Why is Pollution from U.S. Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade: Online Appendix

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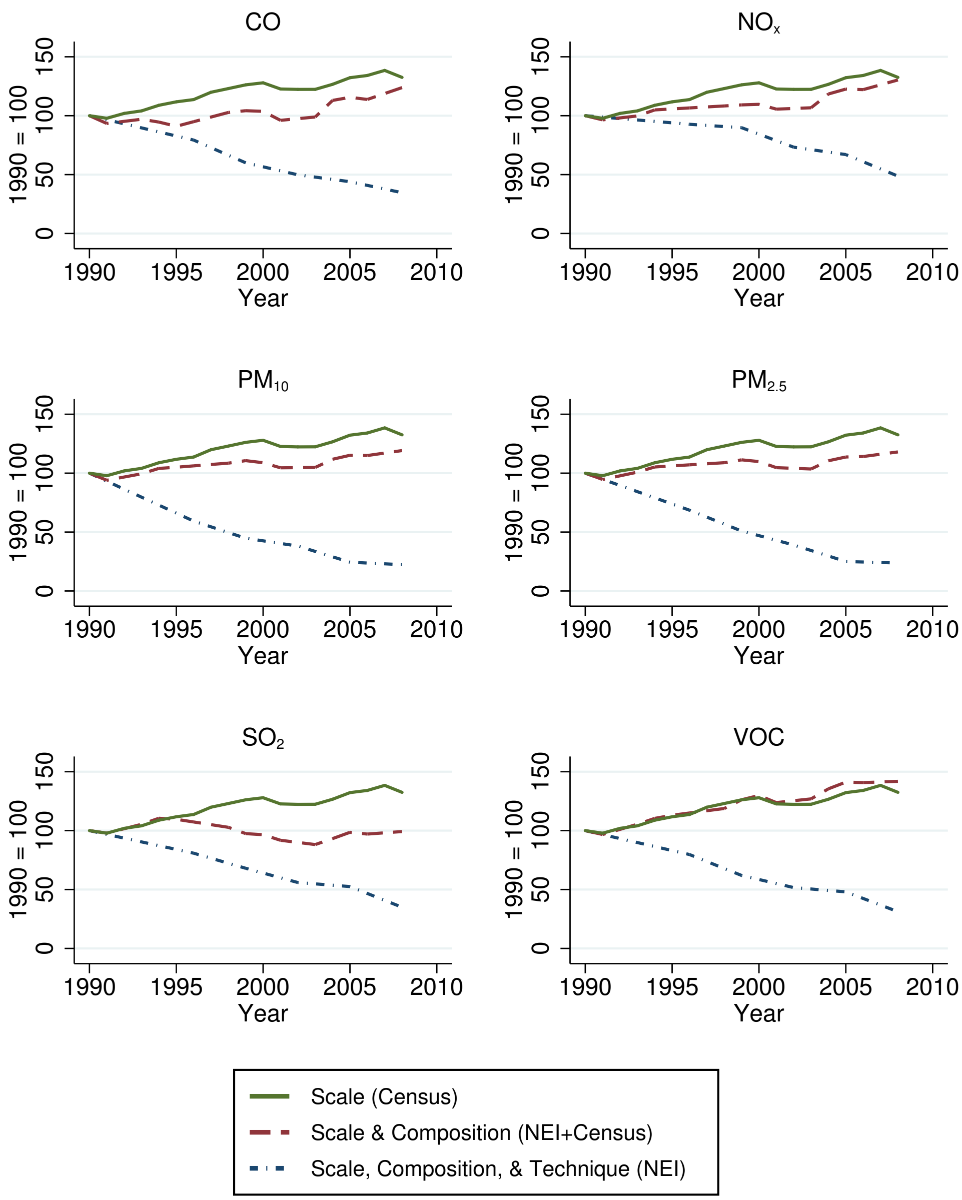
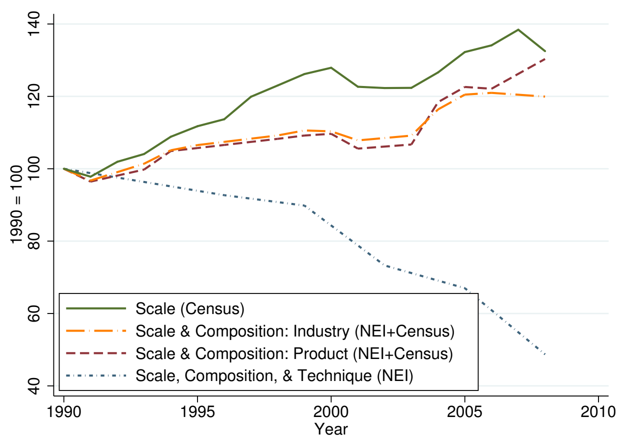
Figure 1: Emissions Statistical Decomposition From United States Manufacturing



NOTES: This figure plots the observed and counterfactual trends in emissions for 6 separate pollutants based on the statistical decomposition from equation (2). The solid line of each panel 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 dashed 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 dashed-dotted 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, ASM, and NEI.

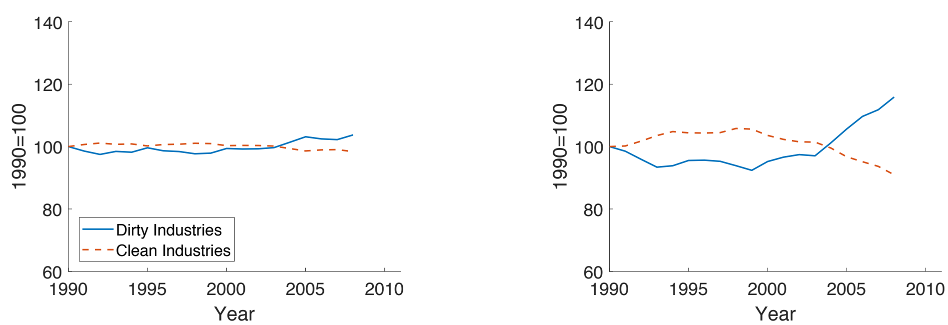
Figure 2: Comparing Product-Level and Industry-Level Statistical Emissions Decompositions



NOTES: This figure plots observed and counterfactual trends in NO_x emissions based on the statistical decomposition from equation (2). The top, solid line plots the counterfactual emissions with the same composition of goods and techniques as in 1990. The middle two dashed lines represent emissions with the same emissions per unit of output as in 1990, using either the industry level emissions factors or the product level emissions factors. 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, ASM, and NEI.

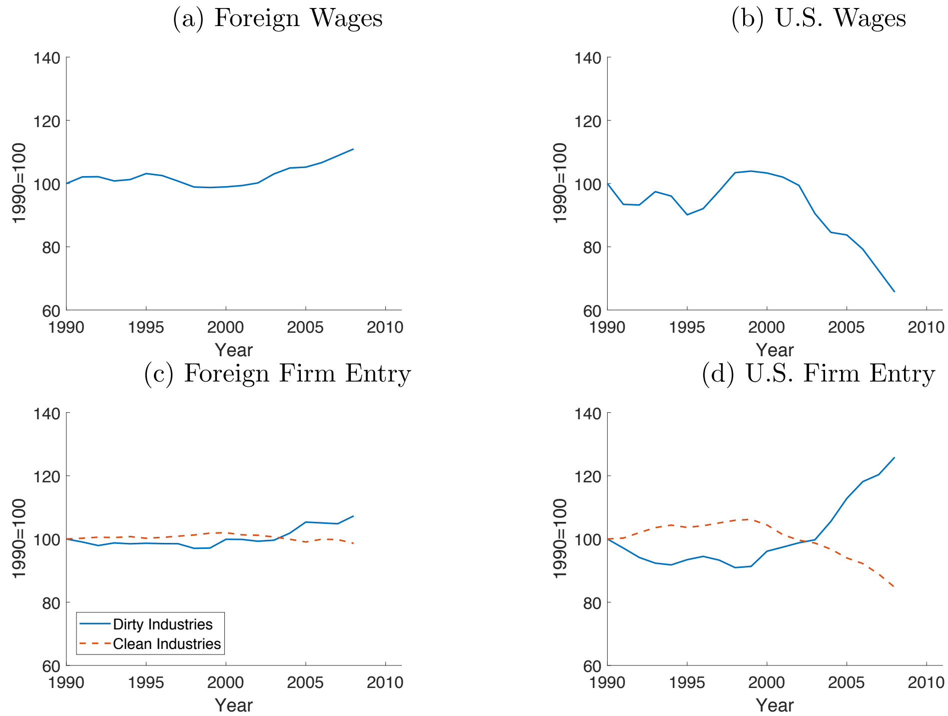
Figure 3: Historic Values of Preference Shocks, 1990-2008

(a) Foreign Expenditure Shares (b) U.S. Expenditure Shares



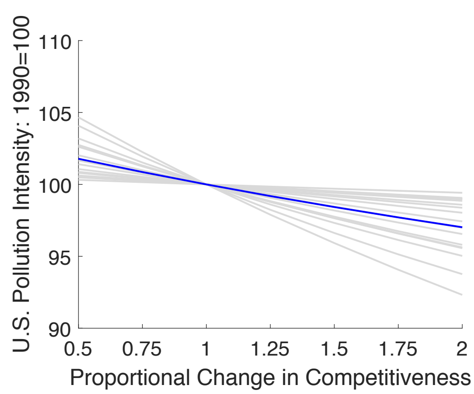
NOTES: This figure plots the time path of shocks to expenditure shares that we recover from the model outlined in Section II and derived using equation (22). The model delivers the value of the indicated shock for each of the 17 industries in our sample in each year. Here, we summarize the results graphically by plotting the unweighted mean separately for both dirty industries (solid line) and clean industries (dotted line). As described in the main text, dirty industries are defined as those with a value of the pollution elasticity α_s above the economy-wide mean of 0.011, and clean industries are defined as those with a value of this pollution elasticity below 0.011.

Figure 4: Historic Values of Endogenous Variables, 1990-2008.



Notes: This figure plots the time path of endogenous variables that we recover from the model outlined in Section II. 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. As described in the main text, dirty industries are defined as those with a value of the pollution elasticity α_s above the economy-wide mean of 0.011, and clean industries are defined as those with a value of this pollution elasticity below 0.011.

Figure 5: Counterfactual Pollution Intensity Under Arbitrary Shocks to Foreign Competitiveness, by Sector



Notes: This figure plots 6 separate counterfactual exercises for each sector. In each counterfactual, foreign competitiveness takes on a value ranging from 0.50 to 2 times baseline levels, in 0.25 increments. For each counterfactual, we measure the resulting change in NO_x pollution intensity, which is indicated on the y-axis, with the baseline value normalized to 100. Pollution intensity is defined as pollution emissions per real unit output. Each grey line describes pollution intensity for a single sector, and the blue line shows the cross-sector mean.

Table 1: Statistical Decomposition - 2008 Values

	CO (1)	NO_x (2)	PM10 (3)	PM2.5 (4)	SO_2 (5)	VOC (6)
	Panel A: Baseline Values					
Scale (Census)	1.32	1.32	1.32	1.32	1.32	1.32
Scale & Composition (NEI+Census)	1.24	1.30	1.19	1.18	0.99	1.42
Scale, Composition, & Technique (NEI)	0.34	0.49	0.22	0.24	0.35	0.31
	Panel B: Single-Product Plants					
Scale (Census)	1.32	1.32	1.32	1.32	1.32	1.32
Scale & Composition (NEI+Census)	0.93	1.08	0.95	0.89	1.09	1.19
Scale, Composition, & Technique (NEI)	0.34	0.49	0.22	0.24	0.35	0.31
	Panel C: Uniform Apportionment					
Scale (Census)	1.32	1.32	1.32	1.32	1.32	1.32
Scale & Composition (NEI+Census)	1.33	1.40	1.27	1.25	1.06	1.46
Scale, Composition, & Technique (NEI)	0.34	0.49	0.22	0.24	0.35	0.31

NOTES: This table displays the observed and counterfactual 2008 levels of emissions for 6 separate pollutants, relative to their 1990 values. The full counterfactual trend lines are plotted in Appendix Figure 1. The counterfactuals stem from the statistical decomposition embodied in equation (2). "Scale" refers to 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. "Scale & Composition" refer to 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. "Scale, Composition, & Technique" refers to 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, ASM, and NEI.

Table 2: Sector Definitions

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

NOTES: This table presents the sector definitions used in the analysis and their corresponding two-digit International Standard Industrial Classification, third revision (ISIC Rev. 3) codes.

Table 3: Estimates of Pollution Elasticity, by Pollutant

Sector	Total (Main Estimates) (1)	CO (2)	NO_x (3)	PM_{10} (4)	$PM_{2.5}$ (5)	SO_2 (6)	VOCs (7)
Food, Beverages, Tobacco	0.0040	0.0016	0.0054	0.0057	0.0061	0.0047	0.0054
Textiles, Apparel, Fur, Leather	0.0022	0.0004	0.0024	0.0013	0.0013	0.0028	0.0064
Wood Products	0.0103	0.0101	0.0089	0.0183	0.0252	0.0030	0.0142
Paper and Publishing	0.0223	0.0204	0.0275	0.0161	0.0222	0.0275	0.0172
Coke, Refined Petroleum, Fuels	0.0212	0.0151	0.0248	0.0066	0.0089	0.0354	0.0224
Chemicals	0.0205	0.0243	0.0241	0.0081	0.0089	0.0159	0.0265
Rubber and Plastics	0.0048	0.0008	0.0038	0.0021	0.0023	0.0042	0.0191
Other Non-metallic Minerals	0.0303	0.0048	0.0539	0.0972	0.0713	0.0363	0.0064
Basic Metals	0.0557	0.1033	0.0218	0.0227	0.0295	0.0450	0.0159
Fabricated Metals	0.0019	0.0003	0.0016	0.0007	0.0009	0.0011	0.0085
Machinery and Equipment	0.0015	0.0010	0.0014	0.0011	0.0015	0.0014	0.0034
Office, Computing, Electrical	0.0023	0.0031	0.0011	0.0010	0.0013	0.0022	0.0028
Radio, Television, Communication	0.0005	0.0003	0.0005	0.0002	0.0002	0.0004	0.0014
Medical, Precision, and Optical	0.0014	0.0001	0.0039	0.0014	0.0021	0.0013	0.0025
Motor Vehicles, Trailers	0.0016	0.0004	0.0010	0.0003	0.0004	0.0011	0.0068
Other Transport Equipment	0.0019	0.0003	0.0025	0.0015	0.0013	0.0018	0.0060
Furniture, Other, Recycling	0.0047	0.0005	0.0024	0.0027	0.0037	0.0027	0.0219

Notes: This table presents estimates of the pollution elasticity for each sector and pollutant. Column (1) corresponds to column (2) of Table 2 that 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 4: Relationship Between Implied Manufacturing Pollution Tax and NO_x Budget Program

	(1)	(2)	(3)	(4)
$1[\text{NBP}_r] \times 1[\text{NBPRegulated}_s] \times 1[\text{Year}_t > 2002]$	1.195	1.195	1.186	1.186
	(0.422)	(0.424)	(0.404)	(0.405)
N	1583	1583	1583	1583
Industry×region FE	X	X	X	X
Industry×year FE		X		X
Region×year FE			X	X

NOTES: This table reports regression coefficients from 4 separate versions of equation (24), one per column. The dependent variable in all regressions is the model-driven measure of pollution taxes for a region×industry×year. All specifications control for the lower order interaction terms that ensure identification of the difference-in-difference-in-differences regression equation presented above. Standard errors are clustered by industry×region and are in parentheses.

B Theory

This appendix derives results of the model in more detail. We begin by summarizing the main notation.

o: origin country
d: destination country
s: sector
L_o: factor supply
w_o: nominal wage
$f_{od,s}$: fixed cost for firm from country o to sell in country d
$l_{od,s}$: labor used to produce $q_{od,s}$, some of which is used for pollution abatement
$p_{od,s}$: price of goods shipped $o \to d$
$q_{od,s}$: quantity of goods shipped $o \to d$
$r_{od,s}$: revenue from goods shipped $o \to d$
$z_{od,s}$: units of pollution emitted to produce $q_{od,s}$
$X_{od,s}$: Total national value of exports from $o \to d$
$b_{o,s}$: location parameter of Pareto distribution (i.e., country-sector productivity)
$c_{o,s}$: variable cost of production
$f^e_{o,s}$: fixed cost for firm to make a productivity draw
$t_{o,s}$: tax imposed on each unit of pollution z
$E_{o,s}$: national expenditure on sector s
$R_{o,s}$: national revenue from sector s
$M^e_{o,s}$: attempted entrants
$M_{o,s}$: successful entrants
$NX_{o,s}$: net exports (exports minus imports)
$P_{o,s}$: price index
$Z_{o,s}$: national pollution emissions
e: emissions rate, i.e., tons pollution per unit output, $\equiv$ z/q
φ: productivity draw (output per unit labor)
ω: indexes varieties
a: a firm's abatement expenditure (share of factors for abatement, not production)
$G(\cdot), g(\cdot)$: Productivity distribution and density
α_s: pollution elasticity
σ_s: elasticity of substitution
θ_s: shape parameter of Pareto productivity distribution
$\beta_{d,s}$: Cobb-Douglas expenditure share
$\varphi^*_{od,s}$: productivity which makes a firm earn zero profits from exporting to d
$\pi_{od,s}$: profit from o to d trade for a firm in sector s
$\tau_{od,s}$: iceberg trade cost
$\lambda_{od,s}$: share of country d's expenditure in sector s going to country o

II.A Intermediate Results Used to Derive Expressions from the Main Text

This subsection describes several intermediate steps that will be used below to derive results shown in the main text. Several parts of this subsection mirror more standard models of heterogeneous firms with monopolistic competition except they incorporate pollution taxes and abatement.

Consumers

Solving the representative agent's utility-maximization problem for the optimal quantity $q_{od,s}$ gives the following consumer demand for variety ω in destination country d:

$$q_{od,s}(\omega) = \frac{(p_{od,s}(\omega))^{-\sigma_s}}{(P_{d,s})^{1-\sigma_s}} E_{d,s} \tag{25}$$

where the price index (the cost of one unit of utility) is

$$P_{d,s} = \left[\sum_o \int_{\omega \in \Omega_{o,s}} p_{od,s}(\omega)^{1-\sigma_s} \right]^{\frac{1}{1-\sigma_s}} \tag{26}$$

Firms

Firms engage in monopolistic competition. They choose prices $p_{od,s}$ and abatement investments a to maximize profits. Recall from main text equation (10) that the firm's first-order condition for pollution abatement is

$$1 - a = \left(\frac{w_o}{\varphi t_{o,s}} \frac{\alpha_s}{1-\alpha_s} \right)^{\alpha_s} \tag{27}$$

Combining this with the first-order condition for prices implies that prices equal a constant markup over marginal costs:

$$p_{od,s}(\varphi) = \frac{\sigma_s}{\sigma_s - 1} \frac{c_{o,s}\tau_{od,s}}{\varphi^{1-\alpha_s}} \tag{28}$$

where

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

In some of the following results, a simpler expression for firm profits is useful:

$$\pi_{od,s}(\varphi) = \frac{r_{od,s}(\varphi)}{\sigma_s} - w_d f_{od,s}. \tag{29}$$

where a firm's revenues are $r_{od,s}(\varphi) \equiv p_{od,s}(\varphi) q_{od,s}(\varphi)$ This expression can be derived from the firm's profit function by substituting in abatement (27) and prices (28) then simplifying. Finally, several derivations below use the following part of Assumption 2 from Section II.A of the main text, restated here for convenience:

$$l_{od,s}(\varphi) = \frac{q_{od,s}(\varphi)}{\varphi(1 - a(\varphi))} \tag{30}$$

Productivity Distribution

The Pareto productivity distribution from equation (5) of the main text is restated here for convenience:

$$G(\varphi; b_{o,s}) = 1 - \frac{(b_{o,s})^{\theta_s}}{\varphi^{\theta_s}} \tag{31}$$

Several results below use the conditional density, which in general is $g(\varphi|\varphi > \varphi^*_{od,s}) = g(\varphi)/(1 - G[\varphi^*_{od,s}])$, where $g(\varphi)$ is the unconditional density. For the Pareto distribution, the conditional density is

$$g(\varphi|\varphi > \varphi^*_{od,s}) = \theta_s \frac{(\varphi^*_{od,s})^{\theta_s}}{\varphi^{\theta_s+1}} \tag{32}$$

Cutoff Productivity

Let $\varphi^*_{od,s}$ describe the productivity level which makes a firm earn zero profits from exporting to destination d, and therefore which makes a firm indifferent about whether to export to d. In other words, if $\pi_{od,s}(\varphi)$ is the profit that a firm with productivity φ in origin country o and sector s earns from exporting to destination country d, then this cutoff is implicitly given by $\pi_{od,s}(\varphi^*_{od,s}) = 0$. Combining consumer demand (25) with firm profits (29) lets us write the cutoff implicitly as

$$w_d f_{od,s} = \frac{1}{\sigma_s} \frac{p_{od,s}(\varphi^*_{od,s})^{1-\sigma_s}}{P_{d,s}^{(1-\sigma_s)}} E_{d,s}$$

Substituting in prices (28) then solving for $\varphi^*_{od,s}$ gives

$$\varphi^*_{od,s} = \left(\frac{\sigma_s}{\sigma_s - 1} \frac{c_{o,s}\tau_{od,s}}{P_{d,s}} \left(\frac{\sigma_s w_d f_{od,s}}{E_{d,s}} \right)^{\frac{1}{\sigma_s - 1}} \right)^{\frac{1}{1-\alpha_s}} \tag{33}$$

Free Entry

In equilibrium, the fixed cost of drawing a productivity must equal an entrepreneur's expected profit from drawing a productivity:

$$w_o f^e_{o,s} = (1 - G[\varphi^*_{oo,s}])\mathbb{E}[\pi|\varphi > \varphi^*_{oo,s}]$$

Here $\varphi^*_{oo,s}$ is the productivity level which makes a firm earn zero profits from producing domestically. Substituting in prices (28), profits (29), the Pareto conditional density (32), and the cutoff productivity (33) gives

$$f^e_{o,s} \frac{\theta_s - (\sigma_s - 1)(1 - \alpha_s)}{(\sigma_s - 1)(1 - \alpha_s)} = \sum_d \frac{(b_{o,s})^{\theta_s}}{(\varphi^*_{od,s})^{\theta_s}} \frac{w_d}{w_o} f_{od,s} \tag{34}$$

This concludes our explanation of intermediate steps, and we now combine several of these results to derive equations highlighted in the main text.

II.B Deriving Equation (26), the Sector-Specific Price Index

We obtain the price index for a country and sector by rewriting the price index (26) as

$$P_{d,s}^{(1-\sigma_s)} = \sum_o \int_0^{M_{od,s}} p_{od,s}(v)^{1-\sigma_s} dv$$

where $M_{od,s}$ is the mass of firms exporting. Substituting in prices (28), the Pareto conditional density (32), and the productivity cutoff (33) lets us rewrite this price index as

$$(P_{d,s})^{-\frac{\theta_s}{1-\alpha_s}} = \sum_o M^e_{o,s} \left(\frac{w_o}{b_{o,s}}\right)^{-\theta_s} (\tau_{od,s})^{-\frac{\theta_s}{1-\alpha_s}} (f_{od,s})^{1-\frac{\theta_s}{(1-\alpha_s)(\sigma_s-1)}} (t_{o,s})^{-\frac{\alpha_s\theta_s}{1-\alpha_s}} \left(\frac{E_{d,s}}{w_d}\right)^{\frac{\theta_s}{(1-\alpha_s)(\sigma_s-1)}-1} \chi_s \quad (35)$$

where $M^e_{o,s}$ is the mass of entrepreneurs drawing a productivity, $E_{d,s}$ is total expenditure, and χ_s is a constant.[1]

II.C Deriving Bilateral Expenditure Shares

The value of bilateral trade equals the proportion of firms exporting, times the mass of firms operating, times exports per exporter:

$$\begin{aligned} X_{od,s} &= \frac{Pr(\varphi > \varphi^*_{od,s})}{Pr(\varphi > \varphi^*_{oo,s})} M_{o,s} \mathbb{E}[r_{od,s} | \varphi > \varphi^*_{od,s}] \\ &= \frac{M^e_{o,s} (w_o/b_{o,s})^{-\theta_s} (\tau_{od,s})^{-\frac{\theta_s}{1-\alpha_s}} (f_{od,s})^{1-\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)}} (t_{o,s})^{-\frac{\alpha_s\theta_s}{1-\alpha_s}}}{(P_{d,s})^{-\frac{\theta_s}{1-\alpha_s}}} \left(\frac{E_{d,s}}{w_d}\right)^{\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)}} (w_d)\, \chi_s \quad (36) \end{aligned}$$

The second equality follows from using demand (25), prices (28), the Pareto distribution (31), free entry (34), and the cutoff productivity (33). Here $E_{d,s}$ denotes the expenditure of country d on goods from sector s, and we have collected parameters into the constant χ_s. This constant has the same value as in equation (35). We can then write $\lambda_{od,s}$, the share of country d's expenditure on sector s that is purchased from country o, as

$$\lambda_{od,s} = \frac{M^e_{o,s} (w_o/b_{o,s})^{-\theta_s} (t_{o,s})^{-\frac{\alpha_s\theta_s}{1-\alpha_s}} (\tau_{od,s})^{-\frac{\theta_s}{1-\alpha_s}} (f_{od,s})^{1-\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)}}}{\sum_i M_{i,s} (w_i/b_{i,s})^{-\theta_s} (t_{o,s})^{-\frac{\alpha_s\theta_s}{1-\alpha_s}} (\tau_{id,s})^{-\frac{\theta_s}{1-\alpha_s}} (f_{id,s})^{1-\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)}}} \quad (37)$$

II.D Deriving Equation (11), the Second Equilibrium Condition

To derive the second equilibrium condition in equation (11), we substitute in the cutoff productivity (33), the free entry condition (34), and the price index (35). This gives the following version of the second equilibrium condition:

$$f^e_{o,s} \frac{\sigma_s\theta_s}{(\sigma_s-1)(1-\alpha_s)} = \sum_d \frac{(w_o)^{-1} (w_o/b_{o,s})^{-\theta_s} (\tau_{od,s})^{-\frac{\theta_s}{1-\alpha_s}} (f_{od,s})^{1-\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)}} (t_{o,s})^{-\frac{\alpha_s\theta_s}{1-\alpha_s}}}{\sum_i M^e_{i,s} (w_i/b_{i,s})^{-\theta_s} (\tau_{id,s})^{-\frac{\theta_s}{1-\alpha_s}} (f_{id,s})^{1-\frac{\theta_s}{(\sigma_s-1)(1-\alpha_s)}} (t_{i,s})^{-\frac{\alpha_s\theta_s}{1-\alpha_s}}} E_{d,s}$$

Substituting in the definitions of the price index from (35) and bilateral trade from (36) gives equation (11) from the main text. The version of this equilibrium equation shown in the main text is short and intuitive. The version of this equation shown above is more practically useful for deriving the second equilibrium condition in changes and relating it to changes in trade costs, productivity, and environmental regulation.

II.E Deriving Equation (12), the First Equilibrium Condition in Changes

Recall the first equilibrium condition in levels, equation (9) from the main text:

$$L_o = L^e_o + L^p_o + L^t_o + L^m_o + L^{nx}_o$$

[1]The positive constant is given by $\chi_s = \frac{(\sigma_s)^{1-\frac{\sigma_s\theta_s}{(\sigma_s-1)(1-\alpha_s)}}}{(\sigma_s-1)^{-\frac{\theta_s}{1-\alpha_s}}} \frac{(\alpha_s)^{\frac{\alpha_s\theta_s}{1-\alpha_s}}}{(1-\alpha_s)^{-\theta_s}} \frac{\theta_s}{\theta_s-(\sigma_s-1)(1-\alpha_s)}$

This shows that labor in this model is demanded for five purposes: firm entry; production and abatement; pollution taxes; market entry; and net exports. We explain each in turn, then sum them to describe total labor demand.

First, labor in this model is used to pay the fixed cost for drawing a productivity (in other words, labor is demanded for firm entry). The labor demanded for this purpose equals the mass of entrepreneurs drawing a productivity times the fixed cost per draw:

$$L^e_{o,s} = M^e_{o,s} f^e_{o,s}$$

Second, labor in this model is used to producing widgets and abating pollution. The labor demanded for this purpose equals the mass of entrepreneurs drawing a productivity times expected labor for production and pollution abatement:

$$\begin{aligned} L^p_{o,s} &= M^e_{o,s}\mathbb{E}[l_{od,s}(\varphi)\tau_{od,s}] \\ &= M^e_{o,s}\theta_s f^e_{o,s} \end{aligned}$$

The second equality follows from substituting in several terms: $l_{od,s}(\varphi) = q_{od,s}(\varphi)/(\varphi(1-a(\varphi)))$ from assumption 2; demand (25); abatement investments (27); prices (28); the Pareto conditional density (32); and free entry (34).

Third, labor in this model is used to pay pollution taxes. The quantity of labor demanded for this purpose equals total expenditure on pollution taxes divided by the wage rate

$$\begin{aligned} L^t_{d,s} &= \frac{t_{d,s} Z_{d,s}}{w_d} \\ &= \frac{\alpha_s}{1-\alpha_s}\theta_s M^e_{d,s} f^e_{d,s} \end{aligned}$$

The second equality follows from substituting in several terms: demand (25); prices (28); abatement (27); pollution (30); and the Pareto conditional density (32).

Fourth, labor in this model is used to pay the fixed cost of entering foreign markets. The amount of labor demanded for this purpose equals the sum over all foreign countries of the mass of firms exporting to a country times the fixed cost of exporting to that country.

$$\begin{aligned} L^m_{d,s} &= \sum_o M_{od,s} f_{od,s} \\ &= \frac{\theta_s - (\sigma_s - 1)(1-\alpha_s)}{\sigma_s\theta_s}\frac{E_{d,s}}{w_d} \end{aligned}$$

The second equality follows from calculating the expected revenue of exporters then substituting in demand (25); prices (28); and the productivity cutoff (33).

Fifth, labor is used to pay for trade deficits. The amount of labor demanded for this purpose equals the sum over all foreign countries of the mass of firms exporting to a country, times the first cost of exporting to that country:

$$L^{nx}_{d,s} = -\frac{NX_{d,s}}{w_d}\frac{(\sigma_s-1)(\theta_s-\alpha_s+1)}{\sigma_s\theta_s} + \beta_{d,s}\frac{NX_d}{w_d}$$

This trade imbalance term is defined so that the model can exactly match historic data on expenditure and production decisions.

Summing these five terms then solving for L_d gives an expression for the labor market clearing condition:

$$\begin{aligned} L_d &= \frac{1}{1-\sum_s \frac{\theta_s-(\sigma_s-1)(1-\alpha_s)}{\sigma_s\theta_s}\beta_{d,s}} \\ &\sum_s \left[M^e_{d,s} f^e_{d,s}\left(\theta_s + 1 + \frac{\alpha_s\theta_s}{1-\alpha_s}\right) - \frac{\theta_s - (\sigma_s-1)(1-\alpha_s) - \sigma_s\ \theta_s}{\sigma_s\theta_s}\beta_{d,s}\frac{NX_d}{w_d} - \frac{NX_{d,s}}{w_d}\frac{(\sigma_s-1)(\theta_s-\alpha_s+1)}{\sigma_s\theta_s}\right] \end{aligned}$$

The left-hand side of this equation describes labor supply and the right-hand side labor demand. Writing the ratio of counterfactual to observed labor demand, L'_d/L_d, and simplifying using the Pareto technology assumption (31), the Pareto conditional density (32), demand (25) and the free entry condition (34) gives the main text equation (12).

II.F Deriving Equation (13), the Second Equilibrium Condition in Changes

To derive equation (13), we write the second equilibrium condition in levels (11) under a counterfactual by adding an apostrophe to each variable. Each counterfactual variable can then be written as the product of that variable's baseline level and its proportional change (i.e., $x' = \hat{x}/x$). Substituting in expenditures shares (37) and simplifying gives equation (13).

II.G Deriving Equation (14), Proportional Changes in Pollution

Recall the following from Assumption 3 of the model:

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

We then use abatement (27), prices (28), the Pareto distribution (31), and demand (25) to derive the following firm-level expected pollution emissions:

$$\mathbb{E}[z_{od,s}(\varphi)\tau_{od,s}|\varphi > \varphi^*_{od,s}] = \frac{(\sigma_s - 1)\alpha_s\theta_s}{\theta_s - (\sigma_s - 1)(1 - \alpha_s)} \frac{w_d}{t_{o,s}} f_{od,s}$$

Again applying the Pareto distribution (31), bilateral demand (37), and taking ratios of counterfactual to baseline pollution gives equation (14).

II.H Deriving Equation (19), the Foreign Competitiveness Shock

We obtain equation (19) in the main text by expressing the expenditure shares equation (37) in changes and then solving for equation (18) from the main text.

$$\hat{\Gamma}^*_{od,s} \equiv (1/\hat{b}_{o,s})^{-\theta_s} (\hat{\tau}_{od,s})^{-\theta_s/(1-\alpha_s)} (\hat{f}_{od,s})^{1-\theta_s/(\sigma_s-1)(1-\alpha_s)} \left(\hat{t}_{o,s}\right)^{-\alpha_s\theta_s/(1-\alpha_s)}$$

We do not need to measure the terms in parentheses on the right-hand part of equation (19) from the main text because they are specific to destination d so appear in both the numerator and denominator of the part of this model where this shock is used (the second equilibrium equation in changes, equation (13)), and so cancel in that equation.

II.I Deriving a Simpler Expression for the Environmental Regulation Shock

To obtain the expression for environmental regulation described in equation (23), we express the first equilibrium condition (11) in changes then solve for $\hat{R}_{d,s}$. This derivation uses the fact that $\hat{M}^e_{o,s} = (1/\hat{w}_o)(\sum_d X'_{od,s}/X_{od,s})$.

We obtain this expression for $\hat{M}^e_{o,s}$ in a few steps. First, we solve the expression for foreign competitiveness in equations (18) and (19) for the change in trade flows, $\hat{\lambda}_{od,s}$. Second, we substitute this into the second equilibrium condition in changes in equation (13). Finally, we simplify the result to obtain this expression for $\hat{M}^e_{o,s}$.

C Data Overview and Additional Empirical Details

III.A Matching the 1990 Annual Survey of Manufacturers to the 1990 National Emissions Inventory

We match the 1990 Annual Survey of Manufacturers (ASM) to the 1990 National Emissions Inventory using name and address string matching techniques. The ASM does not provide name and address information for plants, but the ASM can be linked to the Census Business Register via a unique, longitudinal identifier that does. The Business Register consists of the universe of establishments in the United States on an annual basis and forms the basis for the more commonly known and used Longitudinal Business Database (LBD).

We perform a match between the 1990 NEI and the Business Register for each Business Register year between 1985 and 1996. Both the NEI and the Business Register contain establishment level name and address information that we use to perform the match: county, state, SIC code (4-digit, 3-digit, and 2-digit), facility name, street, city, and zip code. We perform exact matching on county, state, and SIC codes and "fuzzy" matching on facility name, street, city, and zip code. We use the "COMPGED" feature of SAS's PROC SQL to create a "generalized edit distance" score reflecting the degree of difference between two text strings. For each variable in which we use fuzzy matching techniques, we choose a score that minimizes both false positives and false negatives by visually checking the performance of the matches.

We then iterate over combinations of the match variables listed above, selecting the match with the highest score in each round, and removing the residual observations from each dataset before matching again. At the end of the matching process, we are able to match 77.4 percent of the 1990 NEI manufacturing observations (i.e., SIC code between 2000-3999). The match percentage also reflects the fact that the ASM is a sample and not a survey, and thus we should not expect a match rate near 100 percent.

In addition, the unmatched plant observations are not significantly different along emissions totals, relative to the matched observations. For each pollutant, we ran a plant-level regression of emissions on an indicator for whether the plant matched the census data, controlling for 4-digit SIC fixed effects and clustering standard errors by 4-digit SIC codes. Of 6 pollutants, the coefficient on the match variable is significant at the 10 percent level (though not at 5 percent) for PM_{10} and $PM_{2.5}$; for other pollutants we fail to reject the null hypothesis that matched and unmatched plants have the same emissions. For the plants that are matched and emit particulate matter, the matched plants tend to emit slightly more particulates than the unmatched plants. Not all ASM plants appear in the NEI because the NEI is only designed to include data from plants with at least 100 tons per year of one of the major pollutants.

III.B Product Level Decomposition: Details

Section I in the text describes the statistical decomposition using the product-level production data from the Census and Annual Survey of Manufacturers (CMF and ASM, respectively). Here we provide additional details.

Bernard, Redding, and Schott (2011) provide a detailed overview of the Manufacturing Product trailer for research purposes. In terms of descriptive statistics, the typical two-digit SIC code in Manufacturing has 24 four-digit industries and 76 five-digit products, although there is heterogeneity across industries in the amount of product detail. For example, the number of products per sector ranges from a low of 12 in Leather (SIC 31) to a high of 178 in Industrial Machinery (SIC 35) (Bernard, Redding, and Schott, 2011).[2]

Within the CMF and ASM product trailers, there are several industries which report only aggregate product codes (i.e., within a 4-digit industry, more than 95 percent of output is produced in a product code

[2]As noted by Bernard, Redding, and Schott (2011), there is also substantial variation in the precision of product classifications. For example, Passenger Cars (SIC 37111) and Combat Vehicles (SIC 37114) are examples of products in the Motor Vehicle industry (SIC 3711), while Textbook Binding and Printing (SIC 27323) and Religious Books, Binding and Printing (SIC 27323) are examples of products in the Book Printing industry (SIC 2732).

that ends in "-", "0", or "W"). In the case that 50 percent or more of the product shipments within in a 4-digit SIC industry come from one of these aggregate product codes, we aggregate to the 4-digit SIC level.

There are two primary issues that emerge when looking at changes in the composition of products and how these affect manufacturing emissions over time. The first issue is associated with the introduction of new products; we calculate emissions factors using total product-level production and emissions in 1990. If new products are introduced after 1990, they will not have an emissions factor, and thus will lead to false inferences from the decomposition. In order to address product entry, we fold all new products into the adjacent product category, as defined by 5-digit SIC product codes. This implicitly assumes that the emissions factor from the new product is the same as the emissions factor calculated for the adjacent product code.

The second issue emerges from the transition between SIC and NAICS product code definitions between 1997 and 1998. We construct a product code crosswalk between 5-digit SIC product codes and 7 digit NAICS product codes. This allows us to construct a consistent 5-digit SIC by year dataset from 1990 until 2008. We develop this product-level SIC-NAICS concordance using 3 separate but complimentary strategies:

1. For the industries that only report aggregate product shipments (i.e., at the level of 4-digit SIC codes or 6-digit NAICS codes), we use the NBER-CES crosswalk which provides a linkage between 4-digit SIC codes and 6-digit NAICS codes. In the event that a 6-digit NAICS code maps into more than one 4-digit SIC code, the NBER-CES crosswalk provides value shares in order to apportion NAICS output to the relevant SIC code.

2. For products that are consistently reported at the NAICS 7-digit product level, we develop a crosswalk using the 1997 Census of Manufacturing product trailer. In 1997, Census collected both NAICS and SIC product codes which we use to build the crosswalk. For 7-digit NAICS product codes that map into more than one 5-digit SIC product code, we construct apportionment shares based on the fraction of total 1997 output that is split between the respective SIC codes.

3. Lastly, there are some 7-digit NAICS codes in years 1998+ that do not match either of the two crosswalks above. For these residual product codes, we use a crosswalk developed by the Bureau of Labor Statistics between SIC and NAICS product codes.[3] There are still some cases for which NAICS 7-digit product codes map into more than one 5-digit SIC product code. In these cases, the BLS does not provide relative output shares for the "many to 1" crosswalk that would allow us to apportion NAICS output to the relevant SIC product code. This lack of apportionment for split products means that the product series in years 1998+ will overstate the amount of output for NAICS product codes that map into multiple SIC product codes. We adjust for this structural break by multiplying the scale + composition line in years 1998+ by an adjustment factor. This adjustment factor is computed by fitting a linear trend to years 1996 and 1997 and projecting the 1998 point; the value that we multiply the observed 1998 value to recover the predicted 1998 value is the adjustment factor we use to scale all post-1998 output.

Once we have a consistent 5-digit SIC product-level dataset, we construct product shares in each year by taking the total product output produced in a given year and dividing that by total manufacturing output in that year. In non-Census years, we use the weights provided by the Census to scale up plant-level output by the inverse sampling probability of the survey. We multiply these product shares by the product-level emissions factors and sum over all products in a year. Lastly, we multiply this annual number by total manufacturing output in that year in order to recover the scale+composition line in Figures 3 and 1.

[3]Source: https://urldefense.proofpoint.com/v2/url?u=http-3A__www.bls.gov_ppi_ppinaictosic15.htm&d=AwIFaQ&c=-dg2m7zWuuDZ0MUcV7Sdqw&r=a0JqX4ibH77Bx2Kpq1YnZLh0hR2TzpM1ZpfzjHqqTT0&m=ikhWR7s5FQkUNMczenUZrOI6MFlWL89tekAhlHFe5qE&s=SnuKGRQabLYEWjLd02OHuSmBxmbRIODlBoHFRNj25y0&e= (accessed on July, 1 2014).

III.C Additional Data Details

Concordances

We use several publicly available industry concordance files to express all datasets in the same classification systems. Whenever possible, we use concordance files that provide weights or shares. When shares or weights for multiple variables are available, we use employment shares. In cases where a given observation cannot be linked at the most detailed possible industry code (e.g., 6-digit NAICS code to 4-digit SIC code), we construct concordances for each possible further aggregation of this industry (e.g., 5-digit NAICS to 4-digit SIC, then 4-digit NAICS to 4-digit SIC, etc.). We link each observation at the most detailed possible industry level.

The subsection above describes linking SIC and NAICS product codes. To concord SIC and NAICS industry codes, we use a file constructed in Fort and Klimek (2016). This file takes an internal concordance file from the U.S. Census then cleans and documents it, and imputes missing values for some narrowly divided industry cells by using averages from more aggregate industry categories. Unlike standard census NAICS-SIC concordances, this file provides shares; and unlike the NBER-CES database, it represents all industries and does not only focus on manufacturing.

To concord between different years of NAICS codes (e.g., between 1997 NAICS and 2002 NAICS; or between 2002 NAICS and 2007 NAICS), we use concordance files available in the U.S. Census Bureau's Factfinder application. The Census Bureau calls these "Industry Bridge Statistics" and gives them the table code 00CBDG2.

To concord NAICS codes to ISIC codes, we use a crosswalk file from Statistics Canada. This file does not provide data on weights, so we define weights according to the number of industries linked. For example, if one NAICS industry is linked to 5 different ISIC industries, we assign 20 percent of the NAICS industry to each of the ISIC industries.

Gross Output Data

We setup gross output using these data as follows. First, we concord reporting sectors. Some country×years report values for combinations of two-digit ISIC codes (e.g., one value covering both ISIC=15 and ISIC=16). In these cases, we take reports from the same country in other years, calculate the share of output coming from each of the two underlying ISIC 2-digit codes in those other years, and apportion the focal year to the two codes according to those shares.

We use a few steps to to incorporate country×years not in the OECD data. First, we extract data on each country×year's total manufacturing GDP from the World Bank's World Development Indicators (WDI), which covers both OECD and non-OECD countries. Second, we calculate the ratio of manufacturing GDP (from WDI) to manufacturing gross output (from OECD STAN) for the OECD in total, separately by year. This ratio gradually declines from 0.33 in the year 1990 to 0.26 in 2008. Dekle, Eaton, and Kortum (2008) report a similar value for this ratio of 0.31. Third, we divide the WDI manufacturing GDP values by the GDP/Output ratios calculated in the second step to calculate gross output per country×year, for both OECD and non-OECD countries. Fourth, we calculate the composition of total OECD manufacturing gross output across the 17 sectors in our data, separately by year. Fifth, we assign the country×year gross output calculated in step three to sectors using the proportions calculated in step four. For OECD countries, we use reported data from OECD STAN; for other countries, we use these calculated values.

As discussed in the main text, we use these values for years 1990-1995. For years 1995-2008, we use production and trade data from the World Input Output Dataset (WIOD), which begins in the year 1995 (Timmer, Dietzenbacher, Los, Stehrer, and de Vries, 2015). WIOD directly reports gross output for the U.S. and other countries, including a rest-of-the-world category, so does not require the aforementioned imputation. We scale each production and trade flow in WIOD so they exactly match the OECD gross output data in 1995.

Data for Estimating Pollution Elasticity

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 a, respectively).[4] We "winsorize" the reported emissions data at the 99th percentile of the 4-digit NAICS-year emissions distribution, and we use sample weights from both the Annual Survey of Manufacturers and the Pollution Abatement Costs and Expenditure Survey to inflate survey values to be nationally representative. Total abatement costs consist of the sum of abatement operating costs plus the rental cost of capital associated with the observed abatement capital at a plant.[5] Total expenditures consist of the sum of expenditures on salary and wages, materials, energy, and the industry-specific capital rental rates for a given level of capital stock.

Manufacturing and Energy Consumption Survey and CO_2 Emissions

MECS is a nationally representative survey of U.S. manufacturing which was conducted in 1991, 1994, 1998, 2002, 2006 and 2010. We download publicly available tables, which are available at the 2-digit SIC or 3-digit NAICS level. We extract data on total inputs of energy for heat, power, and electricity generation by industry, measured in trillions of BTUs. These data exclude energy used as feedstock (e.g., they exclude the petroleum which is a physical part of plastics).

For confidentiality reasons, public versions of the MECS data supress a few fuel$\times$industry$\times$year cells. We impute these values as follows. First, we calculate total BTUs for the fuel$\times$year, and subtract BTUs for industry$\times$years within that fuel that are not suppressed. Second, within each year, we then calculate the share of all BTUs (total across fuels) that each industry accounts for. Finally, we allocate the non-specified BTUs (calculated in the first step) across industries according to the relative proportions calculated in the second step.

Given these data on million BTU of each energy source, we calculate CO_2 emissions using physical emissions rates from the U.S. Environmental Protection Agency.

EPA Air Program Markets Data

In order to operate cap-and-trade programs like the NO_x Budget Trading Programs, the EPA maintains a public database listing each facility which participates in the program and its attributes.[6] We obtain a list of facilities which were regulated under the NO_x Budget Trading Program in each year of its operation, 2003-2007. Each facility includes identifying information such as longitude and latitude, address, and a generic industry description, which we use to link these data to the National Emissions Inventory.

[4] We proxy for measures of physical output $q_{i,t}$ using plant revenue, deflated by industry-specific output price deflators, where the industry-specific output price deflators come from the NBER-CES database.

[5] Capital rental rates are from unpublished data constructed by the Bureau of Labor Statistics for use in computing their Multifactor Productivity series. These data are commonly used in the productivity literature to proxy for industry-specific capital rental rates. See e.g., Syverson (2011). We only observe abatement capital stocks in 2005 (not 1990). We impute 1990 abatement capital stocks using our observed measure of depreciation expenditures in both 1990 and 2005. Specifically, we use the 2005 ratio of abatement capital stocks to abatement depreciation expenditures, and we multiply this ratio by the 1990 abatement depreciation expenditure for a plant to back out the 1990 abatement capital stock of the plant.

[6] The data are available at https://urldefense.proofpoint.com/v2/url?u=http-3A__ampd.epa.gov_ampd_&d=AwIFaQ&c=-dg2m7zWuuDZ0MUcV7Sdqw&r=a0JqX4ibH77Bx2Kpq1YnZLh0hR2TzpM1ZpfzjHqqTT0&m=ikhWR7s5FQkUNMczenUZrOI6MFlWL89tekAhlHFe5qE&s=7mYZMH3I9I3bQFxPnze5IKdiE9IML9vBovn4qZuymUw&e=. These data were formerly called the Clean Air Markets Database.

III.D Macroeconomic Parameters

To estimate the elasticity of substitution across product varieties, we use the implication of the model that a sector's expenditure on labor for production is proportional to the sector's revenue:

$$w_o L_{o,s}^p = (1-\alpha_s)\,\frac{\sigma_s - 1}{\sigma_s} R_{o,s} \tag{38}$$

Here $L_{o,s}^p$ represents labor used in production and $R_{o,s}$ represents revenue.[7] We use the 1990 Annual Survey of Manufactures to calculate these elasticities separately for each of the 17 aggregated ISIC sectors. Intuitively, this approach is observing markups in data, then using our assumption of the market structure (monopolistic competition) to back out the demand elasticity which rationalizes those markups.

Column 4 of Table 2 presents our estimates of σ_s for each sector.[8] The elasticity of substitution ranges from 2.89 to 8.18 across industries, with a cross-sector mean of 4.76. We expect a smaller elasticity of substitution for industries with more differentiated products. The pattern across sectors generally follows this pattern. The largest elasticity of 8.18 in absolute value is for the Coke, Refined Petroleum, and Nuclear Fuels sector, which has fairly homogeneous products. The smallest elasticity of 2.89 is for the Medical, Precision, and Optical Products sector, which has fairly differentiated products. These correspond to markups of between 14 and 53 percent, which fits the range from other published studies, which for U.S. manufacturing industries typically range from 10 to 50 percent (Hall, 1986; Martins, Scarpetta, and Pilat, 1996; Ganapati, Shapiro, and Walker, 2016).

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 θ_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

$$\ln(Pr\{x > X_{i,s}\}) = \gamma_{0,s} + \gamma_{1,s}\ln(X_{i,s}) + \epsilon_{i,s} \tag{39}$$

We estimate equation (39) separately for each sector 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 (39). 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 90th percentile of sales within each sector.[9]

[7] 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.

[8] The reported elasticity is calculated as $\sigma_s = (1-\alpha_s)/((1-\alpha_s) - wL_s/X_s)$, where α_s is the pollution elasticity estimated above and wL_s/X_s is factor costs divided by the value of shipments. Columns 1-3 of Table 2 present these intermediate inputs into the construction of σ_s.

[9] 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 90th percentile of the sales distribution is strongly linear with respect to firm rank.

Table 1: Sensitivity Analysis: U.S. Pollution Emissions in Counterfactual Divided by 1990 Emissions, Separately for Each Shock

	Foreign Competitiveness (1)	U.S. Competitiveness (2)	U.S. Environmental Regulation (3)	U.S. Expenditure Shares (4)	Trade Deficits (5)
1. Actual Change			46.464		
2. Main Estimate	95.429	81.188	47.528	111.28	102.33
3. No Firm Heterogeneity	93.504	83.868	47.526	111.25	102.30
4. Parameter θ: Top 50 Percent	89.757	83.64	48.161	110.82	104.17
5. Parameter θ: Top 25 Percent	91.064	83.333	48.015	110.95	103.66
6. Parameter α: 0.25× Main Estimates	95.354	75.549	48.845	111.28	102.33
7. Parameter α: 4× Main Estimates	93.487	88.595	46.042	111.26	102.32
8. Partial Equilibrium	100.000	100.000	48.98	100.000	100.000

NOTES: This table presents a set of sensitivity analyses for the main set of counterfactuals in the text. For the sensitivity analysis listed in each row, we calculate each counterfactual separately for each of the six criteria pollutants. The table shows the unweighted mean of these results across these pollutants. We show the mean outcome averaged across years 2005 and 2008. Row 1 presents the actual observed change in pollution emissions between 1990 and 2005-2008, averaged across the six pollutants. The value of 40.47 means that emissions in the years 2005-2008 were 40.47 percent of their value in 1990. Row 2 shows the main estimates from the model, where each column corresponds to a separate counterfactual. For example, column (1) shows that if foreign competitiveness took its actual historic value and all other shocks were held fixed, then manufacturing emissions in 2005-2008 would have been 107.14 percent of their observed 1990 values. Row 3 shows counterfactuals in a model where parameters are chosen so all firms have the same productivity and there is no firm heterogeneity. Rows 4 and 5 explore sensitivity of these counterfactuals to changes in the Pareto shape parameters that govern the distribution of firm productivity. Rows 6 and 7 explore model sensitivity to changes in the estimated pollution elasticity.

III.E Discussion of Other Shocks, Wages, and Firm Entry Changes

Appendix Figure 3 shows the time path of the historical shocks in the paper.[10] Although we recover the value of each shock for each country×sector, it is cumbersome to describe values for 17 different sectors. Instead, we plot shocks separately for "clean" and "dirty" sectors. Dirty industries are defined as those with a value of the pollution elasticity α_s above the economy-wide mean of 0.011, and clean industries are defined as those with a value of this pollution elasticity below 0.011.

Appendix Figure 3a shows that foreign expenditure shares on dirty versus clean goods changed relatively little until 2005, when spending on dirty industries grew by around 10 percent. U.S. expenditure shares show similar patterns. This increase in expenditure shares for dirty goods is especially driven by the increasing expenditure in the Coke, Refined Petroleum, and Nuclear Fuels sector, reflecting increases in global commodity prices.[11]

Our measures of these historic shocks depend on the changes in wages in each country and changes in

[10] The model and counterfactuals account for competitiveness shocks to each country. As discussed earlier, although the price index $\hat{P}_{d,s}$ appears in our measure of competitiveness shocks, we don't need these price data to analyze counterfactuals. This is because destination price indices appear in only the numerator and denominator of the second equilibrium condition and cancel. As a result, the historical shocks to U.S. and foreign competitiveness outside of a particular counterfactual are not informative, and we omit competitiveness shocks from Appendix Figure 3.

[11] 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.

Table 2: Sensitivity to Starting Values and Algorithms

	Minimized Objective Function	2008 Difference in Pollution, Regulation-only Counterfactual
Main Results	1.32E-30	—
Starting Values Randomly Chosen:		
Mean	2.48E-30	3.98E-13
Minimum	4.31E-31	4.26E-14
Maximum	7.81E-29	1.42E-14
Standard Deviation	(3.11E-30)	9.29E-15
Algorithm: Trust-Region Reflective	1.32E-30	0
Algorithm: Levenberg-Marquardt	1.32E-30	0

NOTES: This table presents a set of sensitivity analyses for the counterfactuals presented in the paper, for NO_x emissions. The table varies the starting values and the algorithm associated with solving the system of nonlinear equations used in our counterfactuals. The main results in the paper use a starting value equal to one and a trust-region, dogleg algorithm. This table presents results from a randomly chosen set of starting values drawn from a uniform distribution [0.75,1.25]. The table reports the mean, minimum, maximum, and standard deviation of the 1,000 different results. The last two rows of the table present results using two different minimization routines. The second column shows the absolute value of the difference in the pollution emissions under a regulation-only counterfactual as calculated in a given row relative to the value calculated in the first row.

firm entry in each country and sector. Appendix Figure 4 plots these values. U.S. wages stagnated in the 1990s as U.S. output grew more slowly than global output. U.S. wages grew slightly in the late 1990s and early 2000s, as U.S. output growth modestly outpaced global output growth. Wages then declined in the 2000s as growth from foreign countries, especially China, accelerated. Foreign wages display the opposite pattern: modest growth in the early 1990s and late 2000s but a slight decrease in intervening years.

Appendix Figure 4 also shows patterns in firm entry. In both the U.S. and abroad, entry grew more quickly in dirty sectors than in clean sectors, as indicated by the solid line rising after the year 2005 in panels (c) and (d). This increase in entry to dirty sectors in the late 2000s reflects rising energy prices and revenues—greater value of output in dirty sectors increases the expected profit from entry, attracting more firms to these sectors.

One additional issue in describing the shocks concerns trade imbalances. In a dynamic model, trade imbalances would represent intertemporal concerns like saving or consumption smoothing. In the comparative statics we examine here, trade imbalances appear as transfers from one country to another. The natural way for this static model to exactly recreate historic data is to allow for separate shocks to trade imbalances. In the decomposition, we read off actual trade imbalances from the data.[12]

III.F Algorithm to Calculate Equilibrium

To analyze counterfactuals, we use country×industry data from the year 1990 on production, trade, and U.S. pollution emissions ($X_{od,s}$ and $Z_{o,s}$), and the parameter vectors for each industry: the pollution elasticity, elasticity of substitution, and Pareto shape parameter (α_s, σ_s, and θ_s). With the full set of data and parameters, we then use the following algorithm to solve for a specific counterfactual:

[12] We define net exports, NX_o, as a country's exports minus its imports. As in Hsieh and Ossa (2016), we also allow scaled sectoral imbalances, given by $NX_{d,s}(\sigma_s - 1)(\theta_s - \alpha_s + 1)/w_d\sigma_s\theta_s$.

1. Characterize the counterfactual scenario by choosing values for shocks to foreign and U.S. competitiveness, U.S. environmental regulation, and expenditure shares in each of the years 1990-2008 $\{\hat{\Gamma}_{od,s}$, $\hat{t}_{o,s}$, and $\hat{\beta}_{o,s}\}$. These values can be hypothetical or they can describe the actual, historical values of these shocks.

2. Find the changes to wages and firm entry in each country×sector×year ($\hat{w}_o$ and $\hat{M}^e_{o,s}$) which make the equilibrium conditions (12) and (13) hold with equality for all countries and sectors and years, by solving a system of nonlinear equations and then inputting the values chosen in step 1.[13] 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 (14) 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 expenditure shares are $\{\hat{\Gamma}^*_{od,s}$, $\hat{t}^*_{o,s}$, $\hat{\beta}^*_{o,s}\}$, calculated using equations (19) through (22). By construction, these values solve the two equilibrium conditions (12) and (13) in every country, industry, and year for the wage changes and firm entry changes ($\hat{w}^*_o$ and $\hat{M}^{e*}_{o,s}$) 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 study a specific set of counterfactuals. Consider the shock to foreign competitiveness. To measure how foreign competitiveness affected pollution, we define the shocks as follows:

$$\{\hat{\Gamma}_{od,s}, \hat{t}_{o,s}, \hat{\beta}_{o,s}\} = \begin{cases} \{\hat{\Gamma}^*_{od,s}, 1, 1\} & \text{if } o \neq U.S. \\ \{1, 1, 1\} & \text{if } o = U.S. \end{cases} \tag{40}$$

This says that the foreign competitiveness shock $\hat{\Gamma}_{od,s}$ took on its historic value $\hat{\Gamma}^*_{od,s}$, $o \neq U.S.$, but other shocks remained fixed at their 1990 values (i.e., the proportional change for every other shock equals one). Given the shocks defined in equation (40), we use steps 2 and 3 of the algorithm 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 recreates the historic decline in pollution. Second, although we are 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.

Appendix Table 2 explores the sensitivity of the results to different sets of starting values needed for the algorithm to solve systems of nonlinear equations (12) and (13). We randomly draw 1,000 different sets of starting values from the uniform distribution [0.75,1.25].[14] Each set of starting values represents changes in wages in each country and firm entry decisions in each country×sector. The objective function appears to

[13] To solve the system of nonlinear equations, we use a standard trust-region dogleg algorithm. However, as we discuss below and show in Appendix Table 2, other algorithms and randomly-chosen starting values give equivalent results.

[14] We choose this range to cover common values of shocks observed in data and described in Appendix Figure 4. Some starting values well outside this region fail to converge.

be somewhat flat in a narrow range around the main set of results; different starting values obtain slightly different values of the changes in wages and firm entry decisions which are not numerically equivalent to the main results. However, column (1) shows that the differences between these equilibria are very small and appear only between the 29th and 31st decimal point. Because we only have 32 digits of calculation precision, these differences in equilibria may reflect numerical precision due to computational limits. We also report results using two alternative algorithms for solving systems of nonlinear equations—a trust-region reflexive algorithm and a Levenberg-Marquardt algorithm. Both yield very similar, though not numerically equivalent values of the objective function, and yield the same estimate of how regulation affects pollution.

Column (2) of Appendix Table 2 shows that the ratio of U.S. pollution emissions in 2008 relative to 1990 is nearly identical in every set of starting values and algorithms we use. Across the thousand alternative sets of starting values, the standard deviation is 8.33E-31. These results suggest that our quantitative conclusions are the same with other starting values or algorithms.

III.G Additional Model Sensitivity Analyses

We now consider the sensitivity of the paper's main results to parameter estimates and model assumptions. Table 1 begins by investigating model sensitivity to alternative parameter specifications. The first row shows that by 2008, NO_x emissions from U.S. manufacturing were 46.46 percent of their 1990 values. The paper's main estimates imply that environmental regulation alone would have caused pollution emissions to equal 47.53 percent of their 1990 value by 2008 (column (3), row (2)). Rows 3 and 4 explore how sensitive this conclusion is to changes in the underlying Pareto shape parameter estimates. Because the Pareto distribution best approximates the size distribution for the upper tail of firms, our main estimates of these parameters use the largest 10 percent of firms in each industry. Estimating the Pareto shape parameters using the top 50 percent of firms in each industry, or using the top 25 percent of firms in each industry, hardly affects the main conclusions. These two alternatives imply that environmental regulation would have led NO_x emissions to be 48.16 or 48.02 percent of their 1990 value by 2008, which are extremely close to the main results.

Rows (5) and (6) of Appendix Table 1 explore sensitivity to changes in the pollution elasticity α_s. Row (5) assumes that the pollution elasticity is one-fourth of our estimated values, and row (6) assumes that the true values of α_s are four times the values of our main estimates. The former implies that environmental regulation alone would have led pollution emissions to be 48.85 percent of their 1990 value in 2008; the latter implies that environmental regulation alone would have led pollution emissions to be 46.04 percent of their 1990 value by 2008. These alternative parameter values modestly affect the magnitude of how environmental regulation affects manufacturing NO_x emissions. However, across the four alternative sets of results, the qualitative conclusion persists that regulation explains most of the change in pollution.

III.H Pollution Intensity and Total Factor Productivity: Details

Figure 2 plots the relationship between plant level pollution intensity in total factor productivity. This section provides additional details underlying this figure. We use the 1990 Annual Survey of Manufacturers (ASM) which provides information on input decisions and total output at the plant level. We match the ASM to the National Emissions Inventory (NEI) using name and address matching techniques. Details of the match can be found in Appendix III.A. We use the sampling weights in the ASM to adjust plant-level output by the inverse sampling probability of a plant in the survey.

For each plant and each pollutant we divide total emissions by inventory adjusted real output.[15] We use industry-specific price deflators from the CES-NBER Productivity database to deflate output using

[15] Inventory adjusted total output is defined as the total value of shipments, minus the difference between finished goods inventory between the beginning and end of the year, minus the difference between work in progress inventory at the beginning and end of the period.

an SIC-4, industry-level index normalized to 1 in 2008. We then compute a plant-level index measure of total factor productivity, using a Cobb-Douglas production technology and assuming constant returns to scale.[16] Production inputs include labor, capital, and materials. We approximate the output elasticities of production inputs using industry-level cost shares from the NBER-CES productivity database. All inputs were deflated using industry, input-specific price deflators from the NBER-CES productivity database.

We divide the sample into 10 deciles based on total factor productivity. We then compute the mean values of log productivity and log pollution per unit of real output within each decile, weighting the decile mean by plant-level inventory-adjusted, real output. Figure 2 plots the results for each of the six pollutants in our sample. Each pollutant scatter plot is accompanied by a linear fit, relating plant-specific emissions intensities to total factor productivity at the same plant. The line is fit to the entire sample, not simply the decile means.

[16] Plant TFP is computed as its logged output minus a weighted sum of its logged labor, capital, materials, and energy inputs. That is

$$TFP_{it} = y_{it} - \alpha_{lt} l_{it} - \alpha_{kt} k_{it} - \alpha_{mt} m_{it} - \alpha_{et} e_{it}$$

where the weights α_j are the input elasticities of input $j \in \{l, k, m, e\}$. Index productivity measures are common in the literature partly because they are easy to construct and also because they are a nonparametric first-order approximation to a general production function. See e.g., Syverson (2011).

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