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The effects of exports on facility environmental performance: Evidence from a matching approach

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ABSTRACT

This paper employs matching techniques to investigate the effects of facility export status on environmental performance. Using facility-level criteria air emission data in the US manufacturing industry, we find the industry-specific effects of export status on emission intensity, measured by emissions per value of sale. In some industries, there is consistent and robust evidence supporting the superior environmental performance of exporters relative to non-exporters in terms of emission intensity for all criteria air pollutants tracked. In other industries, we find weak evidence that exporters appear to have a higher emission intensity than non-exporters. This industrial heterogeneity in the effects of exporting on the environment is closely related to industrial characteristics including pollution abatement capital expenditure, trade costs, capital intensity and others.

KEYWORDS Criteria air emissions; exports; propensity score matching, industrial heterogeneity

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1. Introduction

As public concerns over global warming, industrial pollution, and trade liberalization gradually rise, economists have been long engaged in examining the environmental consequences of international trade. The empirical literature in this area, using aggregate-level (e.g. country-level) data, has provided mixed results over the past two decades (Antweler, Copeland, and Taylor 2001; Cole and Rayner 2000; Cole and Elliott 2003; Frankel and Rose 2005; Ganguli 2013; Managi, Hibiki, and Tsurumi 2009; McAusland and Millimet 2013). With the emergence of longitudinal micro-level data, much of the attention in the trade community has been recently directed towards understanding the firms' heterogeneity across export status (Bernard and Jensen 1999; Saad 2017; Tybout 2003). Some recent empirical studies seek to explore the firm-level relationship between export orientation and environmental performance, and their findings suggest that exporters appear perform better than non-exporters in the environmental activities

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(Batrakova and Davies 2012; Cao, Qiu, and Zhou 2016; Girma and Hanley 2015; Holladay 2016). Possible reasons could lie in that exporters are more likely to adopt 'greener' technologies or invest more in pollution abatement in the first place (Cui 2014; Forslid, Okubo, and Ulltveit-Moe 2014; Cao, Qiu, and Zhou 2016). However, to our knowledge, few studies pay close attention on whether the environmental effects of plants' exporting decisions vary with industry and pollutant.

In this paper, we examine the environmental effects of firms' export decisions, with a focus on heterogeneity in industries and pollutants. To relax the widely assumed parametric assumption about the relationship between the outcome variable (e.g. environmental measure) and the treatment (e.g. export status), this paper utilizes a semi-parametric approach, i.e. propensity score matching (PSM).[1] For each of four different criteria air emissions, we match exporting polluters with similar non-exporting ones within the same industry in terms of their conditional likelihood of exporting, namely propensity scores. To remove the location-specific confounding unobservable that may affect facility environmental behaviors, we further restrict the matched pairs from the same US state or even the same county. We then use the estimated treatment effects for the treated at the matched-pairs level as dependent variables, and employ the ordinary least squares (OLS) regression to unveil the role of detailed industry characteristics in explaining the heterogeneous effects of exports on the environment across industries.

To this end, we compile a unique facility-level dataset in the US manufacturing industry for years 2002, 2005, and 2008. The data include four types of facility-level criteria air emissions, i.e. sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and total suspended particulates (TSPs). In addition, we have data regarding facilities' social-economic characteristics and their exposure to environmental regulations. The latter is measured by pollutant-specific county nonattainment designation under the Clean Air Act Amendments (CAAA).

We obtain several interesting results. First, we find strong evidence that exporting status has statistically significant effects on emission intensity. Second, our empirical results show industrial heterogeneity. In some industries, there is consistent and robust evidence supporting exporters are superior in environmental performance relative to non-exporters for all four tracked criteria air pollutants. In other industries, however, there is limited evidence that exporters perform even worse than non-exporters for some pollutants. Third, industry characteristics including trade costs and pollution abatement expenditure are closely related to the industrial heterogeneity.

This paper contributes to the growing empirical literature that uses country variation panel data to explore the environmental effect of trade. Pioneering this study, Copeland and Taylor (1994 1995) theoretically decompose the environmental impact of trade liberalization into the scale, technique, and composition effects.[2] Using this theoretical guide, a number of empirical studies document conflicting evidence on the environmental impacts of trade at the country level. Specifically, Antweler, Copeland, and Taylor (2001) empirically investigate the aforementioned three decomposed effects. Another work by Cole and Elliott (2003) provides a comprehensive empirical analysis of four common pollutants. They examine the effects of environmental policies and of capital-labor endowments when decomposing the composition effects of trade. To circumvent the shortcomings of the endogeneity problem that trade may be determined simultaneously with income and environmental outcomes, Frankel and Rose (2005) employ exogenous geographic determinants of trade as instrumental variables. Using cross-country data, they find trade appears to have beneficial effects on some measures of environmental quality, e.g. SO_2, though not all. There is little evidence that trade has detrimental effects on the environment. Along this line, Managi, Hibiki, and Tsurumi (2009) revisit this question with a larger and more globally representative sample, including developing countries. A recent paper by McAusland and Millimet (2013) studies the environmental effects of international and intranational trade. Using trade data between US states and Canadian provinces in 1997 and 2002, this study finds robust evidence that international trade intensity lowers toxic release, while intranational trade has harmful impacts on the environment. Unlike the above existing studies, we focus on understanding the consequence of exporting decisions on the environmental performance at the facility level. Another recent work by Erdogan (2014) introduces an environmental policy and factor endowment into a multi-country general equilibrium model, based upon the Melitz framework. She calibrates the model to quantify the environmental consequences of free trade and the economic impacts of environmental harmonization regulations.

This paper is closely related to the literature exploring the role of exporters in environmental activities. Using plant-level data from different countries and various measures of environmental performance, some parallel studies seek to examine whether exporters are environmentally friendlier than non-exporters. Relative to non-exporters, exporters are found more likely to have lower fuel per sale in Ireland (Batrakova and Davies 2012), to emit less CO_2 constructed from fuel consumption data in Sweden conditional on size (Forslid, Okubo, and Ulltveit-Moe 2014), to generate less CO_2 emission intensity in India (Barrows and Ollivier 2014), to denote their innovation as having beneficial environmental effects in the UK (Girma and Hanley 2015), and to release less toxic pollutants in the US controlling for sales (Holladay 2016).[3] A recent paper by Cui, Lapan, and Moschini (2016) develops an intuitive model to explain the firm-level correlation among productivity, export decision, and environmental pollution. Productive firms are likely to select to export, while the most productive exporters are more likely to adopt environmentally friendly technology. Hence, exporters might behave better in the environmental performance than non-exporters. Using criteria air pollution data from the US manufacturing industry, they find robust evidence documenting the negative correlation between the estimated total factor productivity and emission intensity, measured by pollution per sale, and the negative correlation between exporting status and emission intensity. None of the above existing studies highlights the industrial-specific effects of exporting status on environmental performance. We revisit the hypothesis of beneficial environmental impact of exporting using a different empirical approach (i.e. the matching method) with a focus on the industrial heterogeneity.

This paper proceeds as follows. Section 2 introduces the empirical methodology. Section 3 discusses data sources and provides summary statistics of the data. Empirical results are presented in Section 4. The last section concludes the paper.

2. Empirical methodology

Let $D_i \in \{0, 1\}$ be the treatment variable of whether facility i enters the export market, and Y_i be the observed logarithmic emission intensity. An OLS of Y_i on D_i (and other control variables) might be insufficient for our study because (1) the effect of exporting is not necessarily constant among firms and we aim at unveiling the heterogeneous impact; (2) the treatment effect could be nonlinear; and (3) the number of non-exporters dominates that of exporters in the sample. If a firm never exports due to non-eligibility of participation, it would be of little interest to consider its environmental performance were it an exporter.

The matching technique is grounded in the potential outcomes framework developed by Rubin (1974). Let Y_{i1}, Y_{i0} be the potential logarithmic emission intensities under its exporting and non-exporting status, respectively. The observed outcome is $Y_i = D_i Y_{i1} + (1 - D_i) Y_{i0}$. We are interested in the counterfactual questions: Does an exporter pollute less on average than if it were a non-exporter? If the answer depends on the exporters' industrial characteristics, what are the important factors? Formally, our goal is to identify the average treatment effect on the treated (ATET), defined as $E(Y_{i1} - Y_{i0}|D_i = 1)$, as well as the factors to which the variations of the treatment effects are attributed. Under this framework, we do not assume homogeneity and linearity of the treatment effects.

The PSM relies on the ignorablity assumption: exposure to treatment is independent of potential outcomes conditional on a set of covariates. Rosenbaum and Rubin (1983) show that this assumption implies the independence between the treatment and potential outcomes conditional on the propensity score, i.e. $e(\boldsymbol{X}_i) \equiv P(D_i = 1 |\boldsymbol{X}_i)$, where $\boldsymbol{X}_i$ is the covariate set. The true functional form of the propensity score is unknown but testable, since the treatment must be independent of covariates conditional on the propensity score, known as the balancing condition (test).

For our problem, we follow Becker and Ichino (2002)'s procedure.[4] In the first step, regardless of pollutant types, we regress the binary decision of exports in the current year on the one-year lagged covariates while assuming the propensity score takes a Logit form, that is, $e(\boldsymbol{X}_i) = \Lambda[g(\boldsymbol{X}_i)]$, where $\Lambda(\cdot)$ is the Logistic c.d.f. and $g(\boldsymbol{X}_i)$ is a polynomial function of $\boldsymbol{X}_i$. We first attempt $g(\boldsymbol{X}_i)$ in its linear form. In case of violating the balancing condition, less parsimonious forms involving higher order terms are experimented until the balancing condition cannot be rejected. Once an acceptable form of the propensity score is determined, for each criteria air pollutant, we collect a pool of non-exporters whose propensity scores are close to exporters within the same 2-digit SIC industry. The outcome differences reflect the impact of the treatment variable. Thus, in the second step, we compute the ATET results using well-developed matching estimators, i.e. the nearest neighbor matching, radius matching, and kernel matching. These alternative estimators differ in how the neighborhood of a treated unit is defined and how the weights are constructed in averaging the untreated pool. None can dominate others, while their joint consideration provides a robust assessment of the ATET estimates. Besides matching within the 2-digit SIC industry, further matching restrictions on the geographical location, year, parent company, or size category are applied to absorb the confounding unobservable.

The covariates used in the first step of the propensity score estimation in our paper include four different sets of variables. They include: (1) facility characteristics including labor productivity measured by the deflated sales per employment and facility foreign ownership indicator; (2) two measures of trade costs: one is a facility's distance to the nearest port as a proxy of trade variable cost, and the other is the 4-digit SIC industry freight rate; (3) county-level environmental regulations proxied by pollutant-specific county nonattainment designations, which reflect the facility's exposure to environmental regulations; and (4) year dummies controlling for the time trend.

Since the ATET results exhibit systematic differences among industries, we study the role of industry characteristics on the relative environmental performance between exporters and non-exporters. As the variables of interest are continuous-valued, we use regressions to examine the heterogeneous treatment effects. The dependent variable is the estimated treatment effects on the treated (TET) results at the matched-pairs level. The explanatory variables include the wage rate, capital intensity, energy intensity, and equipment investment intensity at the 4-digit SIC level, as well as the pollution operating costs and abatement capital expenditures at the 2-digit SIC level. As suggested in the Meltiz-type trade model, trade costs play significant roles in determining firms' decisions to export. We further include the 4-digit SIC industry-level trade cost, sum of *ad valorem* duties and freight rate. Moreover, Holladay (2016) finds that import competition could drive out the least productive and most pollution-intensive domestic plants. Hence, we include a measure of import competition.

3. The data

We compile a novel facility-level pollution dataset in the US manufacturing industry for 2002, 2005, and 2008.[5] A facility is defined as a place where economic activities generate air emissions. The dataset is assembled from a variety of sources. The National Emission Inventory (NEI) database from the US Environmental Protection Agency (EPA) reports facility-level criteria air pollutants for all areas of the United States.[6] The data acquired in this paper include SO_2, CO, O_3, and TSPs. The measure of O_3 is the sum of volatile organic compounds (VOCs) and oxide of nitrogen (NO_x), since these two pollutants involve the formation of ground-level O_3. We define TSPs as the sum of primary particulate matter-10 (PM-10) and primary particulate matter-2.5 (PM-2.5).[7]

The facility-level economic characteristics are retrieved from the National Establishment Time Series (NETS) Database.[8] The NETS database, developed through a joint venture with Dun and Bradstreet by Walls and Associates, is a unique and nationwide business establishment database covering over 300 fields and 40 million unique establishments for every year since 1990. The data used in this study include the number of employees, value of sales, export indicator, foreign ownership indicator, Data Universal Number System (DUNS) number, geographic location (i.e. latitude and longitude), five-digit Federal Information Processing Standard (FIPS) county code, and four-digit SIC code. These two facility-level databases are merged and matched using the DUNS number, a unique business establishment identifier assigned by Dun and Bradstreet. A detailed algorithm of matching the NEI database with the NETS data is provided in the Appendix.

We look for a proxy of trade cost variables as one of the key factors to determine a facility's decision to export. One proxy of the facility-specific trade variable cost is the geographic distance of the facility to its nearest US port.[9] This geographical distance measures the costs associated with transporting products from the manufacturing sites to the port of shipment. The World Port Source online database provides geographic locations (i.e. latitude and longitude) for a total of 548 US ports including harbor, river port, seaport, offshore terminal, and pier, jetty or wharf. For each polluting facility in the merged dataset, we compute the distance to its nearest port among all 548 US ports based on the 'Haversine' formula, given the latitude and longitude of two points.[10]

To measure polluting facilities' environmental pressure, we further augment the merged facility-level dataset with pollutant-specific county environmental regulations under the CAAA legislation. In general, polluting facilities located in nonattainment counties are subject to more stringent environmental regulations than those in attainment counties. Consequently, we adopt this county nonattainment designation as a proxy

Table 1. List of dirty manufacturing industries.

Industry description	Dirty pollutant	Number of exporters	Number of non-exporters
SIC 24: Lumber and wood products	TSPs	459	2045
SIC 25: Furniture and fixtures	O_3	432	933
SIC 26: Paper and allied products	O_3, SO_2, CO, TSPs	453	1227
SIC 27: Printing and publishing	O_3	393	2183
SIC 28: Chemicals and allied products	O_3, SO_2	1142	2521
SIC 29: Petroleum and coal products	O_3, SO_2, CO	90	1703
SIC 30: Rubber and misc. plastics products	O_3	833	1981
SIC 32: Stone, clay, and glass products	O_3, SO_2, TSPs	373	2901
SIC 33: Primary metal industries	O_3, SO_2, CO, TSPs	665	1664
SIC 34: Fabricated metal products	O_3	1078	3708
SIC 37: Transportation equipment	O_3	716	1683

Note: For the definition of dirty industry, please refer to Table A2 of the Annual Industrial Sector Pollutant Release by Industry in Greenstone (2002).

for a facility's exposure to environmental regulations. The regulatory county status information is obtained from the Green Book Nonattainment Areas for Criteria Pollutants reported by the EPA. For each of four criteria air pollutants, i.e. CO, SO_2, O_3, and TSPs, the Green Book indicates whether only part of a county or whole county is in nonattainment. In accordance with the Green Book, we assign a county to the nonattainment category for each pollutant, if the whole or part of the county is designated as nonattainment status. For the case of O_3, a county is assigned as nonattainment, if it is nonattainment for NO_2 and/or O_3. The latter includes 1-hour and 8-hour standards. For TSPs, we classify a county as TSPs-specific nonattainment if it is nonattainment for PM-10 and/or PM-2.5.

We are interested in industries with heavy emitters of criteria air pollutants for two reasons.[11] First, these industries account for more than 80% of the manufacturing sector-wide criteria air emissions. Meanwhile, manufacturers in these dirty industries have been actively participating in the export market. Consequently, the environmental performance of polluters in the dirty industry is likely to be sensitive to international trade. Second, each dirty industry in the merged dataset has a relatively large number of observations. Hence, a treated unit (exporter) can be more reliably matched with a pool of control units (non-exporters). Table 1 presents a list of dirty industries together with the number of exporters and non-exporters.

The industry covariates used in the OLS regressions to reveal the industrial heterogeneity include industry characteristics obtained from the NBER-CES manufacturing industry data and from the Pollution Abatement Costs and Expenditure in 2005 reported by the US EPA. The former provides wage, the number of production workers, employment, value of shipment, value added, capital, energy, and equipment investment at the 4-digit SIC level, while the latter provides pollution operating costs and abatement capital expenditure at the 2-digit SIC level. The wage rate is computed as the log ratio of production worker wages to the number of production workers. The capital intensity is calculated as log capital per employment, while the energy intensity is measured by log energy expenditures per value added. Similarly, the equipment investment intensity and the material cost intensity are calculated as the log equipment investment per employment and log material costs per value added, respectively. Following Bernard, Jensen, and Schott (2006), the *ad valorem* duties are the ratio of duties collected to the free-on-board (FOB) value, while the *ad valorem* freight rate is the markup of the

Table 2. Summary statistics.

Variable	Obs.	Mean	Std. Dev.	Exporter Mean	Non-Exporter Mean
Sale (1000 $)	29,183	27,582.9	67,843.6	40,003.3	23,928.8
Employment	29,183	192.4	447.6	280.2	166.6
Export dummy	29,183	0.2	0.4	1.0	0.0
SO_2 (ton)	16,186	138.7	892.6	163.4	130.7
CO (ton)	17,883	169.3	1719.6	163.5	171.2
O_3 (ton)	27,080	113.2	477.4	112.5	113.4
TSPs (ton)	22,710	44.0	197.3	49.9	42.3
SO_2 per sale	16,186	0.049	1.393	0.012	0.061
CO per sale	17,883	0.073	3.135	0.017	0.091
O_3 per sale	27,080	0.043	0.851	0.033	0.046
TSPs per sale	22,710	0.017	0.400	0.010	0.019

cost-insurance-freight (CIF) value over the FOB value relative to the FOB. The industry-level data on *ad valorem* duties, CIF, and FOB values are acquired from the online data source of US Manufacturing Exports and Imports compiled by Schott (2010). Moreover, a measure of import competition is provided by the ratio of the CIF import value to the value of shipment at the 4-digit SIC industry level.

3.1. Descriptive statistics

An unbalanced panel dataset of 29,183 facility-by-year observations is analyzed. There are 13,707 unique polluting facilities located among 1859 US counties. The value of sales is deflated by the 4-digit SIC industry-level value of shipment provided by the NBER-CES Manufacturing Industry Database.

Table 2 provides summary statistics on a number of variables for the entire sample. Each facility emits at least one pollutant, but not all facilities have emission reports for all four criteria air pollutants. Moreover, the dataset contains some observations with extremely low emissions. As noted at the bottom of the table, these outliers only account for a small portion of total relevant observations.[12] The last two columns for Table 2 compare exporters with non-exporters along many dimensions. Exporters are larger than non-exporters in terms of the value of sales and number of employees. This result is consistent with the growing empirical trade literature that examines the differences between exporters and their competing counterparts. When it comes to environmental performance, exporters emit more SO_2 and TSPs but less CO and O_3 than non-exporters. In terms of pollution intensity, measured by emissions per value of sales (tons per dollar), exporters display better environmental performance than non-exporters for all criteria air pollutants we track in this paper.

To further shed light on the industrial heterogeneity, for each pollutant and industry, Figure 1 shows scatter-plots mean (log) emission intensity by export status. The dotted line in this figure is the 45-degree line that implies the same mean values between exporters and non-exporters. In the case of O_3, there is a large discrepancy in the mean emission intensity across industry, while in the case for the remaining pollutants, the mean emission intensities scatter along the 45-degree line. These four pollutant-specific figures clearly show industries for paper (SIC 26), printing (SIC 27), stone (SIC 32) and primary metal (SIC 33) are distinct from others. In these industries, the relative emission intensities of exporters to non-exporters are either above or on the 45-degree line,

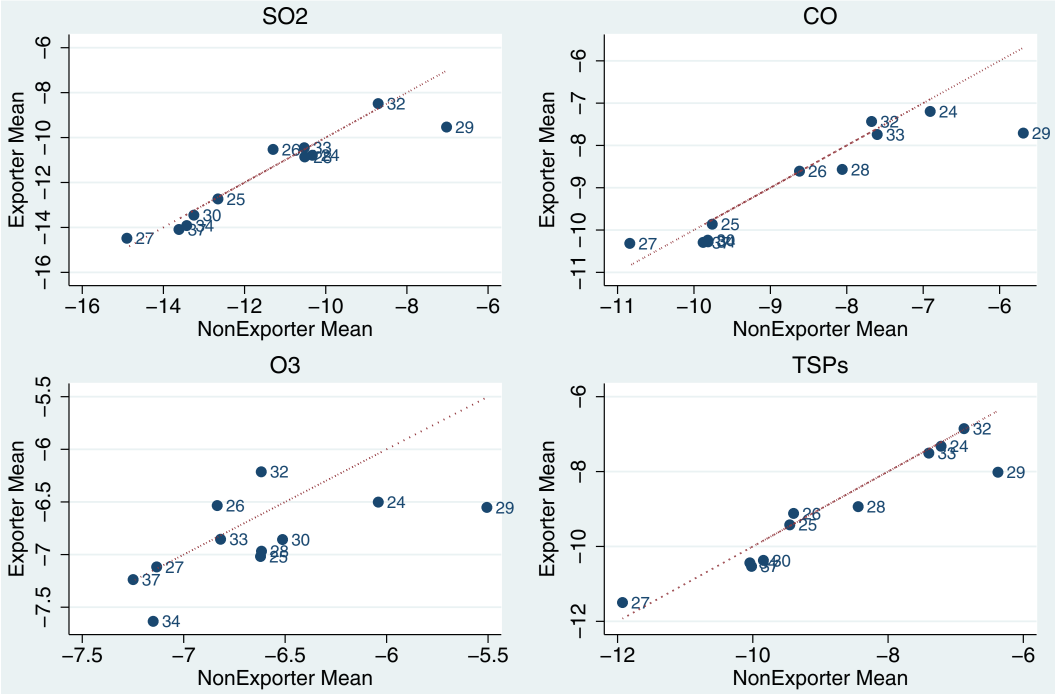

Figure 1. Scatter of mean log emission intensity (1000 US$ per ton) by the 2-digit SIC industry and pollutant. The dotted line refers to the 45-degree line, above which indicates that exporters pollute more than the non-exporters. The emission intensity is computed as the sample average of the raw data, without assuming a regression model and the propensity score matching.

suggesting exporters appear not to perform better than non-exporters in the environmental perspective. By contrast, the petroleum and coal product industry (SIC 29) shows its relative mean value is far below the 45-degree line. Within this industry, exporters, on average, emit much less pollution per sale than non-exporters for all the four pollutants tracked in this paper.

4. Empirical results

In this section, we first use the matching results to reveal the industrial and pollutant heterogeneous effect of exporting status on emissions per value of sale. Moreover, we are interested in investigating the economic and policy implications about the role of industrial characteristics in explaining the relative environmental performance between exporters and non-exporters. With this objective, the OLS regression is employed to examine the effects of industry and plant characteristics on the estimated TET results at the matched-pairs plant level.

4.1. Matching results

The outcome of interest is emission intensity measured by log emissions per deflated value of sales. For each criteria air pollutant, the ATET for exporting status on emission intensity is estimated across industry. The baseline ATET results are obtained by matching exporters with non-exporters within the same 2-digit SIC industry in terms of their propensity scores.[13]

Table 3 summarizes the key findings of ATETs with alternative matching estimators across pollutants. Rows in these tables correspond to the 2-digit SIC industries and the

Table 3. Differences of emissions between exporters and non-exporters measured by ATET.

	O_3		CO		TSPs		SO_2	
	Neighbor	Radius	Neighbor	Radius	Neighbor	Radius	Neighbor	Radius
SIC24: Lumber and wood	– 0.567***	– 0.398***	– 0.575***	– 0.306*	– 0.601***	– 0.254*	– 0.701***	– 0.510***
	(0.163)	(0.115)	(0.263)	(0.173)	(0.220)	(0.147)	(0.289)	(0.198)
SIC25: Furniture and fixtures	– 0.677***	– 0.659***	– 1.133***	– 0.731***	– 0.883	– 0.726	– 1.266***	– 0.995***
	(0.308)	(0.255)	(0.375)	(0.282)	(0.508)	(0.418)	(0.596)	(0.468)
SIC26: Paper and allied	0.133	0.220	– 0.178	– 0.192	0.188	0.124	0.327	0.366
	(0.196)	(0.149)	(0.280)	(0.219)	(0.315)	(0.246)	(0.475)	(0.376)
SIC27: Printing and publishing	0.088	0.040	0.459	0.305	0.380	0.274	0.479	0.185
	(0.155)	(0.114)	(0.307)	(0.218)	(0.353)	(0.257)	(0.337)	(0.246)
SIC28: Chemicals	– 0.159	– 0.269***	– 0.146	– 0.343***	– 0.281*	– 0.448***	– 0.106	– 0.226
	(0.123)	(0.088)	(0.176)	(0.127)	(0.164)	(0.118)	(0.277)	(0.206)
SIC29: Petroleum and coal	– 0.913***	– 0.851***	– 1.798***	– 1.653***	– 1.149***	– 1.073***	– 2.085***	– 2.059***
	(0.426)	(0.350)	(0.456)	(0.375)	(0.442)	(0.332)	(0.729)	(0.629)
SIC30: Rubber and misc. plastics	– 0.335***	– 0.124	– 0.085	– 0.208	– 0.613***	– 0.434***	– 0.436	– 0.473
	(0.150)	(0.109)	(0.229)	(0.175)	(0.247)	(0.194)	(0.369)	(0.281)
SIC32: Stone, clay and glass	0.219	0.338***	– 0.033	0.226	– 0.005	0.110	0.384	0.357
	(0.214)	(0.139)	(0.256)	(0.173)	(0.205)	(0.144)	(0.377)	(0.258)
SIC33: Metal	0.038	– 0.034	– 0.114	0.015	– 0.015	– 0.085	0.379	0.302
	(0.167)	(0.123)	(0.246)	(0.183)	(0.205)	(0.150)	(0.307)	(0.230)
SIC34: Fabricated metal	– 0.459***	– 0.277***	– 0.352***	– 0.352***	– 0.207	– 0.199	– 0.143	– 0.221
	(0.123)	(0.092)	(0.172)	(0.125)	(0.182)	(0.134)	(0.208)	(0.161)
SIC37: Transportation equipment	– 0.281***	– 0.287***	– 0.359	– 0.365***	– 0.374***	– 0.350***	– 0.440	– 0.360***
	(0.166)	(0.113)	(0.249)	(0.171)	(0.231)	(0.158)	(0.301)	(0.204)

Note: With exporting status as the treatment variable, ATET results of emissions are obtained by propensity score matching techniques including nearest neighbor and radius-matching estimators. Columns correspond to pollutant and estimators. Standard errors are reported in parenthesis. ***Significant at the 1% level; *significant at the 10% level.

standard errors are reported in parenthesis. In general, we find heterogeneous effects, varying with industries and pollutants, of facilities' exporting decisions on emission intensity.

The first two columns of Table 3 present the ATETs for O_3. For industries of lumber (SIC 24), furniture (SIC 25), chemicals (SIC 28), petroleum (SIC 29), fabricated metal (SIC 34), and transportation equipment (SIC 37), without additional geographic matching restrictions, we find exporters, on average, emit less O_3 per sales than non-exporters within the same industry. In those industries, the ATETs results are statistically significant at the 1% level for most matching estimators. In paper (SIC 26) and printing (SIC 27) industries, however, the ATETs are positive, but not statistically significant, indicating little evidence on the environmental curse of exports. The positive, statistically significant coefficients of ATETs are documented for some matching estimators when it comes to the stone, clay, and glass industry (SIC 32). In the remaining dirty industries, the effects are mixed, but not statistically significant at any conventional level. Thus, in those industries, we could not conclude the environmental impacts of trade at the facility level.

For CO polluting industries of furniture, chemicals, and petroleum, all matching estimators consistently document the negative, statistically significant coefficients for ATETs. In those dirty industries, we find consistent evidence supporting exporters, on average, pollute less than their competitors by 62% in the furniture industry, 24% in the chemical industry, and 81% in the petroleum industry. Without any geographical matching restrictions, for lumber, fabricated metal, and transportation equipment industries, the negative ATETs are statistically significant at the convention level for most matching estimators, suggesting environmental gains from trade. In the remaining dirty industries, there exists little evidence on the positive or negative effects of exporting on the environmental performance at the facility level.

When it comes to TSPs, we document the consistently negative ATETs for chemicals, petroleum, rubber, and transportation equipment industries. These estimated ATETs are statistically significant at the conventional levels for most matching estimators. Polluting exporters, on average, perform better than polluting non-exporters in terms of emitting less by 37% in the chemicals industry, 74% in the petroleum industry, 46% in the rubber industry, and 40% in the transportation equipment industry. For the remaining dirty industries, we found little evidence supporting the unintended environmental benefit or curse from export decisions.

Finally, for SO_2 dirty industries, we find negative coefficients for the ATETs for lumber, furniture, petroleum, rubber, fabricated metal and transportation equipment industries for all matching estimators. Unlike for the lumber and petroleum industries, these negative ATETs are statistically significant at the conventional levels. In the paper and printing industries, stone, and primary metal industries, positive ATET estimators are mostly insignificant. In those industries, we find little evidence that supports the environmental consequences for exports at the facility level.

4.2. OLS results

To further reveal the role of industry characteristics in explaining the relative environmental performance between exporters and non-exporters within the same industry, for each pollutant, we examine the effects of industry characteristics on the estimated TET results at the matched-pairs level, using the OLS regression. To this end, for the matched

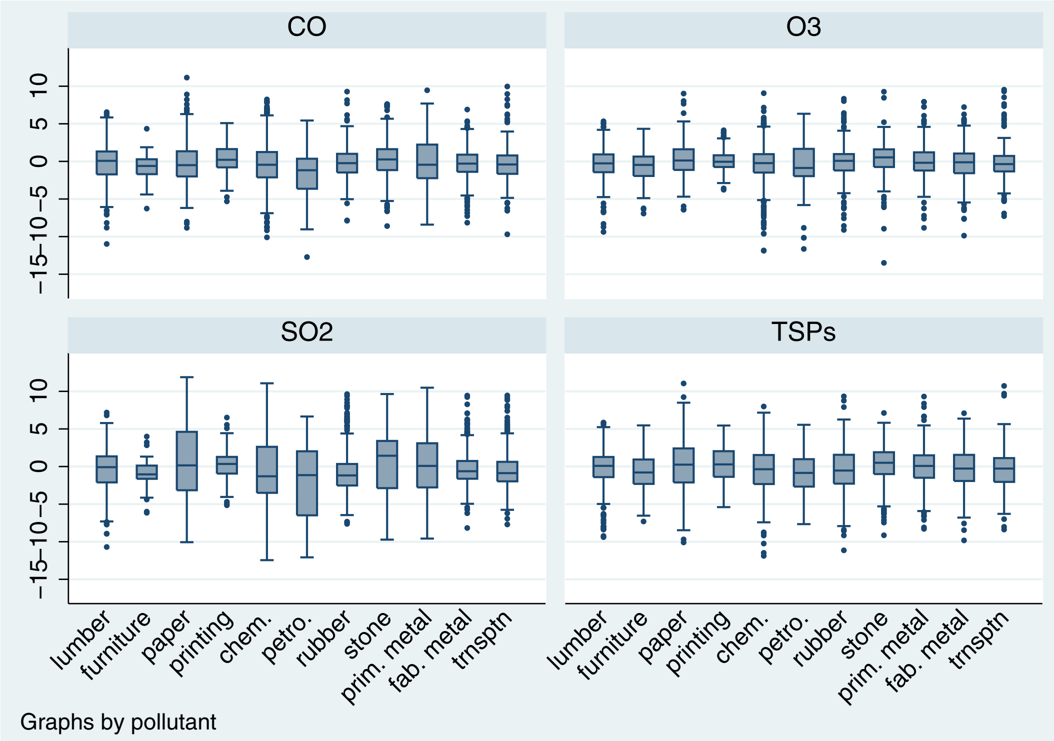

Figure 2. The industry-specific box plot for treatment effects for the treated at the matched pairs. Treatment effects are estimated using the radius-matching method within the nation for the 2-digit SIC industries and pollutants. The box plot summarizes the distribution of the plant-level treatment effects by the median, the first and third quartiles, as well as the 1.5 interquartile ranges below and above the two quartiles.

pairs at the plant level, we assemble a dataset with the TET estimates and industrial characteristics included. The dependent variable, denoted by TET_{ijp}, is the plant-level TET results obtained from the radius-matching estimator while matching within 2-digit SIC industry and the country, as reported in Table 3. The TET estimates capture the relative environmental performance between exporters and non-exporters within the same industry. The smaller the TET estimates, the better environmental behavior exporters are.

Figure 2 presents a series of box plots for the estimated TET results at the matched-pairs level by pollutant and 2-digit SIC industry. The box plot summarizes the distribution of the plant-level treatment effects by the median, the first and third quartiles. The figure shows the heterogeneous industrial effects of the TET at the matched-pairs level. For some industries, the median values are below zero, indicating the relative better environmental performance for exporters, while in other industries, the median values are above zero, suggesting exporters have greater emission intensity than the matched non-exporters. Within each industry, for each pollutant, there is a wide range of the TET estimates at the matched-pairs level.

Table 4 presents the OLS estimates for the effects of industry characteristics on the relative emission intensity between exporters and non-exporters within the same industry.[14] Columns correspond to pollutant types. For each pollutant, we provide results with and without additional plant-level controls. Robust standard errors clustered at the 2-digit SIC industry are reported in parenthesis.

First, we examine the effects of industry costs and expenditures associated with pollution abatement on the plant-level TET estimates. The estimated coefficients for industry operating costs are positive, but not statistically significant at any conventional levels for

Table 4. Effects of industrial and plant characteristics on emission differences between exporters and non-exporters.

	SO_2		CO		O_3		TSPs	
Industry characteristics								
Operating cost	0.0592	0.1543	0.0725	0.1060	0.0904	0.1000	0.1659**	0.1817**
	(0.1358)	(0.1528)	(0.0904)	(0.1036)	(0.0704)	(0.0916)	(0.0660)	(0.0741)
Abatement capital expenditure	−1.1584***	−1.0750***	−0.8988***	−0.8267***	−0.4583**	−0.3702*	−0.8215***	−0.7473***
	(0.2478)	(0.2114)	(0.1637)	(0.1457)	(0.1698)	(0.1677)	(0.2148)	(0.1919)
Import competition	0.3354***	0.2852**	0.3471**	0.3035*	0.0736	0.0284	0.2193*	0.1858*
	(0.1044)	(0.1020)	(0.1522)	(0.1391)	(0.0606)	(0.0543)	(0.1002)	(0.0908)
Ad valorem duties	−12.3984*	−10.8937	−7.8652	−6.5165	−3.6452	−2.1049	−11.7558**	−10.8924**
	(6.5577)	(7.2537)	(4.6938)	(4.6207)	(3.8350)	(3.2272)	(4.1169)	(4.0825)
Ad valorem freight	−0.2501	−0.1078	−0.4818	−0.4026	−0.2279	−0.0426	0.7002	0.7677
	(1.6500)	(1.7042)	(0.8567)	(0.8834)	(0.4646)	(0.5548)	(0.8477)	(0.8990)
Wage	1.8432**	1.8506**	0.6373	0.7153	0.3917	0.8308***	0.4283	0.5452
	(0.8026)	(0.7462)	(0.5413)	(0.5727)	(0.2629)	(0.2124)	(0.5171)	(0.4667)
Capital intensity	2.6044*	3.1434**	0.7290	1.1478	1.6407**	1.9773***	2.4110***	2.7931***
	(1.3166)	(1.2850)	(0.8513)	(0.8512)	(0.5941)	(0.5356)	(0.5529)	(0.5182)
Energy intensity	1.4603***	1.5024***	1.0375***	1.0564***	0.5933***	0.5600***	0.9295***	0.9262***
	(0.1947)	(0.1873)	(0.1316)	(0.1179)	(0.1222)	(0.0967)	(0.1337)	(0.1201)
Equipment intensity	−2.3799*	−2.8085**	−0.4674	−0.8368	−1.3934**	−1.7228***	−2.1206***	−2.4727***
	(1.2708)	(1.2178)	(0.8407)	(0.8334)	(0.5935)	(0.5211)	(0.5338)	(0.4842)
Plant characteristics								
Size		0.3247**		0.0948		−0.0937		0.0323
		(0.1140)		(0.0996)		(0.1505)		(0.0896)
Labor productivity		−1.0466***		−0.7338***		−0.9063***		−0.7115***
		(0.1382)		(0.0749)		(0.0629)		(0.0840)
Foreign ownership		0.2915		0.4008***		0.4228***		0.6177***
		(0.2127)		(0.1103)		(0.1171)		(0.1264)
Constant	−7.4401**	−2.3694	−3.2018	0.1250	−2.4301**	0.5063	−3.0825	−0.0514
	(2.9444)	(2.9086)	(1.9440)	(2.1536)	(1.0050)	(0.9872)	(1.8917)	(1.9802)
Observations	3,092	3,092	3,383	3,383	4,838	4,838	4,027	4,027
R-squared	0.1485	0.1709	0.1749	0.1983	0.0913	0.1448	0.1132	0.1371
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: Pollutant emission differences between exporters and non-exporters are measured by TET at the matched-pair level. That is, the dependent variable is the pollutant-specific treatment effects for the treated from the matched pairs, using the county-level radius-matching estimator. The explanatory variables involve industrial and plant characteristics. OLS estimators under the four pollutants, with and without plant characteristics, are shown in columns. Robust standard errors clustered at 2-digit SIC industry are reported in parentheses. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

all pollutants, but TSPs. Industries with higher pollution abatement operating costs tend to have higher TET estimates, indicating larger TSPs emission intensity for exporters relative to non-exporters. The estimated coefficients of abatement capital expenditure are negative for all pollutants tracked in this paper. These estimates are statistically significant at 1% level in the most cases, suggesting that industries with more capital expenditure in pollution abatement have better environmental performance for exporters relative to their counterparts within the same industry in terms of lower TET estimates.

We then investigate how import competition and trade costs are related with the exporters' relative emission intensity across industries. The estimated coefficients for import competition are positive and statistically significant for all pollutants, but O_3. This result suggests that industries that face fiercer import competition tend to shorten the gap in environmental performance between exporters and non-exporters. As predicted in many environmentally augmented Melitz-type trade model (Cherniwchan, Copeland, and Taylor 2016), firms' productivity is negatively correlated with emission intensity, but is positively correlated with selection to trade. Import competition may drive out the least productive polluting firms, hence the least productive non-exporters, thereby reducing the average emission intensity of the non-exporters. Our empirical results suggest that in most industries, exporters pollute less than non-exporters do. Regression results further implies that import competition shortens the environment gap between exporters and non-exporters within those industries.

Next industrial variable of interest is trade costs. We distinguish trade costs into *ad valorem* duties and *ad valorem* freight rates. The effects of *ad valorem* duties are consistently negative and highly significant at 5% level for TSP. The effects of *ad valorem* freight rate on SO_2, Co and O_3 are also negative, despite insignificantly reverse effects for TSP. Industry trade costs set barriers for firms that seek to enter foreign markets. The higher the trade barrier, the more productive a firm is needed to enter overseas markets. As polluting exporters become more productive, they are more likely to recover their investment in installing pollution abatement equipment. Hence, higher trade costs effectively make exporters pollute less, which further implies that the relative environmental performance between exporters and non-exporters keeps rising as trade cost increases.

Other industry characteristics have different effects on the exporters' environmental performance relative to non-exporters. First, there are consistently positive estimated coefficients for industry wage rate. These positive estimates are statistically significant at 5% level for SO_2 only. Industries with higher wage rate tend to have environmental-damaging effects of exports. Second, the coefficients for capital intensity are positive and statistically significant for all, but CO pollutants, while the coefficient for energy intensity is positive and statistically significant at 1% level for all pollutants. Both positive effects suggest that energy- and capital-intensive industries have higher exporters' emission intensity relative to non-exporters. When it comes to equipment investment intensity, there are negative coefficients with statistical significance for all pollutants, but CO. Although there is lack of detailed information about the type of equipment investment, the results indicate that industries with greater investment in equipment (potentially some might be used in abating pollution or improving emission efficiency) appear to have better environmental performance for exporters over the matched non-exporters.

Last, but not least, some plant-level controls are added. The effect of size is positive and statistically significant at 5% level for SO_2, indicating that employment size leads to worse environmental performance of exporters relative to non-exporters due to the scale effect. There are negative coefficients for labor productivity for all pollutants. These negative estimates with statistical significance at 1% level suggest that productivity plays a key role in helping exporters build up their relative advantage in environmental behavior. Exporters with greater productivity are more likely to adopt clean technology or pollution abatement equipment than non-exporters, because they are the only ones that could earn enough revenues to cover fixed costs for technology investment. When it comes to the foreign ownership, as predicted in Helpman, Melitz, and Yeaple (2004), productive plants are more likely to involve in foreign direct investment. From an environmental perspective, however, there are consistently positive coefficients for foreign ownership indicator. These positive estimates are statistically significant at 1% level for all pollutants, but SO_2, indicating that foreign ownership does not contribute to improvement on plant environmental performance, but lead to higher emission intensity for exporters relative to their matched counterparts.

5. Conclusion

This paper employs matching techniques to investigate the impact of exporting status on emission intensity at the facility level. We have assembled a large, unique panel dataset pertaining to the US manufacturing industry. In particular, we focus on those manufacturing industries with heavy emitters of criteria air pollutants, i.e. SO_2, CO, O_3, and TSPs. Our matching estimates suggest the heterogeneous environmental impacts of export decisions across industries and across pollutants. We find strong evidence: in some dirty industries, but not all, that an exporter has beneficial effects on emission intensity for all four criteria air pollutants. For example, within the industry of petroleum and coal products, exporters have lower emissions per value of sales than their competing counterparts by roughly 74% of SO_2, 81% of CO, 57% of O_3, and 86% of TSPs. On the other hand, our empirical results present the deleterious effects of export orientation on the environmental performance for a few industries. For instance, for the industry of stone, clay and glass products, exporters emit 33% more O_3 per value of sales than their counterparts within the same industry. Furthermore, there is weak evidence these deleterious effects hold for all four pollutants tracked in this paper.

The industrial heterogeneity in the effects of exports on environmental performance is further investigated. We find industries with higher pollution operating costs, import competition, wage rate, capital intensity, and energy intensity tend to have worse environmental behavior for exporters relative to non-exporters within the same industry. Moreover, industry-level trade costs, pollution abatement expenditure and equipment intensity appear to improve exporters' relative environmental performance than their counterparts.

The implications suggested by our empirical findings are significant from the policy perspective. The environmental consequences of trade liberalization are likely to be mixed, varying with industry and pollutant. Any trade policies that aim to reduce pollution might give rise to an unintended consequence. While lowering trade barriers may contribute to reduction in all four types of criterial air pollutants in some industries, for example, in industry of lumber and wood, it may also lead to further environmental degradation caused by other industries; for example, increases in O_3 emissions from the industry of stone, clay and glass. Furthermore, the environmental effects of trade liberalization may be muted in industries of paper and printing.

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Notes

1. The PSM technique has been extensively used to identify the causal effects of exports on firm size and productivity growth (Girma, Greenaway, and Kneller 2003 2004; Loecker 2007; Wagner 2002). In addition, List et al. (2003) employ this technique to identify the effects of environmental regulation on manufacturing plant birth.
2. The scale effect measures the increase in emissions due to the scale-up of economy. The technique effect refers to lower pollution as a result of the improvement in pollution abatement technologies. The composition effect explains the mixed results of changing shares of dirty good on pollution.
3. Holladay (2016) employs the same data set on plants' economic characteristics as we use in this paper. He matches this data with plants' toxic releases, while we match the data with plants' criteria air emissions.
4. See Becker and Ichino (2002) for a detailed discussion.
5. For facility-level pollution data, we only have their reports for years 2002, 2005, and 2008. For the remaining facility economic characteristics, and county and industry characteristics, the data cover the entire period between 2000 and 2008.
6. Some major caveats for this NEI data are summarized in the Appendix; for example, duplicate emission data in 2005.
7. According to the EPA technical document, emission data for filterable and condensable components of particulate matter are incomplete through sample years, and, hence, are not suggested to use in any aggregate level.
8. The NETS data have been utilized to study issues related to job creations and destructions, business relocation, and business ownership (Kolko and Neumark 2008 2010; Neumark, Wall, and Zhang 2011). Neumark, Wall, and Zhang (2011) provide a detailed description of the NETS and an assessment of the quality of the NETS database along many dimensions. One dimension related to our study is the estimated data versus actual data regarding employment size. In our study, this problem is not critical, because about 90% of employment data have indicators suggesting actual data.
9. According to IHS Global Services, US seaborne trade with the rest of the world accounts for 78.05% by volume (millions of metric tons) in 2008.
10. The 'Haversine' formula calculates the great-circle distance between two points, that is, the shortest distance over the earth's surface.
11. As defined in Greenstone (2002), an industry is designated as a dirty emitter of a pollutant if it accounts for at least 7% of industrial sector emissions. See Table A2 (Online Supplemental data) of the Annual Industrial Sector Pollutant Release by Industry in Greenstone (2002) for details.
12. The fraction of observations with annual emissions less than 0.001 tons is as follows: 6.6% for SO_2, 0.46% for CO, 0.16% for O_3, and 1.17% for TSPs.
13. It is possible one treated unit in the east coast might be accidently paired with another control unit in the west coast. These types of matched pairs could bias the estimated ATET results, due to the confounding geographic location-specific unobservable, such as state-level environmental regulations, natural geographic advantage of shipping products abroad, or county-level pollutant nonattainment status. To remove the unobservable, we further restrict the matched exporters and

non-exporters from the same US state and the same year, or the same county. All these matching results along with alternative matching estimators including strata and kernel matching are presented in Tables A1–A4 in the Online Appendix. The price for this restricted matching procedure is a reduced sample size and number of matched pairs, and, hence, less statistically significant estimators.

14. For robustness checks, we conduct the OLS regressions, using alternative measures of TETs at the matched-pairs level from different matching estimators and matching restrictions. Main conclusions are robust to these alternative plant-level TET estimates. These OLS results are available upon request.

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Appendix

A.1 Caveats of the NEI data

Some major caveats of the NEI database pertaining to point sources can be summarized as follows. First and foremost, EPA developed the 2005 NEI data based on a reduced level of effort. Part of this reduced effort involved using some 2002 NEI data in the 2005 NEI as surrogates for emission data representing 2005. Second, the 2008 NEI database was built from emission data in the Emission Inventory System (EIS). Unlike its predecessors 2002 and 2005 NEI, this 2008 database reports a different and new facility identifier, called EIS site ID, instead of previous NEI site ID. A comprehensive and updated coverage of facility identifiers may be obtained from the Emission Inventory System Gateway. This Gateway, however, is only available to EPA staff, EIS data partners responsible for submitting data to EPA, and contractors working for EPA on emissions-related work. Last but not least, as noted in the EPA technical document, emission data for filterable and condensable components of particulate matter (i.e. filterable PM-10, filterable PM-2.5 and condensible PM) is not complete and is not suggested to use at any aggregate level. Users interested in PM emissions should only consider primary particulate matter, which are primary PM-10 and primary PM-2.5.

A.2 Data-matching algorithm

Given the forgoing caveats of the NEI database, the data-matching work consists of two main procedures. First, we match polluting facilities within the NEI database across years, and then retrieve DUNS numbers for these polluters from the Facility Registry System (FRS) of the EPA. Second, we match them with those appearing in the NETS database through the DUNS number.

To match polluting facilities within the NEI data across years, we first discard duplicates of 2005 data. The 2005 NEI database provides flag variables, 'Start Date/End Date' fields, to indicate which data are 2005 emissions and which data are actually taken from 2002 emissions. Around one-third of observations in the 2005 NEI have a flag variable of 'Start Date' referring to year 2002. When it comes to the manufacturing industry, roughly one-quarter of observations in 2005 are duplicates of 2002 emissions. These duplicates are dropped from our study.

We then retrieve facility FRS ID from the FRS of the EPA. The FRS is a centrally managed database that identifies facilities, sites, or places subject to environmental regulations or of environmental interests. EZ Query in the FRS provides data download options for a customized list of facilities, which are associated with NEI or EIS programs. All observations in 2002 and 2005 NEI databases have both records and FRS ID reported in the FRS, and hence can be matched between these two years. However, one-eighth of 2008 NEI database is missing from the FRS, and roughly 7% of facilities in the manufacturing industry in this database do not have any records in the FRS. These missing manufactures are discarded in our study. With the FRS ID, facility DUNS numbers are retrieved separately through the Facility Registry System Query in the FRS. In the end, the facility-level emission dataset we compiled contains criteria air emissions, facility name, FIPS county code, zip code, facility FRS ID, and DUNS number.

In the next step, we match polluting facilities in the NEI database with those that appear in the NETS Database through the DUNS number. The EPA does not provide further information about how DUNS numbers are reported for polluting facilities and why some of them have missing DUNS numbers in the dataset. Due to an incomplete report on DUNS numbers in the FRS, approximately 80% of polluting facilities in the manufacturing industry collected in the NEI database have associated DUNS numbers. To circumvent this shortcoming, a pair of facilities from each source is considered as a match if the following series of criteria are satisfied. They share the same DUNS number and are located in the same area in terms of five-digit FIPS county code. More importantly, for each pair, we compare their facility names from each source to ensure the match.