Pollution Emissions and Foreign-Owned Manufacturing Plants

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Abstract

We document significant variation in the relative pollution emissions of foreign owned and domestically owned manufacturing plants in the U.S. We use a sample of matched plant characteristics and pollution emissions to document the pollution emissions of foreign owned facilities relative to their competitors in the same industry. On average there is no difference in emissions intensity between domestic and foreign owned plants across all manufacturers, but in some industries foreign owned plants are much cleaner, while in others much dirtier. We show that the variation in relative pollution emissions of foreign owned manufacturing plants is correlated with industry characteristics: lower industry-level trade costs, higher fixed costs, and lower returns to agglomeration are associated with cleaner foreign owned plants. These results are consistent with a theoretical framework in which foreign plants have lower productivity, and therefore more pollution intensity, in industries where foreign ownership is more attractive relative to exporting.

JEL Codes: F1, Q5

Keywords: Trade and environment, Firm heterogeneity, Plant-level emissions

1 Introduction

Much has been written on the externalities of international trade with particular interest in whether firms are willing to move dirty production to locations with lax environmental

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regulation, like developing nations (see, e.g., Cole, Elliot, and Strobl (2008)). However, the majority of global foreign direct investment (FDI) flows into developed countries. At the same time, developed nations contribute disproportionately to global greenhouse gas emissions, and even within developed nations environmental justice concerns persist as local pollutants tend to locate near low-income, minority communities. The impact of inward FDI on emissions in developed nations is important but not well understood.

We estimate plant-level pollution emissions differences between foreign and domestic plants in the united states, contributing to a large literature at the intersection of FDI and emissions that has not yet considered the impacts of foreign-acquisition on emissions in a developed economy. In fact, most of the plant-level studies estimate how pollution emissions differs between foreign-owned and domestic-owned plants in developing countries, whereby foreign-investors are assumed from developed economies. Results in this literature are mixed (Cole, Elliot, and Zhang (2017)). A much larger branch of literature (which includes several studies focused on FDI in developed countries) considers the responses of firms to environmental regulation (the so-called "Pollution Haven Hypothesis"). This literature finds, in general, that FDI inflows are negatively related to strict environmental regulation suggesting foreign-owned plants within the US might be pollution intensive (see, e.g., Bialek and Weichenrieder (2021) and Hanna (2010)).

We employ a unique dataset of matched plant characteristics and pollution emissions for 248,802 foreign and domestically-owned manufacturing plants in the US from 1990-2007. Importantly, we observe whether the plant was domestically-owned for the entirety of the panel or whether they had been acquired by a foreign-investor. We then estimate "pollution production functions" that include static indicators for foreign-owned plants. Combined with industry fixed effects, this approach allows us to estimate the pollution emissions of foreign-owned plants relative to domestic-owned plants in the same industry. To our knowledge we are the first to document the pollution emissions of foreign plants in the U.S. using plant-level emissions data.

In what follows, we first delineate our contribution through a review of the literature. We then motivate our empirical approach with a conceptual model and discuss the data. Our empirical method involves two appraoches: we first estimate the overall relationship between foreign ownership and pollution emissions, then we estimate how this impact is heterogeneous across industry characteristics (specifically, industry-level trade costs, fixed costs, and agglomeration economies). Finally, we conclude and discuss how policy implications for our results.

2 Literature Review

The literature related to our paper can be separated into two broad parts: i) studies focusing on differences in plant-level pollution emissions between foreign-owned and domestically-owned establishments and ii) the responsiveness of FDI flows and firm location decisions in response to regional variation in the stringency of environmental regulation.

Papers that estimate the pollution emissions of foreign versus domestic establishments have almost entirely featured developing economies. In contrast, our study explores establishment pollution emissions in the United States. The earlier work operates on a sometimes-unobserved assumption that foreign investors into a developing country come from developed countries. The prevailing predictions was that investors from, for example, OECD countries will typically have cleaner establishments through i) utilizing newer, more energy efficient technology, ii) having better access to capital for green investments and R&D, and iii) the knowledge base and systems of production likely already adhere to their home-country or OECD environmental standards and are replicated in the abroad country (see Cole, Elliot, and Zhang (2017) for a thorough review of this literature).

However, results have not supported these predictions. Studies of developing countries such as Bangladesh, India, Indonesia, Thailand, and Mexico (see Hartman, Huq, and Wheeler (1997), Pargal and Wheeler (1996), and Dasgupta, Hettige, and Wheeler (2000)) find no impact of foreign ownership on establishment emissions. Aung, Overland, and Vakulchuk (2021) find that in developing countries, where environmental regulation may be lax, foreign-plant emissions may differ by the environmental priorities of the country of the parent investor. However, work focusing on use of energy (which contribute to a firm's "scope 2" emissions) find lower energy usage intensity among foreign-owned establishments in Indonesia, Cote d'Ivoire, Mexico, and Venezuela (see Brucal, Javorcik, and Love (2019) and Eskeland and Harrison (2003)). Cole, Elliot, and Strobl (2008) find foreign-owned Ghanaian establishments use cleaner production fuels, like electricity compared to solid or liquid fuels. Wei and Zhou (2023) find that international talent flowing into Chinese enterprises improves their emissions intensity. Also in a study of China, Yi, Hou, and Zhang (2023) find a negative correlation between FDI and industry-level CO2 emissions in manufacturing.

Studies using microdata in the US or other developed nation are far fewer. King and Shaver (2001) study emissions levels for plants in the chemical and petroleum sectors. They find that foreign-owned plants generate more waste than U.S.-owned plants, but also manage more waste internally. Balaguer, Cuadros, and Garcia-Quevedo (2023) finds that Spanish manufacturing plants with foreign investors spend more on environmental protection. To our knowledge, no work has compared the emissions levels of foreign-owned versus domestic-owned establishments in the United States. A working paper by Borga, Pegoue, Legoff, Rodelgo, Entaltsev, and Egesa (2022) compares industry-level emissions intensity per dollar of FDI and find trends suggesting multinationals were found to generally have lower contributions to overall emissions and carbon intensities in most sectors compared to domestic enterprises.

Research on the responsiveness of FDI to the stringency of environmental regulation is much larger and generally consistent with avoidance patterns: firms are generally averse to environmental regulation. This occurs on two margins: inward FDI tends to avoid strict environmental regulation while FDI flows out of a country in response to increases in regulatory stringency. Keller and Levinson (2002) find that average pollution abatement costs in a state are only a moderate deterrent to the level of inward FDI that state receives. However, after controlling for the spatial determinants of FDI and endogeneity of environmental regulation, Millimet and Roy (2016) find that regulatory stringency is negatively correlated with inward FDI and larger than previous estimates. More recent work by Bialek and Weichenrieder (2021) exploring firm-level inward FDI to Germany finds strict regulation significantly reduces new, "Greenfield" projects in polluting industries, but has a smaller impact on mergers and acquisitions (M&A).[1] The smaller impact on M&A could be due to the grandfathering of existing establishmets into environmental regulations; the regulation is not as strict on the domestic targets. In one of the few papers to study environmental regulation's impact on outbound FDI, Hanna (2010) finds evidence that regulation increases foreign assets abroad by 5.3% for firms in the most pollution intense industries. Similarly, Saussay and Zugravu-Soilita (2023) finds increases in domestic environmental stringency increases a firms likelihood in engaging in cross-boarder mergers or acquisitions.

3 Conceptual Model

The empirical analysis that follows provides the first evidence of the variation in the relative pollution emissions of foreign-owned manufacturing plants in the U.S. We first describe a model under which the relative pollution emissions depends upon plant productivity. We then describe a model connecting firm heterogeneity (including ownership heterogeneity) to productivity differences across plants in the same industry.

[1]The most prevalent form of FDI in the United States is through acquisition, not greenfield development. On average, 81% of FDI inflows to the US from 1992-1997 were acquisition. In 2017, approximately 95% of FDI inflows were acquisition (BEA, "New Investment in the United States by Foreign Direct Investors").

3.1 Plant Productivity and Pollution

Cui, Lapan, and Moschini (2015) develop a simple model that describes the interaction between productivity and pollution intensity. The authors first estimate plant total factor productivity (TFP), then investigate how TFP is related to plant emissions intensity. They find plant-level productivity is negatively correlated with the emissions of criteria pollutants. Such a result is explained by the following production model of plant i in industry j at time t:

$$q_{ijt} = exp(A_j + \phi_{ij} + e_{ijt}) * h_j(m_{ijt}, \mathbf{x}_{ijt}) \tag{1}$$

where q_{ijt} is output, m_{ijt} is a variable input, and $\mathbf{x}_{ijt}$ is a vector of all other inputs, A_j is an industry-level scaling constant, ϕ_{ij} is the plant-specific productivity parameter, and e_{ijt} is the zero mean i.i.d. error term. By assuming the function is homogeneous of degree k_j in inputs, the function can be rewritten:

$$q_{ijt} = exp(A_j + \phi_{ij} + e_{ijt}) * m_{ijt}^{k_j} * h_j(1, \mathbf{x}_{ijt}/m_{ijt}) \tag{2}$$

This transformation allows for the simple linearization of the model for structural estimation:

$$ln(q_{ijt}) = A_j + \phi_{ij} + k_j ln(m_{ijt}) + \lambda_{jt} + e_{ijt} \tag{3}$$

Like our paper, plant-level inputs are unknown. However, if input ratios are assumed common for all plants within an industry, $ln(h_j(1, \mathbf{x}_{ijt}/m_{ijt}))$ can be captured by time-varying industry fixed effects λ_{jr}.

By considering a simple pollution production function by which emissions (z_{ijt}) is tied to variable input use, it is straightforward to see how plant-level productivity is negatively related to emissions. Let $z_{ijt} = \alpha_{ijt} * f(m_{ijt})$ where $f(m_{ijt})$ is increasing in inputs and α is decreasing in abatement technologies. Without loss of generality, assuming $f(m_{ijt})$ is linear and plugging in Equation 3 for $ln(m_{ijt})$, emissions can be rewritten as:

$$ln(z_{ijt}) = ln(\alpha_{ijt}) + ln(q_{ijt}) - A_j - \phi_{ij} - \lambda_{jt} - e_{ijt}) \tag{4}$$

The first derivative of Equation 4 with respect to productivity (ϕ_{ij}) is negative, demonstrating that emissions fall at plants as productivity rises. The model interpretation is that productive establishments may use less variable inputs per unit of output, creating less emissions and waste. Related, more productive establishments may spend less on a given unit of output (from Equation 1, ϕ_{ij} increases the marginal productivity of inputs) creating slack in the budget for R&D and green infrastructure investments (among other uses). For example, if regulation or reputation effects make z_{ijt} costly, firms can reduce emission by reducing output. However, more productive firms may invest in abatement technology (lowering α_{ijt}), helping them maintain inpute and production levels while reducing emission costs.

3.2 Firm Heterogeneity and Plant Productivity

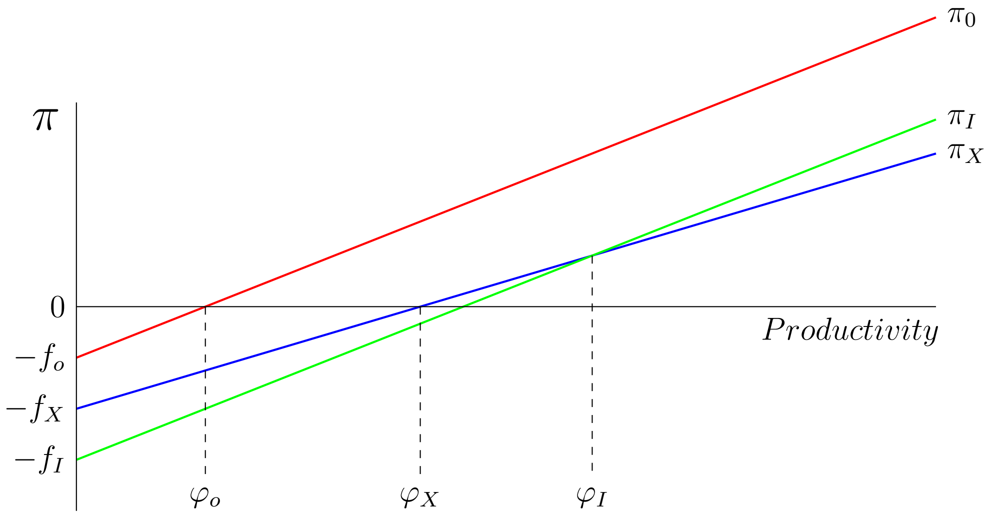
We now present a conceptual model of heterogeneous multinational firms in monopolistic competition by Helpman, Melitz, and Yeaple (2004) which suggests firms may be sorted by productivity based on the their multinational status. In our data we do not observe, nor can we estimate, plant-level productivity. However, we do observe whether plants are domestic or foreign-owned and use the combined models of Cui, Lapan, and Moschini (2015) and Helpman, Melitz, and Yeaple (2004) to generate predictions for the pollution emissions of foreign plants.

In their model, Helpman, Melitz, and Yeaple (2004) suggest potential entrepreneurs pay a fixed cost (f_e) and draw a productivity (φ) at random. After observing productivity the potential entrant chooses whether to pay a separate fixed cost to set up operations and enter the market. Firms that choose to enter the market compete in monopolistic competition. The model introduces separate fixed costs of entry (f_o), exporting (f_x), and foreign direct investment (f_I). Assuming $f_I > f_x > f_o$ produces productivity cutoffs that determine the method by which profit-maximizing firms service foreign markets.

Figure 1 provides an intuitive illustration of the profitability for different productivity levels for domestic production, exporting and foreign direct investment separately. The slope of the profitability of exporting is lower because exporters face trade costs. Producers who draw the lowest productivity (less than φ_o) earn negative profits and exit the market. Producers with profitability levels between φ_o and φ_x earn positive profits from domestic sales, but negative profits from exporting and foreign direct investment and so serve only domestic consumers. Producers with productivity between φ_x and φ_i earn positive profits from domestic production and exporting, but not foreign direct investment. Producers with productivity between φ_x and φ_i earn positive profits from domestic sales, exporting and foreign direct investment, but because profits from foreign direct investment are higher they choose that mode of serving foreign consumers.

Like our paper, Shapiro and Walker (2018) also adopts the Helpman, Melitz, and Yeaple

Figure 1: Profits and Productivity Cutoffs for Serving Foreign Consumers



Note: This figure illustrates how fixed costs can translate into productivity cutoffs that dictate the types of firms that chose to use foreign direct investment to serve foreign consumers. Firms that draw a productivity greater than φ_o earn positive profits from domestic sales and stay in the market. Firms with productivity above φ_x earn positive profits from exporting and choose to serve foreign consumers. Firms with productivity above φ_i earn larger profits from foreign direct investment than exporting and choose to open foreign affiliates.

(2004) framework. Potential entrepreneurs pay a fixed cost (f_e) and draw a productivity (φ) at random. After observing productivity the potential entrant chooses whether to pay a separate fixed cost to set up operations (f_o) and enter the market. Firms that choose to enter the market compete in monopolistic competition. There is one factor of production, which they call labor(l), and polluters have the option to use a fraction of labor (α) to abate emissions. The remaining 1 - α is devoted to producing output. Output (q) at the firm is a function of productivity, labor, and abatement, which is itself a function of productivity: $q = (1 - \alpha(\varphi))\varphi l(\varphi)$. Pollution emissions (z) are determined by production, abatement and productivity levels: $z = (1-\alpha(\varphi))^{\frac{1}{\alpha}}\varphi l(\varphi)$. Emissions are increasing in output and decreasing in abatement.

In this framework, emissions can be considered another factor input and the authors show that total output can be written as a Cobb-Douglas function of pollution and labor: $q = Z^{\alpha}(\varphi l^{1-\alpha})$. Written this way, α becomes the pollution share in the Cobb-Douglas production function. As in Subsection 3.1, Shapiro and Walker (2018) also shows that pollution intensity is decreasing in firm productivity (φ). Higher productivity firms invest more in abatement reducing emissions per unit of output. In the model, only productivity varies across firms in the same industry, so any variation within industry emissions intensity must be driven by productivity differences across firms. In our context, that means the differences in the relative pollution emissions of foreign-owned firms across industries can be driven by differences in relative productivity of those foreign-owned firms. In industries with relatively more productive foreign-owned firms, we would expect those firms to be cleaner.

Unfortunately this result does not map directly into our empirical setting. The relative productivity predictions from Figure 1 are between firms within the same country choosing whether and how to serve foreign customers. We are comparing the pollution emissions of a foreign company's U.S. investments to domestic U.S. firms. Still, recent empirical research estimates a productivity premium for foreign-owned plants. Doms and Jensen (1998) and Girma, Thompson, and Wright (2002) document that foreign-owned affiliates are more productive than domestically-owned producers in the country of the affiliate. According to Guadalupe, Kuzmina, and Thomas (2012), the productivity advantage stems from foreign parents acquiring the most productive host-country firms within an industry and subsequently leveraging productivity spillovers and innovation to increase sales and efficiency. Arnold and Javorcik (2009) finds that foreign acquisition of Indonesian plants is associated with a more than ten percent increase in productivity.

3.3 Plant Productivity and Industry Characteristics

We use the combined models to generate predictions for domestic and foreign-owned plant productivity across three industry characteristics: industry fixed costs, trade costs, and agglomeration returns

Fixed Costs:

High industry fixed costs predict a rightward shift in the industry productivity distribution. Domestic firms face a higher entry threshold for productivity when fixed costs are large. At the same time, FDI is also costlier to achieve and only the most productive foreign investors can afford to incur the duplicate fixed costs of entry f_I. The visual comparative-static can be created in Figure 1 by an equal drop in π_0 and π_I, which creates a greater productivity threshold increase for foreign direct investors versus solely domestic firms. As a result, $\varphi_I - \varphi_0$ grows and foreign plants in the U.S. are predicted to enjoy a greater productivity advantage when fixed costs are large, ceteris paribus.

Trade Costs:

High trade costs result in a downward rotation of π_X lowering the productivity threshold for profitable FDI. Holding all else equal, foreign establishments in the US will be relatively less productive when trade costs are high, ceteris paribus. In other words, lower trade costs will invite less productive (thereby dirtier) foreign-plants into the US.

Agglomeration:

Figure 1 also suggests agglomeration effects can alter the relative productiveness of multinationals. When businesses locate near each other, one major benefit is reduction in variable costs of production through proximity to suppliers, buyers, skilled workers, and ideas (see Glaeser (2010)). Agglomeration creates an upward rotation in π_I. Productive firms will generate greater marginal profits when marginal costs are lower which can happen through agglomeration generated by FDI. As such, foreign-owned establishments in industries with high agglomeration returns may be relatively less productive than foreign-owned establishments in industries with low agglomeration returns, ceteris paribus. Agglomeration returns increase the marginal profit of solely domestic firms as well. If the returns to agglomeration are equal, the visual comparative-static is operationalized in Figure 1 by a equal leftward rotation in π_0 and π_I, which creates a greater productivity threshold decrease for foreign direct investors versus solely domestic firms.

Our model does not capture all the channels through which domestic and foreign owned productivity may vary. Alfaro and Chen (2018) find the entry of foreign multinational firms can affect the productivity of domestic firms as well, not only through productivity spillover to domestic firms, but also by motivating the firms to raise R&D, adopt better technologies, and streamline product composition. Additionally, foreign investors "cherry pick" the most productive domestic firms through acquisition and then increase their output (Guadalupe, Kuzmina, and Thomas, 2012), increased competition in the industry drives product prices down (Melitz and Ottaviano (2008)) and increases prices in factor markets which forces low-productivity domestic firms out. As such, total industry productivity is predicted to rise with foreign firm participation (Alfaro and Chen, 2018). In sum, the entry of foreign-plants into a market results in a de facto increase in the productivity threshold for domestic firms to make profits. These channels are not captured in our model, but could be having an effect instead of or along with trade costs, entry costs and agglomeration economies.

We build our subsequent analysis based on the predictions of this conceptual model. First, we estimate overall emissions differences between foreign and domestic establishments. We then describe emissions intensity of domestic and foreign owned plants across sub-industries with in the broader manufacturing industry. Lastly, we estimate whether emissions intensity differences vary according to the productivity relationships predicted by industry fixed costs, trade costs, and agglomeration returns. Although we cannot test whether productivity is the causal channel by which firms differ according to these characteristics, the results are consistent with the theoretical framework.

4 Data

Estimating the pollution emissions of plants requires detailed data on plant characteristics and pollution emissions. We construct a panel at the plant-year level by matching plant characteristics from the National Establishment Time Series (NETS) with pollution emissions from the Risk Screening Environmental Indicators (RSEI) data set. Our NETS data consists of 248,802 unique manufacturing plants (SIC 20-39), approximately a ten percent extract from the full NETS manufacturing database which is marketed as the universe of manufacturing plants. Due to entry and exit the panel is unbalanced and consists of 2,469,893 plant-year observations covering 1990-2007. On average approximately 150,000 plants are in operation each year. Just under 70,000 plants survive across the seventeen years of our panel and around 50,000 are observed for fewer than five years.

The NETS data is complied by Dunn & Bradstreet as a part of their D&B Rating product, essentially a credit score for business. The data includes a host of plant characteristics including annual observations on sales, employment, credit rating, industry and location. It also captures static indicators on legal status (proprietorship, corporation, etc.), exporter status, CEO gender, ownership structure (including the ultimate parent firm), the number of related plants and the number of plants that report this facility as their parent. We use the location information to determine whether the facility is located in a county that has ever been in nonattainment of the National Ambient Air Quality standards. These counties are subject to higher levels of environmental regulation which has been shown to affect location decisions (List, Millimet, Fredriksson, and McHone (2003)) and FDI flows (Keller and Levinson (2002). Most importantly for this analysis, the NETS includes a static indicator for whether the facility is foreign-owned in the last year it was observed: firms who remain domestic for the entirety of the panel are coded 0 while firms established or acquired by foreign firms are coded 1. Our data does not capture changes in ownership during prior years of the panel.

The NETS has been used in a variety of empirical economic studies and Neumark, Wall, and Zhang (2011) found that it was comparable in data quality to other public and proprietary plant-level data sources including the Quarterly Census of Employment and Wages (QCEW), the Current Employment Statistics (payroll) survey (CES), and the Size of Business data (SOB).[2] Haltiwanger, Jarmin, and Miranda (2013) compares the NETS to several official U.S. government data sets and finds that the accuracy of the NETS is better than older Dunn & Bradstreet databases.[3] Barnatchez et al. (2017) conducts a detailed comparison of the NETS data with the U.S. Census, Quarterly Census of Employment and Wages (QCEW), and County Business Patters (CBP). The results suggest that there are difference between the NETS and official data sets and that those differences are "concentrated among small establishment size classes, particularly the 1-4 employee class" (p.6). Because we focus on manufacturing establishments that report pollution emissions to the EPA this is less of a concern for our analysis.

The RSEI data is compiled from Toxic Release Inventory (TRI) data collected by the Environmental Protection Agency (EPA) under the Comprehensive Environmental Response, Compensation, and Liability Act (commonly known as the Superfund Act). The TRI consists of self-reported emissions of hundreds of toxic chemicals regulated under the Act. EPA collects this data and checks for internal consistency of submissions. There are significant legal penalties for intentionally misreporting toxic emissions. There is some evidence of

[2]In additional to Neumark, Wall, and Zhang (2011), see Levine, Toffel, and Johnson (2012) and Neumark and Kolko (2010) for examples of studies using the NETS.

[3]The authors note that the NETS coverage of non-employer businesses is relatively poor, but this is less of an issue for manufacturing establishments which typically have employees.

under-reporting of emissions, but there does not seem to be any evidence of systematic misreporting by foreign-owned plants.[4] The RSEI takes reported TRI emissions and weights them by the toxicity of the chemical emitted to create a hazard score. This facilitates comparison across plants that emit different types of chemicals by measuring emissions as a function of their potential harm. The RSEI has been used in several studies to proxy for pollution emissions of plants, firms and communities.[5]

We combine the NETS and RSEI data using DUNS numbers (a unique plant identifier created by Dun & Bradstreet which also provides source data for the NETS) where possible. DUNS number is an optional field in the TRI and many are missing or invalid. For plants that do not report a DUNS number, we combine NETS and RSEI data using address and industry information using a fuzzy matching procedure. We are able to successfully match just under seventy-five percent of TRI reporting facilities. The matched facilities were slightly larger in terms of emissions and hazard score than the unmatched, but the ratio of the hazard to emissions were not statistically significantly different.

Table 1 describes the dataset. The first three columns report summary statistics for the entire sample of NETS plants. The first column reports means and standard deviations (in parentheses) for the full sample, Column 2 reports the averages for domestically-owned plants only, Column 3 describes foreign-owned plants. Foreign-owned plants are larger across every dimension. They have approximately 11% more logged sales, slightly more employees, and report TRI emissions just over twice as often as domestically-owned plants.

Not all plants are required to report their toxic chemical emissions to the TRI. Plants that meet three criteria are required to report emissions: plants must operate in selected industries (including all manufacturing industries); have more than ten employees; and manufacture, process, or otherwise use TRI-listed chemicals in quantities above permissible thresholds. Approximately 6.2% of plant-years in our matched data report TRI emissions. More than 14% of foreign-owned plant-years in the data are TRI reporters compared to 6.1% of domestic plant-years, potentially because their larger size makes them more likely to exceed the employment and chemical use thresholds.

The final three columns of Table 1 report summary statistics for our estimation sample

[4] Marchi and Hamilton (2006) find that for some chemicals the reported emissions are not consistent with Benford's Law and Koehler and Spengler (2007) find evidence of under-reporting for polycyclic aromatic hydrocarbons in the aluminum industry. While neither of these studies look at foreign ownership directly the misreporting they discover does not appear to be correlated with productivity, size or other characteristics that are in turn correlated with foreign ownership.

[5] See Holladay (2016) examining plant-level emissions and exporting status and Banzhaf and Walsh (2008) for analysis of sorting at the community-level among other examples.

Table 1: Summary Statistics

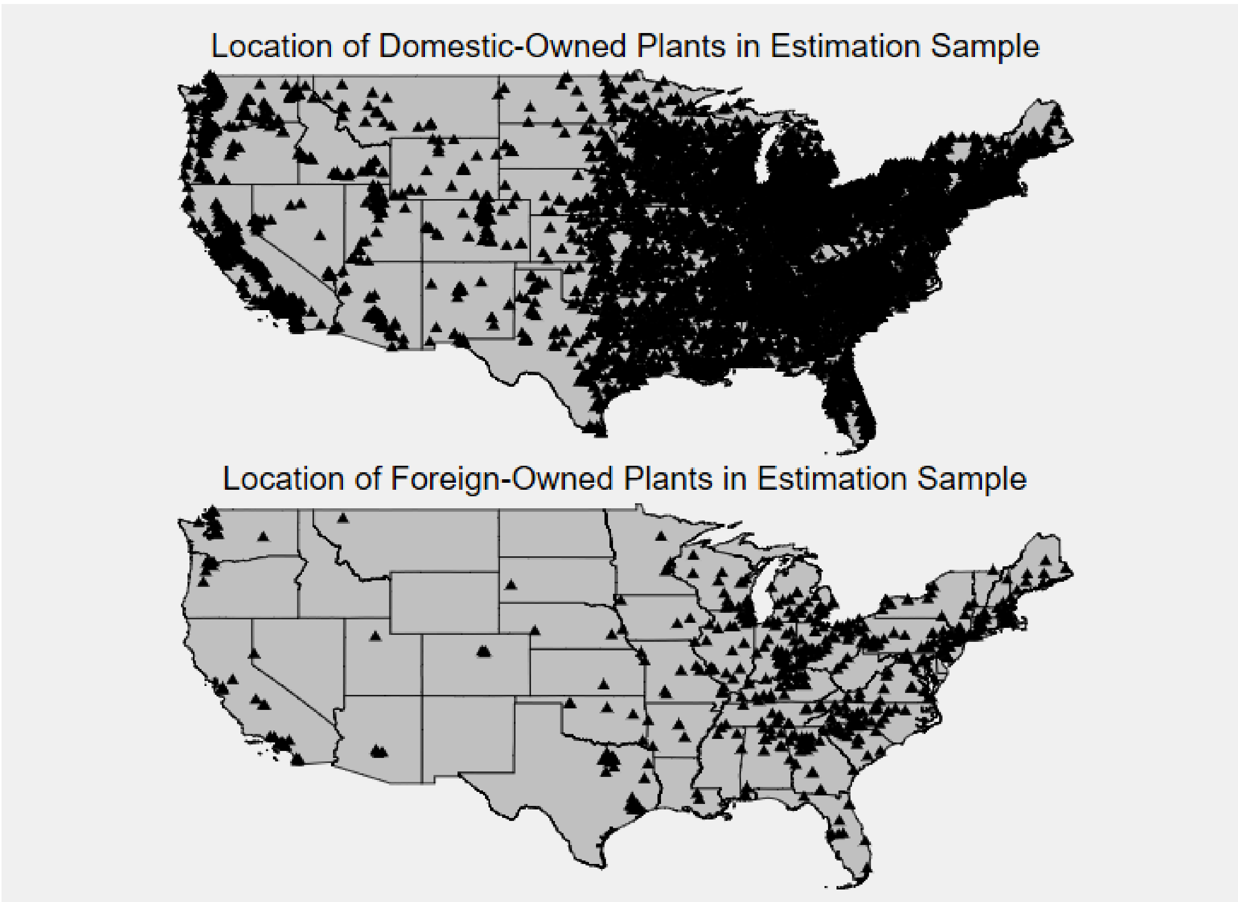
Variable	**Full Sample** Pooled	**Full Sample** Domestic	**Full Sample** Foreign	**Reporters** Pooled	**Reporters** Domestic	**Reporters** Foreign
Log Sales (million $)	13.7	13.7	15.2	16.2	16.2	16.6
	(1.73)	(1.72)	(1.80)	(1.47)	(1.47)	(1.42)
Log Employees	2.84	2.83	3.82	4.78	4.78	4.90
	(1.42)	(1.42)	(1.56)	(1.36)	(1.36)	(1.27)
Relatives	49.2	49.7	8.76	99.0	101.1	8.03
	(554.8)	(558.0)	(65.9)	(219.3)	(221.3)	(37.2)
Subsidiaries	0.59	0.54	4.43	3.31	3.28	3.86
	(8.24)	(7.95)	(20.7)	(10.5)	(10.6)	(7.04)
Credit Rating (D&B Paydex Min)	66.5	66.5	67.5	67.5	67.5	68.5
	(13.5)	(13.6)	(10.4)	(9.52)	(9.56)	(8.22)
Exporter	0.14	0.14	0.35	0.32	0.31	0.48
	(0.35)	(0.34)	(0.48)	(0.47)	(0.46)	(0.50)
Ever Nonattain	0.81	0.81	0.86	0.74	0.74	0.74
	(0.40)	(0.40)	(0.35)	(0.44)	(0.44)	(0.44)
Log Hazard (millions)				14.3	14.3	14.4
				(4.56)	(4.56)	(4.55)
Log Hazard/Log Sales				0.88	0.88	0.87
				(0.28)	(0.28)	(0.28)
Foreign Owned	0.012			0.028		
	(0.11)			(0.17)		
TRI Reporter	0.062	0.061	0.14			
	(0.24)	(0.24)	(0.35)			
Observations	2,469,893	2,437,470	32,423	152,892	148,222	4,670
Firms	248,802	245,712	3,090	19,210	18,667	543

Note: This table reports summary statistics across the matched plant-pollution emissions panel covering the years 1990-2007. The first three columns report summary statistics across the full sample of plants. The final three report summary statistics conditional on reporting emissions to EPA's Toxic Release Inventory. See the text for a description of reporting requirements. Relatives represents the count of plants reporting the same top line parent. Subsidiaries is the count of other plants reporting the plant as a parent. Credit rating is an index of plant's PayDex score, a proprietary credit rating calculated by Dunn & Bradstreet. Ever non-attain is an indicator that is equal to one if the plant is located in a county that has ever been designated in non-attainment under the Clean Air Act. This designation comes with additional environmental regulation. Hazard scores are only available for plants that report to the TRI. Standard deviations are in parentheses. Relatives, kids, exporter, ever nonattain, and foreign-owned do not vary across time.

of TRI reporters. TRI reporters are larger in terms of both sales and employees than non-reporters. They are more likely to export and less likely to be located in a county that is ever in non-attainment with the standards set out in the Clean Air Act. TRI reporters are more similar across domestic- and foreign owned facilities than the full sample. Average log hazard is very similar across domestic and foreign owned TRI reporters, but there is considerable variation at the facility level. Conditional on reporting TRI emissions, the first percentile of hazard is 49.5 and the 99^{th} percentile is 23 billion. In the next section we explore this variation.

Figure 1 demonstrates the spatial distribution of foreign versus domestic establishments across the continental US in our estimation sample. The map indicates that foreign plants do not systematically locate in different regions of the US compared to domestic plants. The image omits 117 domestic plants and 7 foreign plants operating out of US islands, Puerto Rico, Hawaii, and Alaska (in total, 0.6% of our estimation sample).

Figure 2: Distribution of Plants in Estimation Sample



Note: This figure depicts the distribution of establishments across the continental US that are used in our estimation sample. The image omits 117 domestic plants and 7 foreign plants operating out of US islands, Puerto Rico, Hawaii, and Alaska (in total, 0.6% of our estimation sample)

5 Estimating the pollution emissions of Foreign-owned Plants

In this section we document the pollution emissions of foreign-owned plants in the US manufacturing sector. We estimate pollution production functions comparing the pollution emissions of domestic- and foreign-owned plants. We first evaluate selection into TRI reporting status. Unconditionally, foreign-owned plants are more likely to report to the TRI, but the effect goes away when controlling for size differences. Foreign plants are larger (in employment and sales) and potentially use more inputs making them more likely to meet TRI reporting requirements. Next, in a pooled sample foreign-owned manufacturing plant emissions appear roughly comparable to domestically-owned plants. These average results hide significant variation across and within manufacturing industries. In particular, the results suggest that in some industries foreign-owned plants are significantly cleaner while in others they are much dirtier. Even in closely related manufacturing industries pollution emissions of foreign-owned plants can vary drastically.

We develop a straightforward empirical approach to analyze differences in pollution emissions between domestic- and foreign-owned manufacturing plants in the U.S. We estimate a series of reduced form "pollution production functions". The production function for plant i, in industry j, at time t is:

$$ln(E_{ijt}) = \gamma_1 ln(L_{ijt}) + \gamma_2 ln(S_{ijt}) + \gamma_3 ForeignOwned_{ij} + \gamma_4 NonAttain_{ijt} + \delta_j + \tau_t + e_{ijt}, \quad (5)$$

where E_{ijt} is emissions, L_{ijt} is number of employees, S_{ijt} is the value of sales, δ_j and τ_t are industry and year fixed effects, and e_{ijt} is a random error term with zero mean.[6] Hanna (2010) shows that the level of environmental regulation can affect the location decision of multinational plants. We collect data on EPA nonattainment status as a proxy for the level of regulation in each county and create an indicator for counties that have been in nonattainment status at any time during our sample period. $ForeignOwned_{ij}$ is an indicator for a foreign-owned manufacturing facility. The parameter of interest is γ_3, the emissions impact of being foreign-owned compared to domestically owned plants in the same industry holding output and employment constant.

[6] Cui, Lapan, and Moschini (2015) shows that if we assume that all plants in an industry employ the same technology, face the same costs, differ in only productivity, and the production function is HDκ it is appropriate to separate out the observable labor and emissions inputs from the factor shares. This implies that the input ratios, which are not reported in our data, are common within an industry and can be controlled for by a set of time varying industry fixed effects.

We begin by estimating the propensity to report pollution emissions across our entire sample. Table 2 reports a series of regressions evaluating the relationship between foreign ownership and emissions reporting status. Each column reports a linear probability regression with an indicator for whether the plant reports pollution emissions to the TRI as the dependent variable. Column 1 reports the unconditional difference in the fraction of foreign owned plants that report their emissions. The results indicate that foreign owned plants are about 8 percentage points more likely to report emissions, statistically significant at the one-percent level. Column 2 adds a set of industry (SIC4) and year fixed effects. The foreign owned coefficient becomes smaller in magnitude but remains statistically significant. This provides some evidence that foreign ownership is more common in dirty industries, but within industries foreign owned plants remain more likely to report emissions. Column 3 adds an indicator for whether the facility is located in a county that has ever been in nonattainment under the Clean Air Act's National Ambient Air Quality standards. We find plants from non-attainment counties are 3 percentage points less likely to report emissions. The coefficient on foreign ownership is unchanged. Finally, we add log employment and log sales to control for size and output differences between domestic- and foreign-owned plants. After controlling for plant size, foreign-ownership is no longer correlated with reporting status. This is consistent with the hypothesis that foreign-owned plants are more likely to be TRI reporters because they are larger. Overall, the results of table 2 indicate that there are no observable differences between domestic and foreign-owned plants' propensity to report TRI emissions after controlling for industry and plant size.[7]

We now evaluate the pollution emissions of foreign owned plants conditional on reporting emissions. Table 3 reports an analogous series of regressions to table 2 with the log of plant hazard score as the dependent variable. The first column reports the unconditional difference in emissions between domestic and foreign owned plants. Foreign owned plant emissions are not statistically different from domestic manufacturers. Column 2 reports the difference in emissions controlling for industry and year. The results echo the emissions reporter results: as evidenced by the reduction in magnitude of the Foreign Owned coefficient, foreign-owned plants tend to be in relatively dirty industries. Column 3 adds controls for the non-attainment status of the county of the plant. Facilities in non-attainment counties pollute significantly less despite the fact the regulations under the Clean Air Act do not directly target toxic emissions from the TRI. The difference in emissions between domestic

[7]The results are unchanged in a cross-section when we restrict the sample to the final year for which we have plant-level data.

Table 2: Plant Propensity to Report Emissions

	1	2	3	4
Foreign Owned	0.08***	0.05***	0.05***	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Ever Nonattain			-0.03***	-0.03***
			(0.00)	(0.00)
Log(Sales)				0.04***
				(0.00)
Log(Employment)				0.01***
				(0.00)
Constant	0.06***			
	(0.00)			
Industry FE	N	Y	Y	Y
Year FE	N	Y	Y	Y
R^2	0.0015	0.1220	0.1245	0.2252
N	2,469,893	2,469,893	2,469,893	2,469,893

Note: Each column reports the results of a linear probability model where the dependent variable is equal to 1 if the plant reports pollution emissions to the EPA. Standard errors, clustered at the plant level, are reported in parentheses. $***$ significant at the 1% level, $**$ significant at the 5% level, $*$ significant at the 10% level.

Table 3: Plant Pollution Emissions

	1	2	3	4
Foreign Owned	0.12	-0.03	-0.02	-0.09
	(0.20)	(0.20)	(0.20)	(0.19)
Ever Nonattain			-0.26***	-0.19***
			(0.07)	(0.07)
Log(Sales)				0.27***
				(0.06)
Log(Employment)				0.53***
				(0.07)
Constant	14.29***			
	(0.04)			
Industry FE	N	Y	Y	Y
Year FE	N	Y	Y	Y
R^2	0.0000	0.1711	0.1716	0.2139
N	152,892	152,892	152,892	152,892

Note: Each column reports the determinants of plant level pollution emissions. All regressions use log of EPA's hazard measure as the dependent variable. Inclusion in the sample is conditional on reporting emissions to the EPA as described above. Standard errors clustered at the plant level are reported in parentheses. $***$ significant at the 1% level, $**$ significant at the 5% level, $*$ significant at the 10% level.

and foreign-owned plants remains imprecisely estimated. Column 4 adds log employment and log sales to control for plant size. Larger plants pollute more, but the increase is less than proportional, consistent with increasing returns to scale in pollution abatement. The indicator for foreign ownership remains small in magnitude and imprecisely estimated after controlling for size, industry, and attainment status.

The 95% confidence interval on the foreign-owned dummy coefficient is (-0.46,0.30). The imprecision in the estimate suggests that underlying heterogeneity exists in the relationship between foreign ownership and pollution emissions. To explore how this variation relates to industry characteristics, we interact industry indicators (δ_j) with our foreign ownership dummy variable:

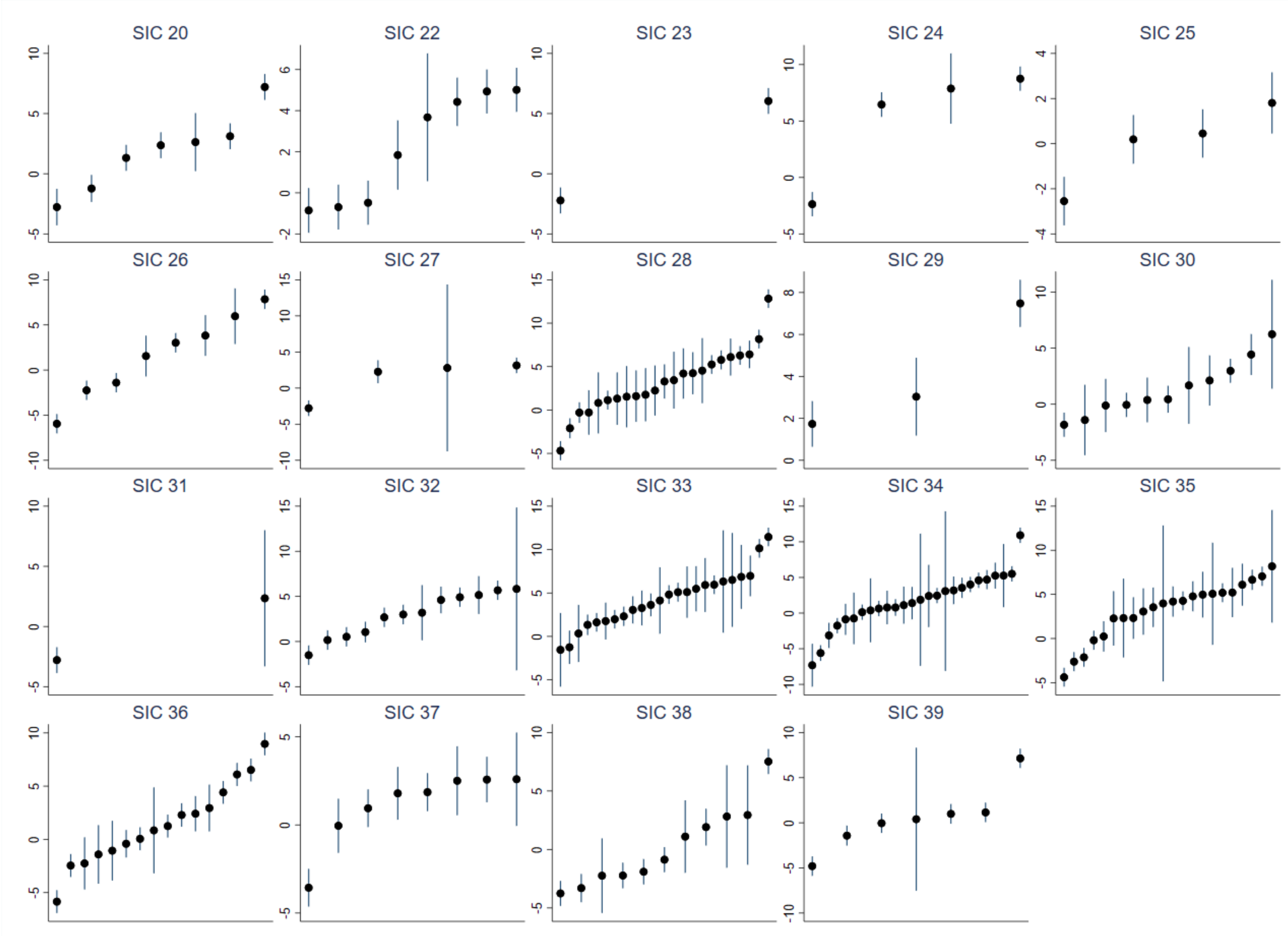
$$\begin{aligned} ln(E_{ijt}) = \gamma_1 ln(L_{ijt}) + \gamma_2 ln(S_{ijt}) + \gamma_3 ForeignOwned_{ij} + \gamma_4 ForeignOwned_{ij} * \delta_j \\ + \gamma_5 NonAttain_{ijt} + \delta_j + \tau_t + e_{ijt}, \end{aligned} \tag{6}$$

We capture the coefficients in Equation 6 and calculate the average difference between foreign and domestic plant pollution emissions by SIC4 industry j: $\hat{\beta}_j = \hat{\gamma_3} + \hat{\gamma_4} * \delta_j$. This approach generates 202 estimates of foreign plant relative pollution emissions by four digit SIC industry. Figure 3 graphs each SIC4 estimate of $\hat{\beta}$ by SIC2 industry. Within each SIC2 panel, $\hat{\beta}$ is sorted and displayed along with its 95% confidence interval.[8] We find there is significant heterogeneity in pollution emissions of foreign-owned plants across closely related manufacturing industries. In all except one two-digit SIC industry (SIC 29) there are four-digit industries in which the foreign-owned plants are significantly cleaner and significantly dirtier than their domestic-owned competitors.

Table 4 provides another way to summarize the heterogeneity in foreign-owned plant's pollution emissions. The variation across four-digit industries is vast: $\hat{\beta}$ ranges from -7.3 to 12.8, or nearly 100% cleaner to many hundreds of times dirtier. Raw hazard scores also vary greatly (with a minimum of 0.071, maximum of 19.2 trillion, and a mean of 1.13 million), driven by differences in the quantity and particularly the toxicity of a plant's emissions. In the next section we investigate the relationship between foreign plant pollution emissions and industry characteristics in an effort to understand the drivers of the variance in the relative pollution emissions of foreign owned manufacturing plants.

[8]Standard errors are computed using the delta method.

Figure 3: Summarizing Estimated Foreign-Owned Pollution Emissions



Note: This figure reports the estimated pollution emissions of foreign-owned plants relative to domestic-owned plants in the same industry. Each dot and whisker represents the estimate ($\hat{\beta}_j = \hat{\gamma_3} + \hat{\gamma_4} * \delta_j$) and 95% confidence interval (standard errors are computed using the delta method).

Table 4: Within Industry Variation in Foreign-Owned Pollution Emissions

SIC	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**	**Description**
24	5.18	5.1	-2.4	8.7	4	Lumber & Wood
33	4.22	3.2	-1.5	11.5	24	Primary Metal
29	4.08	3.0	1.7	7.5	3	Petroleum & Coal
28	3.20	3.7	-4.7	12.8	23	Chemical & Allied
35	3.19	3.3	-4.4	8.2	22	Industrial machinery
32	2.94	2.4	-1.5	5.8	12	Stone, Clay, & Glass
22	2.23	2.6	-0.9	5.0	8	Textile Mills
23	1.91	5.8	-2.2	6.0	2	Apparel & Other Fabric Products
20	0.91	3.9	-5.4	7.2	8	Food & Kindred
34	1.64	3.7	-7.3	10.9	26	Fabricated Metal
26	1.58	4.6	-5.9	7.8	8	Paper & Allied
27	1.35	2.8	-2.8	3.1	4	Printing & Publishing
30	1.35	2.5	-1.8	6.2	11	Rubber & Misc. Plastic
36	1.40	3.8	-5.8	9.0	16	Electronic & Other Electronic
37	1.08	2.1	-3.6	2.6	8	Transportation
39	0.49	3.6	-4.8	7.1	7	Misc. Manufacturing
38	0.18	3.4	-3.8	7.5	11	Instruments & Related
25	-0.03	1.8	-2.5	1.8	4	Furniture & Fixtures
31	-0.22	3.6	-2.8	2.3	2	Leather & Leather Products
All	2.27	3.5	-7.3	12.8	202	

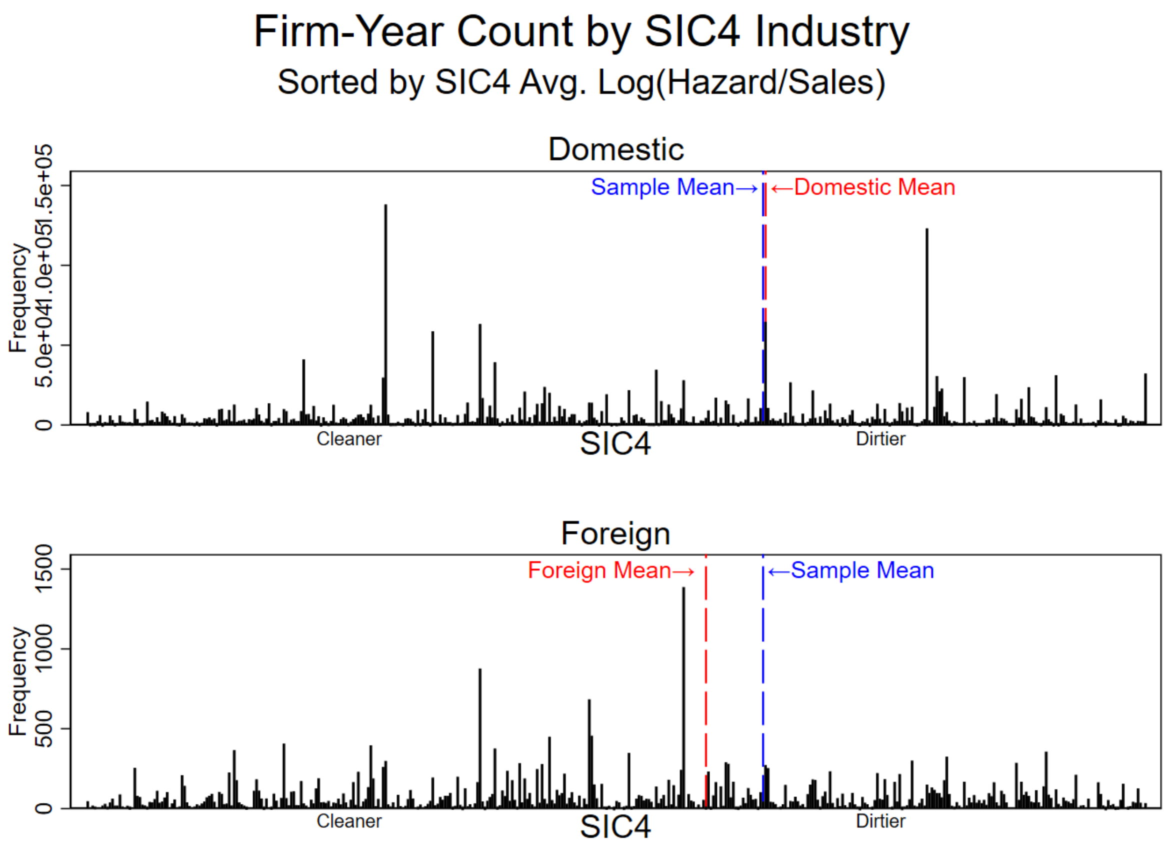
Note: Each row represents summary statistics on the pollution emissions of foreign-owned plants estimated at the four digit SIC level and summarized at the two digit SIC industry level.

6 Exploring the Variation in Foreign-Owned Plant's pollution emissions

On average foreign plants emit about as much as domestic plants, but there is significant heterogeneity within and across industries. In this section, we explore cross-industry variation in foreign-owned plants' pollution emissions.

Figure 4 plots the plant-year counts in each SIC4 industry in our sample, sorted from least emissions-intense industry to most emissions-intense. Within both foreign- and domestic-ownership, there does not appear to be distinct clumping within the relatively cleaner or relatively dirtier portions of the sorted-SIC4 distributions. This is not surprising given our baseline emissions-intensity estimation (Column 1 from Table 3) found no statistically significant difference between foreign and domestic plants when pooled across industries. It does not appear foreign plants are selecting into cleaner or dirtier SIC4 industries in the U.S.

Figure 4: Distribution of SIC4 Industry, Sorted



Note: This figure depicts the counts of firm-years within each SIC4 industry in our sample. SIC4 industries are sorted by average Log(Hazard/Sales) from cleanest to dirtiest. The Sample Mean dashed line is the mean Log(Hazard/Sales) for the full estimation sample. Domestic and Foreign Means are calculated specifically for those subsamples. These distributions of firm-year counts suggest a slightly greater proportion of foreign plants operate in relatively less emissions intense industries.

We have documented that within some industries foreign-owned plants are significantly cleaner than domestic-owned competitors, while in other industries they are much dirtier. We collect a set of industry-level variables and examine their correlation with the relative pollution emissions of foreign owned plants. We test for differences in relative pollution emissions based on variables that the literature has found are correlated with polluting plants' FDI decisions: trade costs, fixed costs of production, and industry agglomeration. We refer the reader back to Section 3.3 for theoretical arguments for their impact on plant productivity. In summary, foreign-owned plants are predicted to have relatively larger productivity premiums over their domestic peers in industries with low trade cost, high fixed cost, and low agglomeration economies.

We augment our plant-level data from the NETS with industry and location-specific characteristics to examine how these characteristics correlate with the relative pollution emissions of foreign owned manufacturing plants. The previous literature has suggested that trade costs, plant fixed costs and local environmental regulation play a role in the location decision of foreign owned polluters. We extend that analysis to evaluate how the pollution emissions of foreign owned plants varies with those industry characteristics.

Ederington, Levinson, and Minier (2005) shows that mobile industries are more sensitive to environmental regulation. They proxy for mobility using the presence of agglomeration economies, trade costs, and fixed costs. To measure fixed costs we collect real capital stock expenditures by industry from the NBER-CES Manufacturing database for each year in our sample. We follow Ederington, Levinson, and Minier (2005) by scaling fixed costs total industry value of shipments. Our trade cost measure comes from Bernard, Jensen, and Schott (2006), who supplies the product-level trade costs (customs, duties, insurance, and freight) weighted by import value. We aggregate these to 4-digit industry level. Finally, we use the data on plant employment, location and industry to calculate the agglomeration index describe in Ellison and Glaeser (1997) for each industry and year. The higher the index value, the more agglomeration we observe in that industry-year. We then introduce the log of these industry variables into the plant level emissions regression described in Equation 7.[9] The results are presented in Table 5.

We introduce the industry variables into a regression based on Equation 5 and interact industry level variables with the foreign owned indicators. We estimate a series of equations of the form:

$$\begin{aligned} ln(E_{ijt}) =& \gamma_1 ln(L_{ijt}) + \gamma_2 ln(S_{ijt}) + \gamma_3 ForeignOwned_{ij} + \gamma_4 * ln(x_{jt}) \\ &+ \gamma_5 ForeignOwned_{ij} * ln(x_{jt}) + \gamma_6 NonAttain_{ijt} + \delta_j + \tau_t + e_{ijt}, \end{aligned} \tag{7}$$

where x_{jt} is one of our industry-level covariates (fixed costs, trade costs, or the agglomeration index).

Each column of Table 5 reports a plant level regression with the log of hazard score as the dependent variable. Inclusion in the sample is conditional on reporting emissions to

[9] All of the industry variable possess a right skew and the natural log mitigates the superfluous influence of outliers.

Table 5: Correlates of Foreign Owned Plant Pollution Emissions

	1	2	3	4	5
Log(Sales)	0.24***	0.24***	0.24***	0.24***	0.24***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Log(Employment)	0.56***	0.55***	0.55***	0.55***	0.55***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Ever Nonattain	-0.13	-0.13	-0.13	-0.13	-0.13
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Foreign Owned	-0.11	1.30	-0.77*	2.58	4.52**
	(0.20)	(0.82)	(0.44)	(1.80)	(1.98)
Log(Trade Costs)	0.27***	0.26***	0.27***	0.27***	0.26***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Log(Fixed Costs)	-0.33***	-0.33***	-0.30***	-0.33***	-0.29***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Log(Agglomeration Index)	0.36	0.36	0.36	0.31	0.28
	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
Foreign Owned*Log(Trade Cost)		0.48*			0.60**
		(0.27)			(0.27)
Foreign Owned*Log(Fixed Costs)			-0.75*		-0.95**
			(0.42)		(0.43)
Foreign Owned*Log(Agglomeration Index)				1.06	1.45**
				(0.71)	(0.73)
R^2	0.2197	0.2198	0.2198	0.2197	0.2201
N	118,936	118,936	118,936	118,936	118,936

Note: Each column regresses a set of plant and industry characteristics on plant level pollution emissions. Sales, employment and the foreign ownership indicator are reported in the NETS at the plant level. "Ever nonattain" is an indicator equal to one if the plant is located in a county that is nonattainment with the national ambient air quality standards laid out by the Clean Air Act. Nonattainment status is associated with additional environmental regulation. Trade costs are reported by Bernard, Jensen, and Schott (2006) using a trade weighted average of trade costs reported in customs paperwork. Fixed costs are taken from the NBER-CES database and standardized via industry total value of shipments. The Agglomeration Index reports the agglomeration index proposed in Ellison and Glaeser (1997) using the full NETS sample. Standard errors clustered at the plant level are reported in parentheses. $***$ significant at the 1% level, $**$ significant at the 5% level, $*$ significant at the 10% level.

the TRI as described in Section 5. Each regression includes year and industry fixed effects. The specifications include the plant level variables reported in Table 3. The results here are consistent with Table 3 although the magnitude of the estimated impact of non-attainment on emissions falls slightly, making the coefficient marginally insignificant. Column 1 reports the plant-level regression along with the levels of all four of our industry level variables. The results illustrate the impact of industry characteristics on plant level pollution intensity. Lower trade costs, higher fixed costs, and less agglomeration are all associated with cleaner U.S. manufacturing plants.

Column 2 introduces the trade cost variable interacted with an indicator for foreign owned. Increasing trade costs are associated with increases in emissions from foreign-owned plants. A 1% higher trade cost significantly correlates to a 0.48% improvement in the relative pollution emissions of foreign plants. Column 3 interacts the foreign ownership indicator with our measure of plant fixed costs. Industries with higher fixed costs have relatively clean manufacturing plants, but foreign firms in high fixed costs are even cleaner. A 1% increase in fixed costs is associated with a 0.75% improvement in foreign plant pollution emissions relative to domestic plants. Column 4 interacts foreign ownership with the agglomeration index. The coefficient is positive and large in magnitude relative the impact of agglomeration across manufacturing as a whole. However, it is possible that the impact of agglomeration may be mitigated by the mobility of foreign investors. That is, even though the impact agglomeration may be large, some plants may face prohibitive fixed costs or be dissuaded from FDI by already low trade costs. After controlling for the impact of trade costs and fixed costs on foreign firms, we find a significant negative correlation between foreign plant pollution emissions the agglomeration level of their industry.

The results suggest that industry characteristics that make opening foreign affiliates in the U.S. more attractive are associated with dirtier foreign owned plants relative to domestic plants. This is consistent with the predictions of our conceptual model: foreign firms differ in productivity from domestic firms depending, in part, on the characteristics of the industry. If we assume foreign assets in the U.S. inherit the productivity of their parents, the productivity premium enjoyed by foreign plants is smaller when fixed costs are low, trade costs are high, and agglomeration returns are high. Productivity is linked to pollution emissions in that i) productive plants use less inputs for a given level of output, generating less emissions or, as in Shapiro and Walker (2018), the opportunity costs of abatement are smaller.[10]

[10]The results are similar a cross-section when we restrict the sample to the final year for which we have plant-level data, but the industry characteristic interactions are imprecisely estimated.

7 Conclusion

We compile a detailed dataset of plant-level characteristics and pollution emissions to test for differences in emissions intensities between foreign and domestic-owned manufacturing plants in the US. Our results suggest that there is significant heterogeneity in the pollution emissions of foreign-owned manufacturers both within and across industries. We then seek to explain this variation using industry characteristics. We show that foreign-owned plants are significantly cleaner in industries with low trade costs, high fixed costs, and low agglomeration levels.

Manufacturer productivity differences are a candidate link between our covariates of interest and foreign-plant pollution emissions. More productive plants produce less waste per unit of output since more productive plants use less inputs per unit of output, ceteris paribus. A number of studies document the negative relationship between manufacturing plant productivity and pollution emissions. For example, Cui, Lapan, and Moschini (2015) develops a trade model in which emissions are an input to production, so more productive plants "use" less emissions to produce. Applying this framework to international trade, Holladay (2016) shows that exporters (who are more productive than their non-exporting peers) pollute less than non-exporters after controlling for output levels. Shapiro and Walker (2018) demonstrate that as manufacturing total factor productivity increases, plant-level pollution per output falls.

It is important to note our results do not explain all the variation in foreign plant pollution emissions. While the pattern of low trade costs, high fixed cost, and low agglomeration is associated with relatively clean foreign-owned plants, a number of other potential channels could generate such a result. Specifically, we observe variation across plants at the SIC4 level. One possible explanation for pollution emissions differences between plants is that they produce different products within those industries that bear different emissions intensities. Another channel is that the technology transferred by parent firms to their foreign affiliates in the U.S. varies according to the regulations, customs, and other facets of the country of the plant's parent firm. We leave these avenues for future research.

Additionally, our work experiences a few limitations. The lack of time-series variation in our data limits this analysis and prevents us from making causal claims about the mechanisms linking foreign ownership to environmental performance. Foreign ownership itself is unlikely to change the pollution intensity of a manufacturing facility. Without information on the timing of foreign ownership, we cannot say whether foreign ownership leads to the adoption of some technology or process that reduces pollution emissions, or whether foreign companies are more likely to purchase relatively clean plants for environmental or other reasons. Future work could extend our analysis by taking advantage of restricted access Census Data from the Census of Manufacturers to identify the timing of foreign ownership changes and track subsequent pollution emissions intensity. It may also be possible to identify natural experiments like exchange rate shocks that make foreign ownership more (or less) attractive. These natural experiments may provide the exogenous variation in foreign ownership required to estimate the causal links between foreign ownership and the mechanisms driving pollution intensity.

Our results contribute to the debate about dirty production processes migrating across country borders. The first, and most important conclusion, is that the pollution emissions of foreign owned plants is extremely heterogeneous. One size fits all policy is unlikely to be efficient or effective. Our results provide information for policy makers on the industries in which foreign plants may have relatively low pollution intensity. Moreover, our results suggest another interesting implication for trade policy particularly surrounding tariffs. Trade liberalization would also be associated with cleaner foreign owned manufacturing plants.

Our results have implications in several policy arenas. Many countries actively encourage foreign direct investment to attract capital. Investments in industries with low trade costs, high fixed costs and lower agglomeration economies will attract relatively clean foreign owned firms. Countries with pollution concerns may wish to target those industries with their FDI incentives. FDI into industries with high trade cost, low fixed cost and high agglomeration economies will likely accompany relatively dirty foreign owned firms and countries should carefully consider the costs and benefits of that type of FDI.

Our results also may help environmental regulators target enforcement. Budgets to monitor pollution emissions are extremely limited. Our results suggest that enforcement could be more beneficial on foreign owned manufacturing plants in industries with low trade costs, high fixed costs or industries with low agglomeration economies.

Finally, our paper shows the linkages between international economic policy and environmental policy. In some cases, trade and investment promotion may be attracting the type of firms that environmental policy is trying to restrict. Linking international economic policy and environmental policy requires coordinating among diverse interests. For example, current trade policy discussions in the US feature using tariffs to reduce imports from abroad while driving firms to establish production within the US (York (2024)). Environmental considerations have not been considered. Our results suggest such a policy would result in worse foreign-plant emissions relative to domestic plants within the US. The conceptual model suggests the channel by which this may operate is through relatively less-productive firms realizing higher economic profits through relocation to the US. Policy makers should ensure that their environmental regulation and international economic policies are aligned to generate the largest possible benefits in both arenas.

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8 Appendix

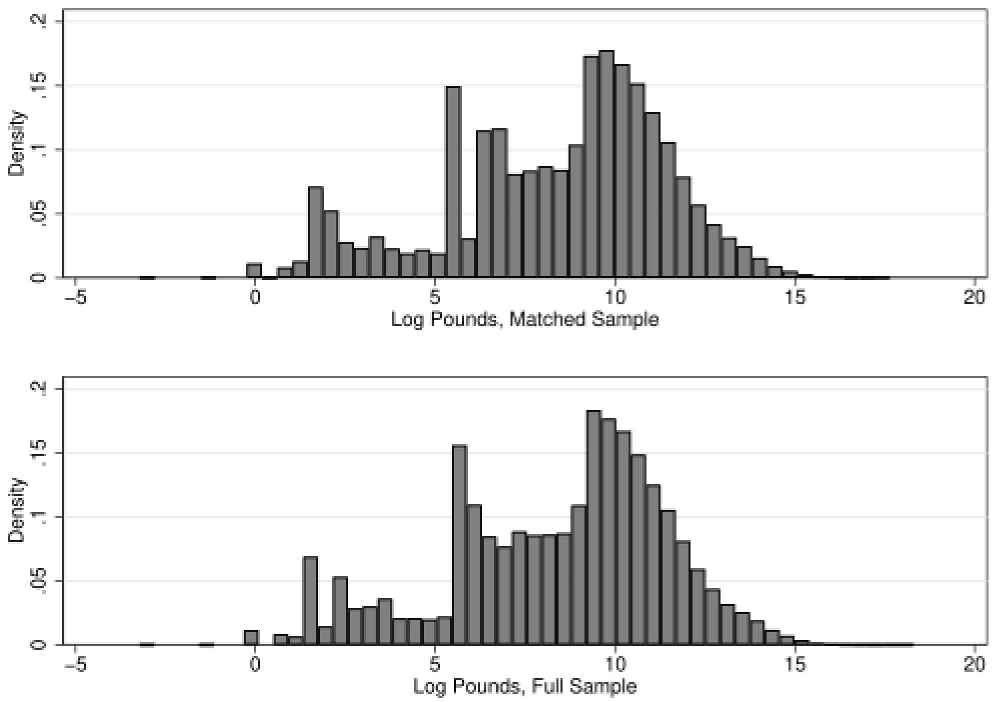
8.1 Data Set Construction

This section describes the process used to create the dataset of establishment characteristics matched to pollution emissions. The original version of this data set was constructed for Holladay (2016) which describes the process in more detail. The matching procedure begins by linking as many establishments listed in the EPA's Risk Screening Environmental Indicators (RSEI) to establishments in the NETS as possible. The first stage was to match on DUNS number, a unique nine character identifier created by Dun & Bradstreet, a data and analytics firm that develops credit scores for business establishments. The data needed to create these credit scores is one of the primary sources for establishment information in the NETS. The EPA makes DUNS number an optional field for pollution reporters, so many establishments have missing DUNS numbers. We use a fuzzy matching procedure to link RSEI observations that do not report a DUNS number to NETS establishments. We match on all the common fields in the NETS and RSEI: the establishment's working name, address, location and industry. We rank matches by probability and visually inspect matches. We define a 90% match probability as our threshold for inclusion in the sample.

This procedure matched three-quarters of the establishments that report pollution emissions in the EPA's Risk Screening Environmental Indicators to an establishment in the NETS. We can compare emissions data for the matched and unmatched samples of polluters. Figure 5 compares the distribution of emissions between the two sub-samples and shows they are extremely similar. The descriptive statistics are nearly identical: mean, median and standard deviation are all within rounding error. This provides evidence that the sample we use in our analysis is a good representation of the set of plants that report pollution emissions to EPA's TRI.

As noted in the main text, establishments reporting emissions tend to be slightly larger than the average establishment in the larger NETS sample. Just over five percent of NETS

Figure 5: Distribution of pounds of emissions for matched and full sample



Note: This figure reports log of pounds of toxic pollution emissions for establishments in the matched TRI and NETS sample compared to the sample of all TRI reporters. The distributions appear similar and the mean, median and standard deviation are nearly identical across the matched and full samples. A version of this figure for a subset of the sample period appears in Holladay and LaPlue III (In Press) establishment observations are matched to TRI reporters. The larger NETS sample contains a number of establishments that do not report emissions because they do not pollute or do not meet the reporting requirements. Because establishments with fewer than 10 employees are exempt from reporting to the TRI we expect to see fewer small establishments.