomposition, we let changes in trade imbalances follow their historical path. We measure net exports as a country’s total exports minus its total imports.

Figures A1a-A1e describe the time path of the historical shocks in the paper. Although we recover the value of each shock for each country×industry, it is cumbersome to describe values for 17 different industries. Instead, we describe some shocks by separating six “dirty” industries with the top third of $\alpha$ values, and eleven “clean” industries with the lowest two-thirds of $\alpha$ values.\footnote{The dirty industries are: Wood Products; Paper and Publishing; Coke, Refined Petroleum, and Fuels; Chemicals; Other Non-metallic Minerals; and Basic Metals. The clean industries are: Food, Beverages, and Tobacco; Textiles, Apparel, Fur, and Leather; 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 A1a plots the time path of foreign competitiveness, showing that foreign competitiveness grew gradually between 1990 and 2000 at the rate of 2-3 percent annually. After 2000, foreign competitiveness grew quickly, at over 10 percent per year. We do not distinguish empirically between various causes of this growth in foreign competitiveness. However, research emphasizes the central role of rapid growth in Chinese productivity (Hsieh and Ossa, 2011; Eaton, Kortum, Neiman, and Romalis, 2011; di Giovanni, Levchenko, and Zhangam, 2014). Figure A1b shows that U.S. competitiveness grew through 2000, as U.S. technology growth outpaced improvements among foreign competitors. U.S. competitiveness then declined as foreign growth outpaced U.S. growth, and U.S. imports expanded. Figure A1c suggests that foreign preferences for dirty versus clean goods changed relatively little over this period. In contrast, Figure A1d suggests that U.S. preferences for products in dirty industries increased after 2004. This rapid increase in U.S. preferences for dirty goods is likely driven by the increasing expenditure in the Coke, Refined Petroleum, and Nuclear Fuels sector, reflecting increases in global oil prices.\footnote{With Cobb-Douglas consumer utility, changes in the share of expenditure in a given sector translate to a change in preferences. This stylized fact that the share of U.S. expenditure on energy products nearly doubled between 2004 and 2008 appears in other data. For example, the Energy Information Agency Energy Information Administration (2011) records that consumer expenditure on all petroleum products grew in nominal terms from $470 billion in the year 2004 to $871 billion in the year 2008.}

Finally, Figure A1e suggests that the stringency of environmental regulation grew rapidly over this period. The implied nominal pollution tax more than doubled between 1990 and 2000 and then increased even more rapidly between 2000 and 2008. In total, the shadow pollution tax on NO$_x$ for the U.S. manufacturing sector increased nearly five-fold between 1990 and 2008. The U.S. CPI increased by about 65 percent between 1990 and 2008, so using that deflator, implicit NO$_x$ pollution taxes increased by about 300 percent over this time period.

Is this a realistic change in the stringency of environmental regulation? We emphasize that the U.S. does
not actually have a pollution tax on NO\textsubscript{x}. A way to think about the meaning of this tax is as follows: if all U.S. environmental regulation relevant to NO\textsubscript{x} emissions from the manufacturing sector 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\textsubscript{x} regulation over these 18 years, such large changes in the implicit tax on pollution seem plausible. An extremely incomplete list of actual changes in NO\textsubscript{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;\textsuperscript{21} the 1990 Clean Air Act amendments, which required large NO\textsubscript{x} emitters in ozone nonattainment areas to install stringent pollution controls by 1995;\textsuperscript{22} 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\textsubscript{x} Budget Trading Program for the Eastern U.S., which began in 2003.\textsuperscript{23}

Our measures of these historic shocks depend on the changes in nominal wages in each country and changes in firm entry which occurred in each country and sector. Appendix Figure A2 plots these values. U.S. wages stagnated in the 1990s as U.S. output grew more slowly than global output did. U.S. wages grew slightly in the late 1990s and early 2000s, as U.S. output growth modestly outpaced global output growth. Finally, nominal wages declined in the 2000s as growth from foreign countries, especially China, accelerated. Foreign wages display the opposite pattern: growth in the early 1990s and late 2000s but a slight decrease in the intervening years.

Patterns in firm entry are more interesting (Appendix Figure A2). Foreign production more quickly in dirty industries than in clean industries, as indicated by the slightly higher solid line in Figure A2c. U.S. firm entry, however, grew more rapidly in clean industries during the 1990s, and then accelerated in dirty industries in the late 2000s. This increase in U.S. firm entry to dirty industries in the late 2000s reflects rising energy prices—greater value of output in dirty industries increases the expected profit from entry, attracting more firms to these industries.

6 Counterfactuals

We begin by discussing the mechanics of how we analyze counterfactuals. Then, we use the model, parameter estimates, and recovered historic shocks to decompose how trade, environmental regulation, productivity, and preferences contributed to observed declines in pollution emissions.

6.1 Counterfactual Algorithm

We analyze counterfactuals using the following algorithm:

1. Characterize the counterfactual scenario by choosing a time path for shocks to foreign and U.S. competitiveness, U.S. environmental regulation, and preferences \{\tilde{\Gamma}_{od,s}, \tilde{\ell}_{o,s}, \text{and } \tilde{\beta}_{o,s}\} (i.e. a hypothetical

\textsuperscript{21}Ozone pollution is formed through photochemical reactions involving NO\textsubscript{x}, VOCs, and heat and sunlight, so ozone nonattainment regulations target NO\textsubscript{x} and VOC emissions.

\textsuperscript{22}The EPA required plants in ozone nonattainment areas to install Reasonably Available Control Technology (RACT).

\textsuperscript{23}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.
time path or actual, historical time path). Combine the time paths of shocks with country-industry data from the year 1990 on production, trade, and U.S. pollution emissions ($X_{od,s}$ and $Z_{o,s}$). Add the parameter vectors for each industry: the pollution elasticity, elasticity of substitution, and Pareto shape parameter ($\alpha_s$, $\sigma_s$, and $\theta_s$).

2. Find the changes to wages and firm entry in each country-sector-year ($\hat{w}_o$ and $\hat{M}_{o,s}$) which make the equilibrium conditions (8) and (9) hold with equality for all countries and sectors and years using a standard algorithm to solve systems of nonlinear equations, and given the values chosen in step 1. This system represents $N + NS - 1$ variables in $N + NS - 1$ unknowns: one unknown wage change per country, one unknown firm entry change per country-sector, and one unknown excluded as numeraire.

3. Use equation (10) to measure the change in U.S. pollution emissions, given the values from steps 1 and 2.

The historic values of shocks to foreign and domestic competitiveness, environmental regulation, and preferences are $\{\hat{\Gamma}_{od,s}^*, \hat{t}_{o,s}^*, \hat{\beta}_{o,s}^*\}$, calculated using equations (15) through (18). By construction, these values solve the two equilibrium conditions (8) and (9) in every country, industry, and year for the wage changes and firm entry changes ($\hat{w}_o^*$ and $\hat{M}_{o,s}^*$) which actually occurred. Hence, if we take observed levels of trade, pollution emissions, and production from the initial year 1990, add the shocks $\{\hat{\Gamma}_{od,s}^*, \hat{t}_{o,s}^*, \hat{\beta}_{o,s}^*\}$ which actually occurred between 1990 and some future year, and calculate the new equilibrium, we recover the historic value of pollution from that year. However, we are interested in what pollution would have been if shocks had not equaled their historic values.

To decompose the change in pollution into the effects of the separate shocks, we proceed as follows. Consider the shock to foreign competitiveness. To measure how foreign competitiveness affected pollution, we define the shocks as follows:

$$\{\hat{\Gamma}_{od,s}, \hat{t}_{o,s}, \hat{\beta}_{o,s}\} = \begin{cases} \{\hat{\Gamma}_{od,s}^*, 1, 1\} & \text{if } o \neq \text{U.S.} \\ \{1, 1, 1\} & \text{if } o = \text{U.S.} \end{cases}$$

(19)

This says that the foreign competitiveness shock $\hat{\Gamma}_{od,s}$ took on its historic value $\hat{\Gamma}_{od,s}^*$, $o \neq \text{U.S.}$, but other shocks remained fixed at their 1990 values (i.e. the proportional change for every other shock is equal to one). Given these shocks, we use steps 2 and 3 described above to recover the pollution emitted in this counterfactual. We do a similar calculation for each shock separately. For example, to measure the pollution change due to environmental regulation, we define the shocks as $\{\hat{\Gamma}_{od,s}, \hat{t}_{o,s}, \hat{\beta}_{o,s}\} = \{1, \hat{t}_{o,s}^*, 1\}$. We then follow steps 2 and 3 of the algorithm described above to measure the implied pollution under these shocks.

Three additional points may clarify this algorithm. First, setting all shocks equal to their historic values at once exactly recreates the historic decline in pollution. Second, although we are forceably choosing the shocks to characterize a counterfactual, the firm-level decisions in the model like entry, exit, abatement, production, and exports are all adjusting freely in response to the shocks. Third, we analyze the model separately for each pollutant. We initially discuss 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. However, we then turn to results for other pollutants.$^{24}$

### 6.2 Historic Decomposition

Figure 3 plots the time paths of NO$_x$ emissions under five separate counterfactuals, indicated in the subfigure headings. In each subfigure, the solid line shows historic pollution emissions, and the 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 dashed line in Figure 3a shows the pollution which the U.S. would have emitted in a counterfactual where foreign competitiveness followed its historic path, but domestic competitiveness, pollution regulation, and preferences remained fixed at their 1990 levels. Each line has been normalized to 100 in the year 1990. By construction, the solid line is the counterfactual resulting from setting the shocks equal to their historic values $\{\hat{\Gamma}_{od,s}, \hat{t}_{o,s}, \hat{\beta}_{o,s}\}$.

Figure 3a suggests that foreign competitiveness has a very limited effect on U.S. manufacturing NO$_x$ emissions. Between 1990 and 2000, pollution in this counterfactual would have increased by a few percentage points. After 2000, when China’s growth accelerated, foreign competitiveness led to modest decreases in U.S. pollution of a few percentage points. By 2008, in this counterfactual, U.S. pollution emissions were about five percent below their 1990 value. But ultimately shocks to foreign competitiveness explain very little of the total decline in U.S. pollution. Given the large effects of China’s economic growth over this time on U.S. manufacturing employment Autor, Dorn, and Hanson (2013), one might have expected foreign competitiveness to cause similarly large decreases in pollution. Figure 3a shows that this was not the case, and a few considerations suggest why. Although China’s exports are concentrated in low-skilled sectors, Appendix Figure A2c implies that they were not concentrated in dirty sectors. Moreover, aggregate data on U.S. manufacturing show that the effect of China’s growth on manufacturing output or on value added was much smaller than it’s effect on employment (see, e.g., (Pierce and Schott, 2012)).

Figure 3b similarly suggests that changes to U.S. competitiveness do not explain much of the change in U.S. manufacturing NO$_x$ emissions. Between 1997 and 2003, the effect of U.S. competitiveness alone caused U.S. pollution emissions to increase by about 10 percent. By the end of the 1990-2008 period, though, the effect of this shock alone was nearly zero. U.S. competitiveness, like foreign competitiveness, explains little of the change in pollution. As highlighted in the introduction, plant-level regressions have found 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. But at the economy-wide level, Figure 3b suggests that changes in U.S. productivity growth had small effects on U.S. pollution emissions.

Figure 3c also suggests that changing consumer preferences account for almost none of the change in pollution emissions. Between the years 1990 and 2000, preferences for clean goods decreased slightly and this led to a decrease in U.S. pollution emissions. After 2000, by contrast, increasing expenditure on pollution-intensive goods leads to an increase in U.S. pollution emissions of roughly 20 percent. Changes in trade

$^{24}$Just 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 Claim 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.
deficits also had small effects on total pollution emissions.

In contrast to counterfactuals addressing changes in competitiveness or changes in preferences, Figure 3d suggests that changes in environmental regulation over this time period account for most of the change in NO$_x$ emissions. Between 1990 and 2000, regulation alone accounts for most of the decrease in pollution, although regulation by itself would have caused about 10 percent less pollution reduction than actually occurred. By the year 2008, regulation explains essentially all of the change in pollution. This shows the paper’s third main finding: environmental regulation alone can explain most of the historic change in pollution emissions.

Figure 4 replicates this counterfactual thought exercise for the other “criteria pollutants” regulated under the Clean Air Act: CO, NO$_x$, PM$_{10}$, SO$_2$, and VOCs. Each subfigure in Figure 4 shows all the counterfactuals for a single pollutant. In each subfigure, the solid line describes historic pollution emissions while the dashed lines describe counterfactual pollution emissions under individual sets of shocks. The exact numbers vary by pollutant, but the overall conclusions are extremely similar across pollutants: environmental regulation explains most of the substantial declines in pollution emissions from U.S. manufacturing, while other shocks play quantitatively small roles.

7 Discussion and Sensitivity Analysis

7.1 Potential Effect of Non-Regulation Shocks on Pollution

The model driven decomposition suggests that environmental regulation alone explains most of the historic decrease in pollution. Does something about the way we have setup the model guarantee this conclusion, or could this model have led to other conclusions? More generally, to what extent can forces other than environmental regulation affect pollution in this model? This subsection explores a series of counterfactuals and concludes that all shocks in the model have potential to affect pollution, although effects of environmental regulation are likely to be largest.

We begin by exploring heterogeneity in counterfactuals for clean and dirty industries separately. In each of these counterfactuals, we take the baseline data in the year 1990, increase or decrease one shock, and calculate the changes in production and pollution abatement decisions which that shock causes. For brevity, we present this sensitivity analysis for NO$_x$ emissions only. Figure A3 in the Appendix plots the resulting patterns of pollution for a suite of counterfactual scenarios.\(^{25}\) The x-axis describes the hypothetical shock and the y-axis records the resulting change in U.S. pollution emissions. 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 U.S. pollution emissions do not change.

Figures A3a and A3b describe a range of shocks to U.S. and to foreign competitiveness, separately for dirty and clean industries. The solid line in Figure A3a shows that as foreign competitiveness in dirty indus-

\(^{25}\)To create these graphs, we consider shocks ranging from 0.25 to 8.0 in increments of 0.25. For example, a shock of 0.25 in Figure A3a represents a counterfactual where foreign competitiveness in dirty industries falls to a fourth of its 1990 value but U.S. competitiveness, U.S. environmental regulation, and both U.S. and foreign preferences 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 0.25 to 8.0.
tries grows, U.S. pollution emissions from manufacturing decline. This occurs because foreign competition in dirty industries abroad lowers expected profits in dirty U.S. industries; production in dirty U.S. industries falls, and U.S. productive factors shift to clean industries. At the same time, competition from dirty industries causes exit of unproductive (and dirty) U.S. firms, increasing the market share of cleaner firms within dirty U.S. industries. Figure A3b suggest the opposite patterns happen with shocks to U.S. competitiveness. As U.S. competitiveness in dirty industries grows, U.S. pollution emissions increase; and as U.S. competitiveness in clean industries increases, U.S. pollution emissions fall. Finally, Figure A3c shows that hypothetical shocks to environmental regulation also have intuitive results. Holding other shocks constant, increasing the stringency of U.S. environmental regulation decreases pollution emissions.

More broadly, Figure A3 has two important implications for the paper. First, U.S. pollution depends on all of the shocks we consider, and not only on environmental regulation. Ultimately, we find that changes to environmental regulation explain most of the recent declines in pollution. Figure A3 makes clear that because shocks to domestic and foreign competitiveness each can affect U.S. pollution, this model could have led to other conclusions. Second, shocks to U.S. or foreign competitiveness have much smaller effects on pollution than do shocks to U.S. environmental regulation. An eight-fold increase in U.S. or foreign competitiveness in clean or dirty industries leads to 30-60 percent changes in pollution. By contrast, doubling U.S. environmental regulation leads to 30 to 60 percent declines in pollution. So while all the shocks have potential to decrease U.S. pollution, changes to environmental regulation have much larger magnitude impacts on U.S. pollution emissions.

7.2 Comparing the Implied Pollution Tax with Actual Regulatory Changes

This paper infers changes in pollution taxes by observing firm behavior, rather than by using announced changes in environmental policy. An important question is the extent to which our inferred measures of the stringency of environmental regulation correspond with known changes in regulation. The previous subsection listed the wide array of NO\textsubscript{x} regulations which affected the manufacturing sector over the 1990-2008 period. In order to assess the plausibility of our estimates, we plot the pollution taxes we recover against time series variation in one well-known change in regulation—the NO\textsubscript{x} Budget Trading Program (NBP).

The NBP was a cap-and-trade program for NO\textsubscript{x} emissions from power plants and large industrial plants in the Eastern U.S. The EPA distributed permits to each source and allowed free trading and banking of permits. Most sources in the NBP were electricity generating units, and most NO\textsubscript{x} reductions came from coal-fired power plants. Nonetheless, many oil refineries, chemical plants, paper mills, and other manufacturing plants were regulated through the NBP.

We obtain data from the EPA’s Clean Air Markets Division on facilities regulated under the NO\textsubscript{x} Budget Trading Program for the year 2005. Although these data use different plant identification codes than the NEI does, both datasets list facility name, longitude, latitude, county, and industry. We link the two datasets by requiring an exact match on county and industry and a non-exact match on facility name, longitude, and latitude.\footnote{The only measure of industry in the NBP data is a facility’s “source category.” We exclude NBP participants with}
Appendix Table A3 describes the share of manufacturing regulated in this cap-and-trade program. The NBP targeted large NO\textsubscript{x} emitters. Although only a third of a percentage point of manufacturing plants in NEI were regulated in the NBP, about 13 percent of manufacturing emissions of NO\textsubscript{x} came from manufacturing plants that were subject to the NBP. The proportion of NO\textsubscript{x} emissions from regulated plants ranges from 24 to 41 percent in a few industries: Paper and Publishing, Coke, Refined Petroleum, and Fuels; Rubber and Plastics; and Basic Metals. We describe these as “NBP Industries” and others as “Non-NBP industries”.\footnote{Two other industries – Radio, Television, Communication; and Furniture, Other, Recycling – have over 20 percent of NO\textsubscript{x} emissions from regulated plants. However, this is because of a single plant with extremely high NO\textsubscript{x} emissions, and these industries have a very low proportion of plants regulated, so we do not designate them as regulated industries.}

Figure A4 plots our implied pollution taxes for the two groups of industries over time. The implicit pollution taxes for the NBP-regulated and the non-NBP regulated industries increase steadily through the year 2003, with the implicit taxes for non-NBP industries growing slightly more rapidly. However, after the first year the NBP was implemented, 2003, the implicit pollution taxes grew far more rapidly for NBP than for non-NBP industries. While this evidence is circumstantial, it does suggest that the measure of regulation derived from the model captures at least one important feature of the regulatory landscape over this time period.

### 7.3 Changing Fuel Inputs

The choice of what fuel and fuel quality to use for manufacturing production, which we refer to as fuel mix, may affect manufacturing pollution emissions. Up to this point the paper has been silent about this topic. While fuel mix is less important in the manufacturing sector than in the electric utilities sector, it still can play some role. For example, some manufacturing processes directly use fossil fuels to create heat and steam needed at various stages of production, and manufacturing plants may substitute from high-sulfur coal towards low-sulfur coal. Plants may also switch from coal to natural gas due to changes in relative prices across fuel types, or they can substitute towards non-fuel inputs due to rising global energy prices.

We attempt to characterize the importance of fuel mix in explaining the observed reductions in U.S. manufacturing emissions. We do not analyze whether environmental regulation or other forces like railroad deregulation, fracking, or others affect fuel mix. We merely quantify the importance of fuel mix and thereby bound the share of the change in pollution emissions which environmental regulation could explain. We address fuel mix here rather than in the paper’s main model for two reasons. First, the detailed fuel information used here, unlike the data used for the main model, are not available separately for each manufacturing sub-industry. For this reason, this section treats manufacturing as a single industry. Second, it is intractable for the main model to address fuel mix directly, and the analysis here provides a simple way to assess its potential importance.

We begin by measuring what pollution emissions would have been if the manufacturing sector had used no abatement technologies, if all pollution had come from fuel combustion, and if fuel mix followed its...
historic path. We call this measure “potential pollution” and define it as:

\[
\text{Potential Pollution}_y = \sum_f e_{fy} Q_{fy} H_y
\]

(20)

where \(e_{fy}\) are pollution emissions per physical unit of fuel \(f\) in year \(y\) in the absence of any abatement technology, \(Q_{fy}\) are the physical units of this fuel burned, and \(H_y\) is total heat input (measured in BTUs) of all fuel to the manufacturing sector. The emissions rate \(e_{fy}\) differs by year because it depends on the sulfur and ash content of each fuel, which change over time.

We construct empirical analogues to equation (20) using data from a variety of sources. We measure \(e_{fy}\), the air pollution emitted by combustion of different fuels in the absence of abatement technology, from EPA engineering estimates (Eastern Research Group, 2001); we measure \(Q_{fy}\) and \(H_y\), the physical and BTU content of energy, from the U.S. Census Bureau’s Manufacturing Energy Consumption Survey (MECS); and we measure the sulfur and ash content of petroleum and coal using EIA coal and petroleum reports. The data cover each year from 1993-2008. Additional details regarding the data construction can be found in Appendix C.

A few summary statistics highlight key trends in the underlying data. Appendix Figure A5a shows that the share of heat input from coal fell from 11.6 percent to 8.8 percent between 1993 and 2008. Much of this coal was replaced with steam purchases, which are included in the “other” category. The SO\(_2\) emitted per BTU of coal declined by about ten percent over this period due to the use of lower-sulfur coal. However, Appendix Figure A5b suggests that the sulfur content of petroleum inputs hardly changed.

How did changing fuel mix affect manufacturing pollution emissions? Appendix Figure A6 shows that if total BTUs of energy consumed for fuel had remained constant and nothing else had changed, pollution emissions from manufacturing would have declined slightly. Between 1993 and 2008, pollution emissions from manufacturing would have fallen by 11 percent for CO, 7 percent for NO\(_x\), 8 percent for PM\(_{10}\), 27 percent for SO\(_2\), and 8 percent for VOCs.

Appendix Table A4 compares these statistics to the historic decreases in pollution emissions. On average across the five pollutants between 1993 and 1998, pollution emissions fell by 54 percent.\(^{28}\) On average across these pollutants, the change in fuel mix would predict a 12 percent decrease in pollution from fossil fuel combustion. To summarize, changing composition and quality of fuels can explain at most 23 percent of the decrease in observed pollution emissions. For SO\(_2\), however, fuel mix is more important for explaining emissions reductions (52 percent).

The paper’s main analysis concludes that environmental regulation alone can account for most of the decrease in pollution emissions over the 1990-2008 period. Over the 1993-2008 time period, we find that changing the mix of fuels used in production can explain a fourth of the decrease in pollution emissions. We do not quantify the extent to which changes in fuel mix are due to environmental regulation versus other forces.\(^{29}\) However, we take these results to conservatively conclude that environmental regulation can

\(^{28}\)Recall that most of the paper analyzes the period 1990-2008, but this section begins in 1993, when fuel quality data become available, so this section is analyzing a smaller decline in pollution than the rest of the paper does.

\(^{29}\)For example, increasing use of low-sulfur coal could be due to environmental regulation or to deregulation of railroads (Busse and Keohane, 2007). We do not distinguish among such underlying causes of changing fuel mix.
account for three-fourths or more of the decrease in pollution emissions from manufacturing.

### 7.4 Other Explanations

This paper builds a model which focuses on several key aspects of pollution emissions, but for simplicity and tractability it abstracts from others. This section discusses how other forces outside the model might affect its conclusions.

One abstraction of the model is industry detail. If firms have changed their focuses of production within one of our 17 sectors from more- to less-dirty industries and products, then our analysis may confound regulation with product substitution. The limit on our level of industry detail is the requirement to have gross output data for foreign countries. This being said, the statistical decomposition presented in Section 2 suggests that compositional changes in the type of goods produced are not able to explain a significant fraction of the observed emissions reductions.\(^\text{30}\) This evidence is indirect but suggests that industry detail may have limited power to explain changes in pollution emissions.

The model also assumes constant returns to scale in pollution abatement. A model with increasing returns to scale in abatement could look very different (see, e.g., Forslid, Okubo, and Ultveit-Moe (2011)). We have considered the implications from 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 may seem 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 make it impossible to apply the methodology we use to calculate the equilibrium.

Lastly, the model is silent on improvements in abatement technology, such as learning-by-doing. The value of the pollution technology \(\alpha\) could change merely because regulation becomes more stringent. For example, increasing the market size of scrubbers creates additional incentives for research and development of more effective scrubbers and could decrease the future price of scrubbers. We conjecture that this sort of mechanism would make our model understate the effects of regulation on pollution emissions. Research on health care has highlighted the importance of induced innovation for pharmaceuticals (Finkelstein, 2004), but empirical research on induced innovation stemming from environmental regulation is in its infancy. We leave this topic for future work.

### 8 Conclusions

Public observers once worried that U.S. economic growth would lead to increasingly dangerous levels of pollution. Instead, U.S. air quality has improved dramatically. This paper focuses on the U.S. manufacturing sector and assesses four candidate explanations for why pollution emissions have fallen since 1990. The first explanation is that production of pollution-intensive goods has moved abroad to China, Mexico, and other foreign countries. Second, increasingly stringent environmental regulation may have led to adoption of increasingly effective abatement technologies. Third, if productivity decreases pollution intensity, then rising

\(^{30}\)It still may be the case that within a 4-digit SIC code, firms are producing different products.
productivity may have decreased pollution emissions. Lastly, consumer preferences may have led people to prefer goods which require less pollution to produce.

We begin with a statistical decomposition which shows that almost all of the change in pollution emissions from U.S. manufacturing is due to changes in pollution intensity within narrowly-defined industries. To quantify the importance of trade, regulation, productivity, and preferences, we build on recent trade and environmental research to develop a model of heterogeneous firms which 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 U.S. manufacturing declining? Most structural research uses quantitative models to forecast how untested future policies like carbon taxes or tariff reductions would affect pollution and welfare, but we use our model to analyze the past—to recover the implied changes in environmental regulation and other shocks which firms actually faced in each year 1990-2008. We then use the implied changes to quantify how pollution and welfare would have changed under scenarios other than those which 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 industries, rather than reallocation across industries or change in real manufacturing output. Second, environmental regulation has grown increasingly stringent, and the pollution tax which explains U.S. data increased several-fold between 1990 and 2008. Third, environmental regulation explains 75 percent or more of the observed reduction in pollution emissions from manufacturing. Trade costs, productivity shocks, and preferences play relatively small roles.

One important question for future work is how accounting for intranational geography affects the kind of analysis this paper undertakes. Productive firms tend to locate in high-density urban areas, while less-productive firms are more likely to locate in sparsely-populated rural areas. Because the marginal damages of a unit of pollution emissions may be greater in urban areas, shocks to preferences, productivity, and/or regulations may change the locations of where firms operate, potentially with important environmental consequences.
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Figures and Tables

Figure 1: Trends in Manufacturing Pollution Emissions and Real Output

Note: This figure plots U.S. manufacturing real output and manufacturing pollution emissions in the years 1990-2008. Real output is measured annually from the NBER-CES database, where we have deflated industry level output by the NBER-CES industry-specific output price deflators. Manufacturing emissions come from the EPA’s National Emissions Inventory, measured in years 1990, 1996, 1999, 2002, 2005, and 2008. Real output and pollution emissions have been normalized to 100 in 1990.
Figure 2: Nitrogen Oxides Emissions From United States Manufacturing

Notes: This figure plots the observed and counterfactual trends in NO\textsubscript{x} emissions based on the statistical decomposition from equation (2). The top line plots the counterfactual for what emissions would have looked like in a world with the same composition of goods and techniques of production as was observed in the base year, 1990. The middle line represents what emissions would have looked like if we maintained the same production techniques (defined as emissions per unit of output) as in the base year, 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. Source: NBER-CES database, NEI, and World Bank IPSS.
Figure 3: Counterfactual U.S. Manufacturing Emissions of NO\textsubscript{x} Under Subsets of Shocks, 1990-2008

(a) Only Foreign Competitiveness Changes

(b) Only U.S. Competitiveness Changes

(c) Only U.S. Preference Changes

(d) Only U.S. Regulation Changes

Notes: This figure plots 5 separate counterfactual exercises, describing the actual and counterfactual time path of NO\textsubscript{x} emissions in the U.S. manufacturing sector. The solid blue line displays the actual time path of emissions, and the dotted red line shows 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 factors, or “shock”, is indicated in the subfigure headings. All other explanatory factors are constrained to take their base year, 1990, values. The year 1990 NO\textsubscript{x} emissions have been normalized to 100 in all figures.
Figure 4: Counterfactual U.S. Manufacturing Pollution Emissions Under Subsets of Shocks, 1990-2008

Notes: This figure plots 30 separate counterfactual exercises, 5 for each pollutant. Each subfigure plots the actual and counterfactual time path of the indicated pollutant emissions in the U.S. manufacturing sector. The solid blue line displays the actual time path of emissions, and the dotted red 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 factors, or “shock”, is indicated in the legend in Subfigure 4a. 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.
<table>
<thead>
<tr>
<th></th>
<th>CO</th>
<th>NO\textsubscript{x} (O\textsubscript{3})</th>
<th>PM\textsubscript{10}</th>
<th>PM\textsubscript{2.5}</th>
<th>VOC (O\textsubscript{3})</th>
<th>Total (Any)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: First Stage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonattain\textsubscript{cp} × Polluter\textsubscript{p}</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td></td>
<td>-0.057**</td>
<td>-0.061***</td>
<td>-0.101</td>
<td>-0.126*</td>
<td>-0.063***</td>
<td>-0.058***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.011)</td>
<td>(0.085)</td>
<td>(0.068)</td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td><strong>Panel B: Reduced Form</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonattain\textsubscript{cp} × Polluter\textsubscript{p}</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.244)</td>
<td>(4.782)</td>
<td>(6.860)</td>
<td>(4.427)</td>
<td>(1.214)</td>
<td>(1.979)</td>
</tr>
<tr>
<td><strong>Panel C: Instrumental Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Abatement Expenditure Ratio</td>
<td>130.030**</td>
<td>98.592</td>
<td>94.118</td>
<td>58.551</td>
<td>124.907***</td>
<td>91.604***</td>
</tr>
<tr>
<td></td>
<td>(64.278)</td>
<td>(72.412)</td>
<td>(78.483)</td>
<td>(46.795)</td>
<td>(36.827)</td>
<td>(25.373)</td>
</tr>
<tr>
<td>N</td>
<td>≈3500</td>
<td>≈3500</td>
<td>≈3500</td>
<td>≈3500</td>
<td>≈3500</td>
<td>≈3500</td>
</tr>
<tr>
<td>First Stage F-Stat</td>
<td>14</td>
<td>30</td>
<td>1.4</td>
<td>3.4</td>
<td>52</td>
<td>42</td>
</tr>
<tr>
<td><strong>Panel D: Pollution Elasticity Parameter</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pollution Elasticity ((\alpha))</td>
<td>0.008**</td>
<td>0.010</td>
<td>0.011</td>
<td>0.017</td>
<td>0.008***</td>
<td>0.011***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.013)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>County-NAICS FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

**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 6 digit NAICS code. The dependent variable in Panel A is the same in each column and represents 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. Nonattain\textsubscript{cp}=1) and whether the industry is a polluting industry (i.e. Polluter\textsubscript{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 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 pollution intensity regressed on 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. Source: ASM, NEI, PACE.
### Table 2: Parameter Estimates

<table>
<thead>
<tr>
<th>Industry</th>
<th>Tons Pollution Per Dollar Costs</th>
<th>Pollution Elasticity ($\alpha$)</th>
<th>Input Share</th>
<th>Elasticity of Substitution ($\sigma$)</th>
<th>Pareto Shape Parameter ($\theta$)</th>
<th>Shape Parameter Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food, Beverages, Tobacco</td>
<td>2.52</td>
<td>0.004</td>
<td>0.74</td>
<td>3.79</td>
<td>4.06</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Textiles, Apparel, Fur, Leather</td>
<td>1.70</td>
<td>0.003</td>
<td>0.79</td>
<td>4.87</td>
<td>4.36</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Wood Products</td>
<td>10.83</td>
<td>0.017</td>
<td>0.83</td>
<td>5.94</td>
<td>7.28</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Paper and Publishing</td>
<td>10.63</td>
<td>0.017</td>
<td>0.79</td>
<td>4.80</td>
<td>3.70</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Coke, Refined Petroleum, Fuels</td>
<td>17.50</td>
<td>0.027</td>
<td>0.88</td>
<td>8.18</td>
<td>7.80</td>
<td>(0.68)</td>
</tr>
<tr>
<td>Chemicals</td>
<td>10.72</td>
<td>0.017</td>
<td>0.70</td>
<td>3.28</td>
<td>2.83</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Rubber and Plastics</td>
<td>2.98</td>
<td>0.005</td>
<td>0.78</td>
<td>4.59</td>
<td>4.59</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Other Non-metallic Minerals</td>
<td>19.73</td>
<td>0.031</td>
<td>0.73</td>
<td>3.66</td>
<td>3.00</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Basic Metals</td>
<td>30.36</td>
<td>0.048</td>
<td>0.85</td>
<td>6.66</td>
<td>6.28</td>
<td>(0.23)</td>
</tr>
<tr>
<td>Fabricated Metals</td>
<td>1.28</td>
<td>0.002</td>
<td>0.79</td>
<td>4.77</td>
<td>5.19</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Machinery and Equipment</td>
<td>1.49</td>
<td>0.002</td>
<td>0.76</td>
<td>4.25</td>
<td>3.51</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Office, Computing, Electrical</td>
<td>2.42</td>
<td>0.004</td>
<td>0.81</td>
<td>5.24</td>
<td>4.09</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Radio, Television, Communication</td>
<td>0.51</td>
<td>0.001</td>
<td>0.79</td>
<td>4.66</td>
<td>3.51</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Medical, Precision, and Optical</td>
<td>1.82</td>
<td>0.003</td>
<td>0.65</td>
<td>2.89</td>
<td>1.96</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Motor Vehicles, Trailers</td>
<td>0.94</td>
<td>0.001</td>
<td>0.82</td>
<td>5.62</td>
<td>4.56</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Other Transport Equipment</td>
<td>1.19</td>
<td>0.002</td>
<td>0.74</td>
<td>3.88</td>
<td>2.84</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Furniture, Other, Recycling</td>
<td>2.51</td>
<td>0.004</td>
<td>0.73</td>
<td>3.77</td>
<td>4.07</td>
<td>(0.04)</td>
</tr>
<tr>
<td><strong>Mean Across Industries</strong></td>
<td><strong>7.01</strong></td>
<td><strong>0.011</strong></td>
<td><strong>0.77</strong></td>
<td><strong>4.76</strong></td>
<td><strong>4.33</strong></td>
<td><strong>(0.11)</strong></td>
</tr>
</tbody>
</table>

*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 industry, where pollution data comes from the NEI and data on input costs come from the ASM. Column 2 presents the industry 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 which is defined as the ratio of costs to revenues using data from the ASM. Both revenues and input expenditures have been deflated by the industry-specific price output and input price deflators, respectively. Column 4 displays the industry-specific elasticity of substitution, which is calculated from equation (13). Columns 5 and 6 present regression estimates and standard errors for the pareto shape parameter, derived from equation 14. The actual parameter is a non-linear transformation of the regression coefficient, where the reported standard errors are calculated using the delta method, clustering by four digit NAICS.
Appendix A  Figures and Tables
Figure A1: Historic Values of Shocks, 1990-2008.

(a) Foreign Competitiveness

(b) U.S. Competitiveness

(c) Foreign Preferences

(d) U.S. Preferences

(e) U.S. Environmental Regulation

Notes: This figure plots the time path of shocks that we recover from the model outlined in Section 3 and derived using equations (15)-(18). 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 graphically by plotting the unweighted mean for the indicated country-year. In subfigures (c) and (d) we plot the unweighted mean separately for both dirty industries or clean industries.
Figure A2: Historic Values of Endogenous Variables, 1990-2008.

(a) Foreign Wages

(b) U.S. Wages

(c) Foreign Firm Entry

(d) U.S. Firm Entry

Notes: This figure plots the time path of endogenous variables that we recover from the model outlined in Section 3. The model delivers the value of firm entry changes for each of the 17 industries in our sample in each year. Here, we summarize the results graphically by plotting the unweighted mean for the indicated country-year. In subfigures (c) and (d) we plot the unweighted mean separately for both dirty industries or clean industries.
Figure A3: Counterfactual U.S. Manufacturing Pollution Under Different Economic Environments

(a) Shocks to Competitiveness of Clean and Dirty Foreign Industries
(b) Shocks to Competitiveness of Clean and Dirty U.S. Industries
(c) Shocks to U.S. Environmental Regulation

Notes: This figure plots 32 separate counterfactual exercises for each line of each subfigure. Each figure considers a counterfactual where the indicated shocks take on a value ranging from 0.25 to 8 times baseline levels (in 0.25 increments). For each counterfactual, we measure the resulting change in NO\textsubscript{x} pollution, which is indicated on the y-axis, with the baseline value normalized to 100. The x-axis describes the counterfactual change in the indicated shock as a proportion of the baseline value. The scenario for each explanatory factors, or “shock”, is indicated in the subfigure headings. Subfigures (a) and (b) conduct the counterfactual exercises separately for “clean” and “dirty” industries, as described in the text. All other explanatory factors are constrained to take their base year, 1990, values.
Figure A4: NO\textsubscript{x} Inferred Pollution Tax, by NO\textsubscript{x} Budget Trading Program Status

Notes: This figure presents the model inferred pollution tax for NO\textsubscript{x} over time, separately for both industries affected by the NO\textsubscript{x} Budget Trading Program and those industries less affected. Within the manufacturing industry, The NO\textsubscript{x} Budget Trading Program primarily affected four of the industries described in Table A1: Paper and Publishing; Coke, Refined Petroleum, and Nuclear Fuel; Other Non-Metallic Minerals; and Basic Metals. The graph plots the unweighted mean across industries of the recovered pollution tax for NO\textsubscript{x}, for these industries versus for all other manufacturing industries. The black vertical line depicts the year when the NBP began operating. We recover shocks from the model outlined in Section 3, and our measure of pollution taxes is derived directly from equation (16).
Figure A5: Characteristics of Fuels for Manufacturing, 1993-2008

(a) Share of Heat Input from Each Fuel

(b) Potential SO$_2$ Emissions per BTU, by Fuel

Notes: This figure plots the time path of fuel use of different fuels in the U.S. Manufacturing industry from 1993-2008. Subfigure (a) plots BTUs of heat input from each fuel divided by total BTUs of fuel, all as used in U.S. manufacturing. The category “Other” includes electricity, steam, and anything else. Subfigure (b) describes pollution emissions that would be released in the absence of abatement technology per BTU, by fuel type. These emissions evolve over time due to changes in the sulfur content of coal and petroleum and to the physical tons of fuel per BTU. Source: EIA, MECS.
Figure A6: Potential Pollution Per BTU from Fossil Fuel Combustion, All Manufacturing, 1993-2008

Notes: This figure plots the time path of potential pollution per BTU in manufacturing given the mix of fossil fuels used in manufacturing in each year. The lines represent the evolution of pollution emissions for the indicated pollutant in the absence of end-of-pipe abatement. Values for the year 1990 are normalized to 100. Source: EIA, MECS.
Table A1: Industry Definitions

<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
<th>ISIC Rev. 3 Codes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Food, beverages, tobacco</td>
<td>15-16</td>
</tr>
<tr>
<td>2</td>
<td>Textiles, apparel, fur, leather</td>
<td>17-19</td>
</tr>
<tr>
<td>3</td>
<td>Wood products</td>
<td>20</td>
</tr>
<tr>
<td>4</td>
<td>Paper and publishing</td>
<td>21-22</td>
</tr>
<tr>
<td>5</td>
<td>Coke, refined petroleum, nuclear fuel</td>
<td>23</td>
</tr>
<tr>
<td>6</td>
<td>Chemicals</td>
<td>24</td>
</tr>
<tr>
<td>7</td>
<td>Rubber and plastics</td>
<td>25</td>
</tr>
<tr>
<td>8</td>
<td>Other non-metallic minerals</td>
<td>26</td>
</tr>
<tr>
<td>9</td>
<td>Basic metals</td>
<td>27</td>
</tr>
<tr>
<td>10</td>
<td>Fabricated metals</td>
<td>28</td>
</tr>
<tr>
<td>11</td>
<td>Machinery and equipment</td>
<td>29</td>
</tr>
<tr>
<td>12</td>
<td>Office, accounting, computing, and electrical machinery</td>
<td>30-31</td>
</tr>
<tr>
<td>13</td>
<td>Radio, television, communication equipment</td>
<td>32</td>
</tr>
<tr>
<td>14</td>
<td>Medical, precision, and optical, watches, clocks</td>
<td>33</td>
</tr>
<tr>
<td>15</td>
<td>Motor vehicles, trailers</td>
<td>34</td>
</tr>
<tr>
<td>16</td>
<td>Other transport equipment</td>
<td>35</td>
</tr>
<tr>
<td>17</td>
<td>Furniture, manufactures n.e.c., recycling</td>
<td>36-37</td>
</tr>
</tbody>
</table>

Notes: This table presents the industry definitions used in the analysis and their corresponding two-digit International Standard Industrial Classification, third revision (ISIC Rev. 3) codes.
Table A2: Estimates of Pollution Elasticity, by Pollutant

<table>
<thead>
<tr>
<th>Industry</th>
<th>Total (Main Estimates)</th>
<th>CO</th>
<th>NO₂</th>
<th>PM₁₀</th>
<th>PM₂,₅</th>
<th>SO₂</th>
<th>VOCs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food, Beverages, Tobacco</td>
<td>0.0040</td>
<td>0.0017</td>
<td>0.0052</td>
<td>0.0060</td>
<td>0.0065</td>
<td>0.0046</td>
<td>0.0055</td>
</tr>
<tr>
<td>Textiles, Apparel, Fur, Leather</td>
<td>0.0027</td>
<td>0.0006</td>
<td>0.0029</td>
<td>0.0018</td>
<td>0.0021</td>
<td>0.0030</td>
<td>0.0081</td>
</tr>
<tr>
<td>Wood Products</td>
<td>0.0170</td>
<td>0.0238</td>
<td>0.0106</td>
<td>0.0184</td>
<td>0.0254</td>
<td>0.0086</td>
<td>0.0158</td>
</tr>
<tr>
<td>Paper and Publishing</td>
<td>0.0167</td>
<td>0.0152</td>
<td>0.0212</td>
<td>0.0125</td>
<td>0.0175</td>
<td>0.0209</td>
<td>0.0115</td>
</tr>
<tr>
<td>Coke, Refined Petroleum, Fuels</td>
<td>0.0275</td>
<td>0.0297</td>
<td>0.0269</td>
<td>0.0077</td>
<td>0.0105</td>
<td>0.0368</td>
<td>0.0244</td>
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<tr>
<td>Chemicals</td>
<td>0.0168</td>
<td>0.0172</td>
<td>0.0235</td>
<td>0.0067</td>
<td>0.0076</td>
<td>0.0132</td>
<td>0.0253</td>
</tr>
<tr>
<td>Rubber and Plastics</td>
<td>0.0047</td>
<td>0.0010</td>
<td>0.0040</td>
<td>0.0022</td>
<td>0.0027</td>
<td>0.0039</td>
<td>0.0186</td>
</tr>
<tr>
<td>Other Non-metallic Minerals</td>
<td>0.0310</td>
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<td>0.0536</td>
<td>0.0994</td>
<td>0.0724</td>
<td>0.0375</td>
<td>0.0091</td>
</tr>
<tr>
<td>Basic Metals</td>
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<td>0.0831</td>
<td>0.0191</td>
<td>0.0206</td>
<td>0.0272</td>
<td>0.0417</td>
<td>0.0155</td>
</tr>
<tr>
<td>Fabricated Metals</td>
<td>0.0020</td>
<td>0.0004</td>
<td>0.0016</td>
<td>0.0009</td>
<td>0.0011</td>
<td>0.0013</td>
<td>0.0089</td>
</tr>
<tr>
<td>Machinery and Equipment</td>
<td>0.0023</td>
<td>0.0019</td>
<td>0.0020</td>
<td>0.0019</td>
<td>0.0024</td>
<td>0.0015</td>
<td>0.0054</td>
</tr>
<tr>
<td>Office, Computing, Electrical</td>
<td>0.0038</td>
<td>0.0052</td>
<td>0.0018</td>
<td>0.0017</td>
<td>0.0021</td>
<td>0.0040</td>
<td>0.0034</td>
</tr>
<tr>
<td>Radio, Television, Communication</td>
<td>0.0008</td>
<td>0.0006</td>
<td>0.0006</td>
<td>0.0003</td>
<td>0.0003</td>
<td>0.0008</td>
<td>0.0021</td>
</tr>
<tr>
<td>Medical, Precision, and Optical</td>
<td>0.0029</td>
<td>0.0002</td>
<td>0.0081</td>
<td>0.0028</td>
<td>0.0044</td>
<td>0.0023</td>
<td>0.0052</td>
</tr>
<tr>
<td>Motor Vehicles, Trailers</td>
<td>0.0015</td>
<td>0.0004</td>
<td>0.0011</td>
<td>0.0004</td>
<td>0.0004</td>
<td>0.0012</td>
<td>0.0062</td>
</tr>
<tr>
<td>Other Transport Equipment</td>
<td>0.0019</td>
<td>0.0003</td>
<td>0.0020</td>
<td>0.0012</td>
<td>0.0012</td>
<td>0.0019</td>
<td>0.0064</td>
</tr>
<tr>
<td>Furniture, Other, Recycling</td>
<td>0.0039</td>
<td>0.0005</td>
<td>0.0027</td>
<td>0.0024</td>
<td>0.0030</td>
<td>0.0037</td>
<td>0.0157</td>
</tr>
</tbody>
</table>

Notes: This table presents estimates of the pollution elasticity for each industry and pollutant. Column (1) corresponds to column (2) of Table 2 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) of Table 2. Columns (2)-(7) scale the economy-wide value of 0.011 according to the tons of each pollutant emitted per dollar of cost inputs.
Table A3: Share of Manufacturing Regulated by the NO\textsubscript{x} Budget Trading Program (NBP)

<table>
<thead>
<tr>
<th>Industry</th>
<th>NO\textsubscript{x} Emissions (Tons)</th>
<th>Number of Plants</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NBP (1)</td>
<td>NBP (4)</td>
</tr>
<tr>
<td></td>
<td>Non-NBP (2)</td>
<td>Non-NBP (5)</td>
</tr>
<tr>
<td></td>
<td>Share in NBP (3)</td>
<td>Share in NBP (6)</td>
</tr>
<tr>
<td>All Manufacturing</td>
<td>163,099</td>
<td>267</td>
</tr>
<tr>
<td></td>
<td>1,091,048</td>
<td>79,016</td>
</tr>
<tr>
<td>Food, Beverages, Tobacco</td>
<td>3,901</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>79,824</td>
<td>3,446</td>
</tr>
<tr>
<td>Textiles, Apparel, Fur, Leather</td>
<td>1,068</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>12,594</td>
<td>5,704</td>
</tr>
<tr>
<td>Wood Products</td>
<td>2,294</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>39,445</td>
<td>4,039</td>
</tr>
<tr>
<td>Paper and Publishing</td>
<td>62,559</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>193,838</td>
<td>3,903</td>
</tr>
<tr>
<td>Coke, Refined Petroleum, Fuels</td>
<td>41,434</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>143,041</td>
<td>1,345</td>
</tr>
<tr>
<td>Chemicals</td>
<td>15,912</td>
<td>48</td>
</tr>
<tr>
<td></td>
<td>157,352</td>
<td>5,174</td>
</tr>
<tr>
<td>Rubber and Plastics</td>
<td>6,443</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>9,282</td>
<td>4,258</td>
</tr>
<tr>
<td>Other Non-metallic Minerals</td>
<td>9,976</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>324,837</td>
<td>8,177</td>
</tr>
<tr>
<td>Basic Metals</td>
<td>15,371</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>49,278</td>
<td>3,506</td>
</tr>
<tr>
<td>Fabricated Metals</td>
<td>401</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>7,726</td>
<td>8,016</td>
</tr>
<tr>
<td>Machinery and Equipment</td>
<td>517</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>9,749</td>
<td>5,782</td>
</tr>
<tr>
<td>Office, Computing, Electrical</td>
<td>822</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>12,059</td>
<td>5,287</td>
</tr>
<tr>
<td>Radio, Television, Communication</td>
<td>348</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>672</td>
<td>1,471</td>
</tr>
<tr>
<td>Medical, Precision, and Optical</td>
<td>348</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>36,320</td>
<td>3,725</td>
</tr>
<tr>
<td>Motor Vehicles, Trailers</td>
<td>87</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>6,073</td>
<td>3,536</td>
</tr>
<tr>
<td>Other Transport Equipment</td>
<td>465</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>4,449</td>
<td>4,858</td>
</tr>
<tr>
<td>Furniture, Other, Recycling</td>
<td>1,154</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>4,508</td>
<td>6,789</td>
</tr>
</tbody>
</table>

Notes: This table presents descriptive statistics, by industry, pertaining to the fraction of manufacturing emissions and plants subject to the NO\textsubscript{x} budget program. The baseline data come from plants that appear in the NEI in 2005. A plant in NEI is identified as a unique combination of a facility ID and a county. NBP plants are identified by plant-level match between the EPA’s Clean Air Markets Database and the NEI. Columns (1)-(3) calculate the amount of NO\textsubscript{x} emissions and share of NO\textsubscript{x} emissions under the NBP. NO\textsubscript{x} emissions in the table include the annual emissions which NEI reports, and not only the May-September emissions which NBP regulates. Columns (4)-(6) count the number of plants in each respective category. Since some plants report SIC industry codes that map into more than one ISIC code, we count a plant separately for each of the industries to which it is linked.
Table A4: How Does Fuel Mix Contribute to Pollution Declines?

<table>
<thead>
<tr>
<th></th>
<th>CO</th>
<th>NO₂</th>
<th>PM₁₀</th>
<th>SO₂</th>
<th>VOCs</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Decrease in Pollution by Year 2008, as % of 1993 Level</td>
<td>46.90</td>
<td>51.40</td>
<td>60.80</td>
<td>51.60</td>
<td>59.10</td>
<td>53.96</td>
</tr>
<tr>
<td>Implied Decrease in Pollution by Year 2008, as % of 1993 Level</td>
<td>11.20</td>
<td>7.40</td>
<td>7.60</td>
<td>27.00</td>
<td>8.30</td>
<td>12.3</td>
</tr>
<tr>
<td>Implied Decreases Divided by Actual Decrease</td>
<td>0.24</td>
<td>0.14</td>
<td>0.12</td>
<td>0.52</td>
<td>0.14</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Notes: This table presents estimates for the predicted fraction of manufacturing emissions reductions that may be explained by fuel switching. The first row calculates the actual decrease in manufacturing emissions observed in the NEI. The second row uses fuel mix and emission factor data from the EIA and MECS to identify the amount of emissions reductions that could be explained by changes in the type of fuel used in manufacturing. The implied decrease in pollution refers to potential pollution per BTU of fuel input, as defined in equation (20). The last line divides the second row by the first, to try to identify the fraction of the observed emissions reductions between 1993 and 2008 that could be explained by the types of fuels used in manufacturing production.
Appendix B Theory

This appendix presents intermediate results of the model in more detail.

As in most models with constant elasticity of substitution preferences, consumer demand for variety $\omega$ in destination country $d$ is

$$q_{od,s}(\omega) = \frac{(p_{od,s}(\omega))^{-\sigma_s}}{(P_{d,s})^{1-\sigma_s}} E_{d,s}$$

where the price index is

$$P_{d,s} = \left[ \sum_i \int_{\omega \in \Omega_{o,s}} p_{id,s}(\omega)^{\sigma_s-1} \right]^{1/1-\sigma_s}$$

Firms engage in monopolistic competition. They choose prices $p_{od,s}$ and abatement investments $\xi$ to maximize profits. The first-order condition for pollution abatement is

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

This first-order condition shows that more productive firms (higher $\varphi$) invest more in pollution abatement, leading them to emit less pollution. Combining this with the first-order condition for output implies that prices equal a constant markup $\frac{\sigma_s}{\sigma_s - 1}$ over marginal costs:

$$p_{od,s} = \frac{\sigma_s c_{o,s} \tau_{od,s}}{\sigma_s - 1 \varphi^{1 - \gamma \alpha_s}}$$

where

$$c_{o,s} = \frac{(t_{o,s})^{\alpha_s} (w_o)^{1 - \alpha_s}}{(\alpha_s)^{\alpha_s} (1 - \alpha_s)^{1 - \alpha_s}}$$

Two conditions are important to the equilibrium. The zero cutoff profit $\varphi^*_o d, s$ describes the productivity level which makes a firm earn zero profits from exporting to destination $d$, and therefore makes a firm indifferent about whether to export to $d$:

$$\varphi^*_o d, s = \left( \frac{\sigma_s c_{o,s} \tau_{od,s}}{\sigma_s - 1 P_{d,s}} \left( \frac{\sigma_s w_d f_{od,s}}{E_{d,s}} \right)^{\frac{1}{\sigma_s - 1}} \right)^{\frac{1}{1 - \gamma \alpha_s}}$$

The free entry condition requires that in equilibrium, entrepreneurs must earn zero ex ante expected profit from paying the fixed cost $f^e_{o,s}$ to draw a productivity value:

$$f^e_{o,s} = \frac{\theta_s - (\sigma_s - 1) (1 - \alpha_s)}{(\sigma_s - 1) (1 - \alpha_s)} = \sum_d \frac{(b_{o,s})^{\theta_s} w_d f_{od,s}}{(\varphi^*_o d, s)^{\theta_s} w_o f_{od,s}}$$

We now describe several important equations that we obtain using the zero cutoff profit and free entry conditions. The value of bilateral trade can be written as follows:

$$X_{od,s} = \frac{M^c_{o,s} \left( \frac{w_o}{b_{o,s}} \right)^{-\theta_s} \left( \tau_{od,s} \right)^{-\frac{\alpha_s}{1-\alpha_s}} \left( f_{od,s} \right)^{1-\frac{\theta_s}{\sigma_s - 1(1 - \alpha_s)}} \left( t_{o,s} \right)^{-\frac{\alpha_s \theta_s}{1 - \alpha_s}}}{\left( P_{d,s} \right)^{-\frac{\alpha_s}{1 - \alpha_s}}} \left( \frac{E_{d,s}}{w_d} \right)^{\frac{\theta_s}{\sigma_s - 1(1 - \alpha_s)}} (w_d) \chi_s$$
where we have collected parameters into the constant \( \chi_s \equiv \frac{(\sigma_s)\theta_s}{(\sigma_s-1)(1-\alpha_s)} \). The labor market clearing condition can be written as

\[
L_d = \frac{1}{\sum_s \theta_s \sigma_s (\sigma_s - 1)(1-\alpha_s)} \sum_s M^e_{d,s} f^e_{d,s} \left( \theta_s \frac{1 - \alpha_s}{1 - \alpha_s} + 1 \right)
\] (21)

The price index may be written as follows:

\[
(P_{d,s})_{\frac{\theta_s}{1-\alpha_s}} = \sum_o M^e_{o,s} \left( \frac{w_o}{b_o,s} \right)_{\frac{\theta_s}{1-\alpha_s}} (\tau_{ods})_{\frac{\theta_s}{1-\alpha_s}} (f_{ods})_{\frac{\theta_s}{1-\alpha_s}} (t_{o,s})_{\frac{\theta_s}{1-\alpha_s}} \left( \frac{E_{d,s}}{\theta_s} \right)_{\frac{\theta_s}{1-\alpha_s}} X_s
\]

Finally, we can write the two equilibrium conditions in levels. The first equilibrium condition is simply labor market clearing (21). The second equilibrium condition is as follows:

\[
f^e_{o,s} (\sigma_s - 1)(1-\alpha_s) = \sum_d \sum_i (w_i)_{\frac{\theta_s}{1-\alpha_s}} (\theta_i)_{\frac{\theta_s}{1-\alpha_s}} (\tau_{id,s})_{\frac{\theta_s}{1-\alpha_s}} (f_{id,s})_{\frac{\theta_s}{1-\alpha_s}} (t_{i,s})_{\frac{\theta_s}{1-\alpha_s}} \left( \hat{P}_{d,s} \right)_{\frac{\theta_s}{1-\alpha_s}} X_s
\] (22)

To analyze counterfactuals, we use the following expression for the change in expenditure shares (7):

\[
\hat{\lambda}_{ods} = \frac{\hat{M}^e_{o,s} \frac{\hat{w}_o}{\hat{b}_o,s} \frac{\theta_s}{1-\alpha_s} (\hat{\tau}_{ods})_{\frac{\theta_s}{1-\alpha_s}} (\hat{f}_{ods})_{\frac{\theta_s}{1-\alpha_s}} (\hat{t}_{o,s})_{\frac{\theta_s}{1-\alpha_s}} \left( \hat{P}_{d,s}^{\theta_s} \right)_{\frac{\theta_s}{1-\alpha_s}}}{\frac{\theta_s}{1-\alpha_s}}
\] (23)

where the change in the price of index for a sector is given by

\[
\hat{P}_{o,s} = \left( \frac{\theta_s}{1-\alpha_s} \right)^{-1} \sum_o \lambda_{ods} \hat{M}^e_{o,s} \left( \frac{\hat{w}_o}{\hat{b}_o,s} \right)_{\frac{\theta_s}{1-\alpha_s}} (\hat{\tau}_{ods})_{\frac{\theta_s}{1-\alpha_s}} (\hat{f}_{ods})_{\frac{\theta_s}{1-\alpha_s}} (\hat{t}_{o,s})_{\frac{\theta_s}{1-\alpha_s}} \left( \frac{\theta_s}{1-\alpha_s} \right)^{-1}
\]
Appendix C  Data

Appendix C.1  Dataset Overview
[To be filled in]

Annual Survey of Manufactures
Pollution Abatement Costs and Expenditure Survey
Manufacturing and Energy Consumption Survey
NBER-CES Manufacturing Industry Database
EPA Clean Air Markets Database
National Emissions Inventory
World Bank IPSS
EPA Nonattainment Greenbook
OECD Structural Analysis Database
OECD Statistics Database
World Development Indicators data