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Abstract

The relevance of analyzing whether exporting firms engage in greater pollution abatement cannot be overemphasized. For instance, the question relates to the possibility of export promotion policies being environmentally beneficial. In fact, the issue is especially relevant for developing countries typically characterized by ineffective environmental regulation. However, despite the significance of the topic, the extant literature examining the environmental consequences of firm-level trade is skewed toward developed countries. Moreover, the existing contributions rarely attend to concerns over non-random selection into exporting. Accordingly, we employ cross-sectional data across Indonesian firms as well as a number of novel identification strategies to assess the causal effect of exporting on abatement behavior. Two of the approaches are proposed by Millimet and Tchernis (2013), and entail either minimizing or correcting for endogeneity bias. The remaining methods, attributable to Lewbel (2012) and Klein and Vella (2009), rely on higher moments of the data to obtain exclusion restrictions. While we largely find exporting to encourage pollution abatement, the estimated impacts are more pronounced after accounting for selection into exporting.

JEL: C26, F18, F23, Q41
Keywords: Exporting, Environment, Pollution Abatement, Instrumental Variables, Treatment Effects

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1 Introduction

Cherniwchan et al. (2017, p. 60) state: "A firm-level focus in answering trade and environment questions is very promising, but researchers have not yet fully exploited its potential." Using data from Indonesia, our objective is to examine the environmental implications of plant-level trade.[1] More specifically, we assess whether exporting facilities engage in more pollution abatement than non-exporters.[2]

The question is crucial due to a number of reasons. First, if serving foreign markets encourages firms to abate, then export promotion policies may have environmental benefits.[3] This is especially relevant for countries such as Indonesia that have weak enforcement of environmental legislation (e.g., García et al. 2007). Second, although the environmental consequences of trade have been extensively analyzed using aggregate data, the evidence from firm-level studies is relatively scarce (e.g., Antweiler et al. 2001; Cole 2006; Cole and Elliott 2003; Chintrakarn and Millimet 2006; Frankel and Rose 2005; Kellenberg 2008; Managi et al. 2009; McAusland and Millimet 2013; Roy 2017; Tsurumi and Managi 2014). Moreover, as discussed below, the few studies based on disaggregate data are skewed toward developed countries. Finally, our topic relates to the increasingly important role of environmental protection as part of corporate social responsibility (e.g., Chuang and Huang 2018; Kitzmueller and Shimshack 2012).

However, the effect of exporting on environmental expenses is not clear a priori. For instance, if environmental expenditures compromise establishments' international competitiveness, exporting may discourage abatement (e.g., Kaiser and Schulze 2003; Distelhorst and Locke 2018). Alternatively, it is plausible that exporting raises plant-level productivity and thereby facilitates investment in abatement (e.g., Bernard et al. 2018; Forslid et al. 2018). Moreover, to the extent that exporting entails significant international monitoring perhaps due to the presence of environmentally conscious consumers, firms serving foreign markets may abate more (e.g., Cole et al. 2006; Distelhorst and Locke 2018). Further, Christmann and Taylor (2001, p. 444-445) state: "An additional concern that might induce export-oriented firms in developing countries to pursue environmental self-regulation is the potential use of environmental regulations in developed countries as protective trade barriers. Firms can address this problem by meeting the highest environmental regulations prevailing in the largest export market." In fact, they contend that "[f]or

[1] Note, there are very few multi-plant firms in the survey consulted for our data (Blalock and Gertler 2008). Hence, we use the terms firm, plant, facility, and establishment interchangeably.

[2] Note, manufacturing establishments' pollution abatement activities include measures such as removal or recycling of pollutants generated during production, equipment modification to reduce pollution, substitution toward less-polluting inputs, and employee training aimed at reducing waste (e.g., U.S. Census Bureau 2008).

[3] Note, as Cherniwchan et al. (2017) discuss, investment in abatement may not necessarily reduce emission intensities (i.e., emissions per unit of output). For instance, abatement may encourage substitution towards polluting inputs via a rebound effect.

export-oriented firms in developing countries, the regulatory and market requirements of major export markets overshadow the regulatory influence of the home market." Accordingly, whether exporters engage in greater pollution abatement is ultimately an empirical question.

That said, identifying the causal effect of exporting on firms' pollution abatement is challenging due to the potential endogeneity of exporting status attributable to two factors. First, a number of unobserved characteristics may influence plant-level environmental performance as well as exporting behavior. For example, credit constraints are likely correlated with establishments' exporting and environmental behavior (e.g., Andersen 2016; Aristei and Franco 2014; Evans and Gilpatric 2017; Fauceglia 2015). As discussed by Leonidou et al. (1998) and Cole et al. (2008), among others, unobserved managerial quality may also have trade and environmental implications at the firm level. Moreover, unobservables such as consumer preferences in overseas markets and plants' outsourcing behavior also qualify as potential confounders (Brunel 2017; Cole et al. 2006, 2014). Second, reverse causation may be an issue since environmental reputation may influence firms' international operations (Martin-Tapia et al. 2008). Similarly, pollution abatement can raise a firm's profitability and thereby its propensity to export (e.g., Pang 2018; Wagner 2012). Although one can resort to an instrumental variable (IV) strategy to address the endogeneity of exports, the issue is exacerbated by the paucity of instruments. In other words, it is difficult to conceive of an exclusion restriction that is associated with exporting behavior but uncorrelated with environmental quality.

In spite of these complexities, a number of firm-level studies have examined the effect of exporting on various indicators of environmental performance. For example, Batrakova and Davies (2012) begin with a theoretical model where exporting entails energy use that can be partially offset by the adoption of energy-efficient technology. The authors argue that the technology-induced reduction in energy use is particularly pronounced for firms with greater energy intensity (i.e., the ratio of energy use to sales). In a panel of Irish firms, they find exporting to raise (reduce) energy intensity at lower (higher) quantiles of the intensity distribution. Dardati and Saygili (2012) also provide theoretical scenarios where firms face fixed costs of either abating or adopting a cleaner technology. While in the first case the relatively efficient firms serve foreign markets, in the latter, technology adoption is limited to the highly productive firms. Employing data on Chilean plants, the authors find exporting to be negatively associated with (proxies for) emissions. In a similar vein, Cole et al. (2008) utilize firm-level data from Ghana and witness exporters to use relatively less energy per unit of value added.[4] Next, Albornoz et al. (2009) and Cole et al. (2006) find exporting and foreign ownership to encourage the implementation of environmental management practices

[4]Note, Dardati and Saygili (2012) as well as Cole et al. (2008) primarily focus on the impact of foreign ownership on environmental performance. However, they control for exporter status in some specifications.

among Argentinean and Japanese firms, respectively. Focusing on Brazil, Da Motta (2006) also witnesses exporting to enhance environmental management.

More recently, Forslid et al. (2018) argue that exporters are likely to invest more in pollution abatement due to their ability to distribute the associated fixed cost over greater production. They theoretically discuss how exporting may increase firm-level abatement and abatement intensity (i.e., abatement per unit of output), but reduce emission intensity (i.e., emissions per unit of output). Relying on data from Sweden, the authors also find descriptive evidence consistent with their claims. In other words, exporting is witnessed to be associated with greater pollution abatement as well as abatement intensity, but lower emissions of carbon dioxide (per output).[5] Similarly, Richter and Schiersch (2017) focus on German manufacturing and find exporters to emit less carbon dioxide per unit of output. While Girma and Hanley (2015) resort to a panel of U.K. firms, their results continue to uncover exporters as more likely to report their innovations as pro-environment. Further, accounting for spatial dependence among Japanese firms, Cole et al. (2013) also find exporters to emit less carbon dioxide relative to output.

Turning to evidence from the United States, Holladay (2016) utilizes establishment-level data from the National Establishment Time Series (NETS) and the Environmental Protection Agency's (EPA's) Risk-Screening Environmental Indicators to find exporting to be associated with lower pollution emissions as well as emissions that are less toxic. Further, Cui et al. (2016) use facility-level data from the NETS and the EPA's National Emissions Inventory to arrive at a similar conclusion with respect to sulfur dioxide, carbon monoxide, ozone, and total suspended particulates (per value of sales). Employing the same data, Cui and Qian (2014) uncover the impact to be heterogeneous across industries. Moreover, Cherniwchan (2017) relies on the timing of the North American Free Trade Agreement (NAFTA) and data from the EPA's Toxic Release Inventory (TRI) and NETS to uncover the environmental benefits of exporting. Finally, in the context of Indonesian plants, while Kaiser and Schulze (2003) witness exporters to incur greater abatement, Roy and Yasar (2015) find exporting to reduce the use of fuels (relative to electricity).[6]

However, the issue of endogeneity of exporting status has received little attention in the existing literature. For instance, a majority of the studies resort to panel data and control for crucial unobservables that vary only across specific dimensions such as location, industry, and firms. Thus, the existing contributions are susceptible to bias arising, for example, from unobservables that vary across firms as well as over time. As discussed above, examples of such unobserved attributes include managerial quality and

[5] Note, the theoretical models in contributions such as Batrakova and Davies (2012), Dardati and Saygili (2012), and Forslid et al. (2018) are based on the heterogeneous firms framework in Melitz (2003).

[6] Note, in case of Indonesian timber manufacturing industries, Rodrigue and Soumonni (2014) find exporting firms to be more likely to abate.

credit constraints. Nonetheless, to our knowledge, two studies resort to an IV approach. First, in Girma and Hanley (2015), the instruments are based on the (contemporaneous and lagged values) of the share of imported materials. Although IV specification tests support the validity of these exclusion restrictions, it seems plausible for imported inputs to directly influence environmental performance. For instance, Batrakova and Davies (2012, p. 468) state: "It is possible that firms develop international ties after starting to export and begin importing more of their inputs and this might bring their relative energy use down significantly." Similarly, Cherniwchan (2017, p. 131) opines that "importing can affect environmental quality by affecting the inputs available to plants." Second, the instruments in Roy and Yasar (2015) are obtained upon assuming only some of the determinants of energy intensity to have differential effects across types of energy. They only help identify the effect of exporting on the use of fuels (relative to) electricity.

In this light, we employ cross-sectional data across Indonesian firms to examine the impact of exporting on pollution abatement. Due to concerns over endogeneity of exporting status, we rely on a number of novel approaches that help identify our causal effect of interest under certain assumptions. Two of the strategies are proposed by Millimet and Tchernis (2013). While the first approach estimates the causal effect for a subsample where the endogeneity bias is minimized, the second method corrects for the bias arising from non-random selection into exporting. The remaining methods follow from Lewbel (2012) and Klein and Vella (2009). These are based on IV but exploit higher moments of the data to obtain exclusion restrictions. Across two measures of pollution abatement costs, all our estimators find exporting to encourage pollution abatement behavior.

The rest of the paper is organized as follows. Section 2 describes the empirical methodology. Section 3 discusses the data. Section 4 presents the results,while Section 5 concludes.

2 Empirical Methodology

2.1 Setup

Employing the potential outcomes framework (see, e.g., Rubin 1974), we begin by denoting the potential abatement activity of firm i due to exporting as $A_i(EXP)$. Here, EXP is a binary indicator taking the value 1 for exporters and 0 in case of non-exporters. Accordingly, for firm i, the individual-level causal effect of exporting is depicted as $\tau_i = A_i(1) - A_i(0)$. Our estimand of interest, the average treatment effect (ATE) of exporting on pollution abatement, is the expected value of τ_i across all firms.[7] It is given by

$$\tau = \mathrm{E}[A_i(1) - A_i(0)]. \tag{1}$$

[7]Note, other estimands such as the average treatment effect on the treated or untreated may also be of interest. The former (latter) refers to the value of τ_i averaged across all exporters (non-exporters). However, we focus on the ATE.

Now, for any firm, only one of the potential outcomes is realized. In other words, for any exporter (non-exporter), one is unable to observe its abatement behavior in the absence (presence) of exporting. Thus, if A_i indicates the realized abatement behavior of firm i,

$$A_i = EXP_i A_i(1) + (1 - EXP_i)A_i(0). \tag{2}$$

To the extent that selection into exporting is random, τ can be consistently estimated by subtracting the average pollution abatement effort of non-exporters from that of exporting plants. Moreover, if the selection is non-random but occurs solely on the basis of a set of observed characteristics, X, τ may still be identified by comparing firms' abatement activities after conditioning on X. In such a scenario, conditioning on the propensity score, $P(X_i) = \Pr(EXP_i = 1|X_i)$, i.e., the conditional probability of exporting given the observables, is in fact sufficient (Rosenbaum and Rubin 1983). However, as discussed above, selection into exporting is likely driven by unobserved attributes as well. Accordingly, identification of the ATE is not trivial and further complicated by the lack of valid exclusion restrictions.

Given this framework, we resort to a number of approaches that (i) minimize or remove the bias in a propensity score-based estimator, or (ii) utilize higher moments of the observed variables to construct instruments. Before discussing these methods, we obtain an expression for the bias due to selection on unobservables in τ.

2.2 Bias due to Selection on Unobservables

To derive the bias in our treatment effects estimator, we begin with a few assumptions (Black and Smith 2004; Heckman and Navarro-Lozano 2004; Millimet and Tchernis 2013). First, the potential outcomes and latent treatment assignment are additively separable in observed and unobserved variables

$$\begin{aligned} A(0) &= g_0(X) + \varepsilon_0 \\ A(1) &= g_1(X) + \varepsilon_1 \\ EXP^* &= h(X) - u \\ EXP &= \begin{cases} 1 & \text{if } EXP^* > 0 \\ 0 & \text{otherwise} \end{cases}. \end{aligned}$$

Second, we assume

$$\varepsilon_0, \varepsilon_1, u \sim N_3(0, \Sigma)$$

where

$$\Sigma = \begin{bmatrix} \sigma_0^2 & \rho_{01} & \rho_{0u} \\ & \sigma_1^2 & \rho_{1u} \\ & & 1 \end{bmatrix}.$$

Under these assumptions, the bias for the ATE can be expressed as

$$\begin{aligned} B[P(X)] &= -\rho_{0u}\sigma_0 \left\{ \frac{\phi(h(X))}{\Phi(h(X))[1-\Phi(h(X))]} \right\} + [1-P(X)] \left\{ -\rho_{\delta u}\sigma_\delta \frac{\phi(h(X))}{\Phi(h(X))[1-\Phi(h(X))]} \right\} \\ &= -\left\{ \rho_{0u}\sigma_0 + [1-P(X)]\rho_{\delta u}\sigma_\delta \right\} \left\{ \frac{\phi(h(X))}{\Phi(h(X))[1-\Phi(h(X))]} \right\}. \end{aligned} \tag{3}$$

Here, $\phi(\cdot)$ and $\Phi(\cdot)$ depict the standard normal density and cumulative distribution function, respectively. While $\delta = \varepsilon_1 - \varepsilon_0$ is the unobserved gain from abatement, $\rho_{\delta u}$ denotes the correlation between δ and u; σ_δ is the standard deviation of δ.

Before proceeding, note that the bias is zero under a few implausible scenarios. First, the bias is clearly zero if both ρ_{0u} and $\rho_{\delta u}$ are zero. In other words, if there is no selection on unobservables affecting abatement activities of non-exporters, or correlated with gains from pollution abatement, then $B[P(X)]$ is zero. As discussed above, due to unobserved attributes such as outsourcing, credit constraints, and management quality, this is unlikely. Second, as highlighted in Millimet and Tchernis (2013), if $\rho_{0u} = 0$, then $\lim_{P(X)\to 1} B[P(X)] = 0$. Third, if the selection terms offset each other such that $\rho_{0u}\sigma_0 = -\rho_{\delta u}\sigma_\delta$, then $\lim_{P(X)\to 0} B[P(X)] = 0$.

2.3 The Minimum-Biased Estimator

To proceed with the minimum-biased (MB) estimator proposed by Millimet and Tchernis (2013), consider the normalized inverse probability weighted (IPW) estimator of Hirano and Imbens (2001) given by

$$\hat{\tau}_{IPW} = \left[\sum_{i=1}^{N} \frac{A_i EXP_i}{\hat{P}(X_i)} \Big/ \sum_{i=1}^{N} \frac{EXP_i}{\hat{P}(X_i)} \right] - \left[\sum_{i=1}^{N} \frac{A_i(1-EXP_i)}{1-\hat{P}(X_i)} \Big/ \sum_{i=1}^{N} \frac{(1-EXP_i)}{1-\hat{P}(X_i)} \right]. \tag{4}$$

Due to non-random selection into exporting, the IPW estimator is susceptible to bias as indicated by equation (3). Referring to the value of $P(X)$ that minimizes $B[P(X)]$ as the *bias minimizing propensity score* (BMPS), the MB approach entails using the estimator in (4) but only observations with a propensity score in a neighborhood around the BMPS. Denoting the BMPS by $P^*(X)$, or simply P^*, the corresponding estimator is expressed as

$$\hat{\tau}_{MB}[P^*] = \left[\sum_{i\in\Omega} \frac{A_i EXP_i}{\hat{P}(X_i)} \Big/ \sum_{i\in\Omega} \frac{EXP_i}{\hat{P}(X_i)} \right] - \left[\sum_{i\in\Omega} \frac{A_i(1-EXP_i)}{1-\hat{P}(X_i)} \Big/ \sum_{i\in\Omega} \frac{(1-EXP_i)}{1-\hat{P}(X_i)} \right] \tag{5}$$

where Ω depicts the set of observations with a propensity score close to P^*. More specifically, we define Ω as the smallest neighborhood around P^* containing at least θ proportion of both exporters and non-exporters.[8] While we set θ as 0.05 and 0.25, observations with propensity scores above (below) 0.98 (0.02)

[8] Note, suppose that the number of non-exporters and exporters are denoted by N_0 and N_1, respectively. Also, say n_0 and n_1 depict the number of non-exporters and exporters, respectively, in a neighborhood around P^*. For $\theta = k$, Ω is the smallest neighborhood around P^* such that $\min\left\{\frac{n_0}{N_0}, \frac{n_1}{N_1}\right\} \geq k$. Also, as discussed in Millimet and Tchernis (2013), smaller values of θ likely reduce bias at the expense of increasing variance.

are always omitted.

In order to solve for P^*, Millimet and Tchernis (2013) propose utilizing Heckman's bivariate normal selection model and linear functional forms for $g_0(X)$, $g_1(X)$, and $h(X)$ to first solve for $\rho_{0u}\sigma_0$ and $\rho_{\delta u}\sigma_\delta$. More precisely, if $g_0(X) = X\beta$, $g_1(X) = \tau + X\beta$, and $h(X) = X\gamma$, then

$$A_i = X_i\beta + \tau EXP_i + \beta_{\lambda 0}(1 - EXP_i)\left[\frac{\phi(X_i\gamma)}{1 - \Phi(X_i\gamma)}\right] + \beta_{\lambda 1}EXP_i\left[\frac{-\phi(X_i\gamma)}{\Phi(X_i\gamma)}\right] + \eta_i \tag{6}$$

where $\beta_{\lambda 0} = \rho_{0u}\sigma_0$ and $\beta_{\lambda 1} = \rho_{0u}\sigma_0 + \rho_{\delta u}\sigma_\delta$. After replacing γ with a first-stage probit estimate, OLS estimation of equation (6) helps identify $\rho_{0u}\sigma_0$ and $\rho_{\delta u}\sigma_\delta$. Subsequently, one can solve for P^* by performing a grid search over the values of $h(X)$ in (3). Millimet and Tchernis (2013) and McCarthy et al. (2013) provide additional details.

2.4 The Bias-Corrected Estimator

Upon estimating (6) and obtaining P^*, estimate of the bias of the MB estimator is expressed as

$$\widehat{B[P^*]} = -\left[\widehat{\rho_{0u}\sigma_0} + (1 - P^*)\widehat{\rho_{\delta u}\sigma_\delta}\right]\left[\frac{\phi(\Phi^{-1}(P^*))}{P^*(1 - P^*)}\right]. \tag{7}$$

Next, one can subtract the bias from the MB estimator and arrive at the latter's bias-corrected (BC) version. More specifically, the MB-BC estimator proposed by Millimet and Tchernis (2013) is

$$\hat{\tau}_{MB-BC}[P^*] = \hat{\tau}_{MB}[P^*] - \widehat{B[P^*]}. \tag{8}$$

As Millimet and Tchernis (2013, p. 988) note, "when restricting the estimation sample to observations with propensity scores contained in a subset of the unit interval, the parameter being estimated will generally differ from the population [ATE] unless the treatment effect does not vary with X." Accordingly, both the MB and MB-BC estimators may not identify the *unconditional* ATE. However, the BC unconditional treatment effect can be obtained as

$$\hat{\tau}_{BC} = \hat{\tau}_{IPW} - \frac{1}{N}\sum_i B[\widehat{\hat{P}(X_i)}]. \tag{9}$$

Before highlighting the heteroskedasticity-based approaches, two comments are warranted. First, the BC estimators rely greatly on the bivariate normal model to estimate the bias attributable to selection on unobservables. Second, although Millimet and Tchernis (2013) discuss deviations from the assumption of joint normality to obtain additional MB and BC estimators, we do not analyze them in detail (see footnote 22).

2.5 Lewbel (2012) Estimator

Turning to our first estimator based on higher moments, suppose the outcome equation is represented as (6) without the selection correction terms so that

$$A_i = X_i\beta + \tau EXP_i + \nu_i \tag{10}$$

with the first-stage given by

$$EXP_i = X_i\delta + \zeta_i. \tag{11}$$

According to Lewbel (2012), if ζ is heteroskedastic such that at least some of the covariates in X are correlated with the variance of ζ but not with the covariance between ζ and ν, then our model is identified.

More specifically, for any set of regressors $Z \subseteq X$ such that

$$\mathrm{E}[Z'\zeta^2] \neq 0 \tag{12}$$

$$\mathrm{E}[Z'\nu\zeta] = 0 \tag{13}$$

$\widetilde{Z} \equiv (Z - \overline{Z})\zeta$ are valid instruments. While they are uncorrelated with ν due to (13), the strength of their (partial) correlation with EXP is directly related to the degree of heteroskedasticity in equation (12). For additional details on the validity of the instruments, see Lewbel (2012, 2018). While we resort to the Breusch-Pagan test for heteroskedasticity to determine the set of variables in Z, estimation is performed using Generalized Method of Moments (GMM). Finally, a number of specification tests are employed to assess the validity of our IV strategy.

2.6 Klein & Vella (2009) Estimator

As another estimator that exploits higher moments for identification, we utilize the parametric implementation of Klein and Vella's (2009) IV estimator. To proceed, suppose the outcome equation continues to be depicted as in (10) with the latent treatment assignment now given by

$$EXP^* = X\gamma - \widetilde{u}. \tag{14}$$

Here, $\widetilde{u} = \exp(Z\pi)u$ and u follows a standard normal distribution; $Z \subseteq X$.[9] In this case, the conditional probability of exporting is given by the heteroskedastic probit specification as in

$$\Pr(EXP = 1|X) = \Phi\left(\frac{X}{\exp(Z\pi)}\gamma\right). \tag{15}$$

Estimating the parameters of (15) via maximum likelihood (ML), the predicted probability of exporting, $\widehat{P(X)}$, may be utilized as an instrument for EXP in equation (10).[10]

[9] Note, we resort to the same variables in Z as in Section 3.5.

[10] Note, even in the case of $\exp(Z\pi) = 1$, i.e., a homoskedastic probit specification, $\widehat{P(X)}$, may be used as an instrument. However, as Klein and Vella (2009) as well as Millimet and Tchernis (2013) remind, identification in such a scenario is

3 Data

The data primarily come from the 2006 wave of *Survei Tahunan Perusahaan Industri Pengolahan*, an annual survey of manufacturing establishments in Indonesia conducted by *Badan Pusat Statistik*, i.e., the Central Bureau of Statistics of Indonesia.[11] For our analysis, we rely on two measures of abatement behavior. While the first amounts to (log) pollution abatement expenses, the second is a binary indicator defined as one if firms report positive abatement expenditure, and zero otherwise. Our treatment dummy represents a firm's exporting status. In addition to industry and province fixed effects, X includes (log) capital-labor ratio, (log) labor productivity, (log) age, (log) total assets, (log) R&D expenditures, as well as shares of imported raw materials, foreign ownership, and skilled employees.[12] As detailed below, some specifications also control for quadratic and interaction terms involving the continuous variables in X. For instance, Millimet and Tchernis (2009, p. 410) note that "applied researchers should provide a series of estimates using increasingly sophisticated specifications of the propensity score model."

Before proceeding, a few comments are noteworthy. First, the set of variables in X is motivated by existing contributions such as Batrakova and Davies (2012), Cole et al. (2008), and Girma and Hanley (2015). Second, the survey does not contain information on capital stock for 2006. Accordingly, it is calculated from the value of capital stock during 2005 and investment over 2006.[13] Third, since we control for (log) labor productivity, i.e., (log) output per labor, for our continuous dependent variable, abatement costs are not scaled by output (Borjas 1980). However, X includes (log) total assets to account for firm size.[14] Fourth, for (log) abatement costs, due to presence of zero expenditure values, an inverse hyperbolic sine transformation is used. Thus, our continuos dependent variable is defined as $\ln\left(A_i + \sqrt{A_i^2 + 1}\right)$. Finally, the variables in the heteroskedasticity specification, i.e., Z are (log) capital-labor ratio, (log) labor productivity, (log) total assets, and (log) R&D expenditures.

Summary statistics provided in Table 1 find exporters to be characterized by greater pollution abate-

mainly attributable to extreme observations. That said, if a heteroskedastic probit proves difficult to converge, we rely on a homoskedastic specification.

[11] Note, while we have access to additional years of the survey, the information on abatement costs is only available for 2006.

[12] Note, the industry dummies correspond to the two-digit International Standard of Industrial Classification (ISIC) Rev.3 sectors.

[13] Note, more precisely, the capital stock for 2006 is obtained as the sum of the (depreciated) stock from 2005 and any additional capital in 2006. In keeping with studies such as Batrakova and Davies (2012), a depreciation rate of 12% is assumed. Also, as in Roy and Yasar (2015), capital price deflators from the webpage of Bank Indonesia (the central bank of Indonesia) are employed to express values in (thousands of) 2006 rupiahs.

[14] Note, we also employed an additional year of data to estimate a production function based on Ackerberg et al. (2015) and Manjón and Mañez (2016), and thereby obtain firm-level total factor productivity. However, in overidentified models, the IV specification tests rendered the validity of the instruments suspect.

ment behavior, capital-labor ratio, productivity, assets, as well as R&D expenditure. In addition, such plants also exhibit higher shares of imported materials, foreign ownership, and skilled employees. To be more precise, while roughly 20% of the establishments engage in exporting, a typical exporting firm spends roughly 6.5 times more in abatement than a representative non-exporter. Also, about 19% (10%) of exporting (non-exporting) plants engage in some pollution abatement. On average, an exporting firm is also nearly ten times larger than a non-exporting facility in terms of assets. Accordingly, our concerns over non-random selection into exporting seem relevant.

4 Results

Turning to our findings, the ATEs corresponding to pollution abatement expenditure and the probability of engaging in abatement are displayed in Tables 2 and 3, respectively. For each table, in Specification 1, the set of covariates is comprised of the variables contained in X. Upon including quadratic terms for each of the continuous attributes in X, we arrive at the results pertaining to Specification 2. The estimates under Specification 3 are obtained after additionally controlling for all interactions between the continuous variables in X. Across the two tables, the 90% confidence intervals (in brackets) are obtained using 250 bootstrap repetitions.[15]

Focusing on Table 2, the ATEs obtained under exogeneity find exporting to be associated with greater pollution abatement expenditure. For example, in case of OLS, exporting appears to encourage abatement expenses by at least 63%.[16,17] While the IPW estimates suggest a slightly smaller impact, both sets of ATEs are statistically significant at the 90% level of confidence. However, due to our concerns over non-random selection into exporting, we refrain from putting too much stock on these results.

In case of the MB estimates, we report two sets of results based on the θ values of 0.05 and 0.25.[18] Here, exporters are again evidenced to engage in greater pollution abatement expenditure. Although the 90% confidence intervals contain zero when $\theta = 0.05$, the ATEs pertaining to the higher value of θ are more precisely estimated. In fact, for $\theta = 0.25$, the effect of exporting on abatement is witnessed to be as large as about 128%.[19] While the statistically significant estimates in case of the MB estimator are often

[15] Note, for the Lewbel (2012) and Klein and Vella (2009) estimators, the coefficient estimates corresponding to the remaining covariates are not displayed but available upon request.

[16] Note, $\exp(0.492) - 1 = 0.635$.

[17] Note, as discussed in Bellemare and Wichman (2019), our elasticity interpretation is valid in spite of the inverse hyperbolic sine transformation.

[18] Note, the number of non-exporters and exporters in the sample are roughly 18000 and 4500, respectively. For $\theta = 0.05$, Ω must contain at least 900 (i.e., 5% of 18000) non-exporters as well as 225 (i.e., 5% of 4500) exporters.

[19] Note, $\exp(0.825) - 1 = 1.281$.

greater than those obtained under exogeneity, it is worth noting that if treatment effects are heterogeneous, the MB estimator does not provide the unconditional ATE. For example, in case of Specification 1, the BMPS is roughly 0.4. However, the sample average value of propensity score is about 0.25. Accordingly, an effect of roughly 112% pertains to plants with a relatively high probability of exporting.[20] From the propensity score model, such plants are relatively larger, more productive, and characterized by greater shares of imported raw materials, foreign ownership, and skilled employees.

Next, for the MB-BC approach, irrespective of the value of θ, the estimated effects are often relatively large and statistically significant. That said, as noted above, the estimator relies on the assumption of bivariate normality to a greater extent. Nonetheless, exporting is evidenced to increase abatement expenses by at least as much as 100%.[21] While the BC method is also based on the assumption of joint normality, it produces an estimate of the unconditional ATE. Restricting attention to the statistically significant BC estimates, exporting is witnessed to encourage pollution abatement costs by at least about 280%.[22]

Prior to discussing the IV estimates based on the Lewbel (2012) and Klein and Vella (2009) strategies, a few comments on the two estimators are relevant. First, Millimet and Tchernis (2013, p. 1006) note that the parametric version of the Klein and Vella (2009) approach is "highly sensitive to misspecification of the functional form." Second, the Monte Carlo analysis in Millimet and Tchernis (2013) find a traditional IV estimator to outperform the Klein and Vella (2009) approach. Third, unlike the Klein and Vella (2009) estimator, the Lewbel (2012) strategy entails an overidentified model, and thereby allows us to conduct overidentification tests to assess the validity of the instruments. Fourth, in case of heterogeneous treatment effects, the parameter identified by an IV estimator may differ from the ATE of interest (Imbens and Angrist 1994).

Both estimators witness exporting to significantly encourage pollution abatement.[23] While the Lewbel (2012) strategy finds exporting to raise abatement expenditure by almost up to 138%, the Klein and Vella (2009) estimator uncovers a more pronounced effect, i.e., to the tune of at least 210%.

Turning to our binary dependent variable, i.e., abatement status, the findings in Table 3 paint a similar picture. As in the case of Table 2, Specification 1 does not account for any quadratic or interaction term involving the continuous attributes in X. While Specification 2 incorporates the role of quadratic terms,

[20] Note, $\exp(0.751) - 1 = 1.119$.

[21] Note, $\exp(0.719) - 1 = 1.052$.

[22] Note, in keeping with Millimet and Tchernis (2013), we also obtained the MB, MB-BC, and BC estimates after relaxing the assumption of joint normality. The results are qualitatively similar with mostly greater point estimates of the ATE as well as the BMPS; they are available upon request.

[23] Note, for either estimator, the usual IV specification tests perform well. While the first-stage F-statistic values are typically large for both, overidentification tests lend further credibility to the instruments based on the Lewbel (2012) approach.

Specification 3 additionally controls for the full set of interactions involving the continuous variables in X. Under exogeneity, the estimates continue to find exporting to be associated with greater pollution abatement. For instance, in case of OLS, exporting is found to increase the probability of pollution abatement by at least 3.3 percentage points. Moreover, both the OLS and IPW estimates are mostly significant at the 90% level of confidence.

Focusing on the MB approach, the estimates are statistically significant only when $\theta = 0.25$.[24] In this case, exporters are evidenced to have a higher probability of abatement behavior to the tune of up to 6 percentage points. However, as in the case of Table 2, the BMPS values suggest that such an effect is mainly applicable to firms with a relatively high probability of exporting. Next, upon incorporating the bias correction term described in (8), the MB-BC estimates are always greater than the corresponding MB results. Interestingly, the bias-corrected impacts (for both the MB-BC and BC estimators) are often imprecisely estimated upon controlling for the quadratic and interaction terms. That said, in Specification 1, exporting is found to promote abatement behavior by at least 16 percentage points.

Finally, even in the case of the binary indicator for pollution abatement, the IV estimators continue to witness exporters to be characterized by a higher probability of abatement.[25] Although the Klein and Vella (2009) estimator finds exporting to raise the incidence of abatement by up to about 18 percentage points, the Lewbel (2012) approach uncovers a relatively modest impact of roughly 5 percentage points.

5 Conclusion

Does exporting cause firms to engage in greater pollution abatement? The significance of this question cannot be overemphasized. For example, if exporting firms spend more on pollution abatement relative to non-exporters, export promotion policies may have environmental benefits. This is especially relevant in the context of developing countries, typically characterized by ineffective environmental regulation. According to García et al. (2007, p. 742-743), among others, "[c]ountries such as Indonesia face a tough challenge in choosing and designing policy instruments to deal with industrial pollution. Conventional regulation (such as requirements to use best available technology) is known to be grossly inefficient, since it provides no incentive for firms to innovate. Furthermore, the whole process of setting standards is easily manipulated by powerful industrial lobbies."

Similarly, the above question is also related to the environmental implications of pollution havens.

[24] Note, again, the number of non-exporters and exporters are about 18000 and 4500, respectively. For $\theta = 0.25$, Ω must contain at least 4500 (i.e., 25% of 18000) non-exporters as well as 1125 (i.e., 25% of 4500) exporters.

[25] Note, again, the IV specification tests for both estimators perform well. However, as discussed above, overidentification tests are only available for the Lewbel (2012) approach.

According to the Pollution Haven Hypothesis, jurisdictions with lax environmental policy may attract pollution-intensive production activities, and thereby raise world pollution (e.g., Copeland and Taylor 2004; Chung 2014; Keller and Levinson 2002; Millimet and Roy 2016). However, to the extent that exporting encourages pollution abatement activities, policies aimed at increasing firm-level exports may alleviate some of these environmental concerns.

In spite of the stakes involved, the existing literature examining the environmental implications of firm-level trade rarely focuses on developing countries. In addition, the issue of non-random selection into exporting is yet to be adequately assessed. Accordingly, we employ cross-sectional data across Indonesian firms to analyze the causal effect of exporting on firms' pollution abatement behavior. Moreover, due to the endogeneity of exporting status combined with the paucity of a traditional instrumental variable, we rely on a number of novel identification strategies. The first two approaches (i.e., the MB and BC estimators discussed above) are attributable to Millimet and Tchernis (2013). While the MB approach utilizes a subset of observations where the endogeneity bias is minimized, the BC methodology corrects for such bias (under certain assumptions). The remaining strategies, based on Lewbel (2012) and Klein and Vella (2009), resort to IV but exploit higher moments of the data to obtain exclusion restrictions.

Overall, we largely find exporting to significantly encourage pollution abatement behavior. While our results are consistent with existing studies witnessing exporters to be largely pro-environment, across each specification, the effect of exporting on pollution abatement is evidenced to be more pronounced after accounting for the endogeneity of exporting. Thus, our findings support the plausibility of Lyon and Maxwell's (2008, p. 244) claim that "[i]n developing countries with weak regulatory systems, international markets may be the strongest force for environmental CSR."

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Table 1. Summary Statistics.

Variable	Exporters		Non-exporters	
	N	Mean	N	Mean
Abatement Expenditure	4546	65890.560	18206	10031.490
Abatement Expenditure (1=Yes)	4546	0.191	18206	0.098
Capital-Labor Ratio	2734	977333.400	9327	96050.220
Labor Productivity	4546	265794.800	18206	100901.700
Total Assets	4546	37900000000.000	18206	3900000000.000
R&D Expenditure	4546	37613.640	18206	3979.835
Age	4546	14.420	18206	14.928
Share of Imported Raw Materials	4384	0.140	17443	0.035
Share of Foreign Ownership	4546	0.195	18206	0.024
Share of Skilled Employees	4546	0.155	18206	0.128

Table 2. Effect of Exporting on Pollution Abatement Expenditure.

	Spec (1)	Spec (2)	Spec (3)
τ_{OLS}	0.538	0.492	0.503
	[0.348, 0.758]	[0.301, 0.713]	[0.299, 0.715]
τ_{IPW}	0.416	0.449	0.435
	[0.183, 0.673]	[0.160, 0.679]	[0.223, 0.696]
$\tau_{MB, 0.05}$	0.447	0.398	0.472
	[-0.067, 1.774]	[-0.224, 1.425]	[-0.132, 1.464]
$\tau_{MB, 0.25}$	0.751	0.604	0.825
	[0.401, 1.013]	[0.223, 0.926]	[0.316, 1.027]
$\tau_{MB\text{-}BC, 0.05}$	1.952	0.719	1.096
	[0.604, 3.785]	[-0.362, 2.542]	[0.124, 2.601]
$\tau_{MB\text{-}BC, 0.25}$	2.256	0.926	1.449
	[0.947, 3.343]	[-0.169, 2.129]	[0.276, 2.478]
τ_{BC}	2.189	0.957	1.347
	[1.072, 3.261]	[-0.331, 2.163]	[0.283, 2.598]
P^*	0.399	0.793	0.728
	[0.170, 0.838]	[0.027, 0.933]	[0.092, 0.950]
τ_L	0.821	0.806	0.867
	[0.591, 1.253]	[0.581, 1.269]	[0.649, 1.236]
τ_{KV}	2.209	1.143	1.496
	[1.065, 3.172]	[0.070, 2.286]	[0.414, 2.586]

Notes: 90% confidence intervals in brackets are obtained using 250 bootstrap repetitions. IPW is the inverse probability weighted estimator; MB is the minimum-biased estimator using $\theta = 0.05$ or 0.25; MB-BC is the minimum-biased bias-corrected estimator using $\theta = 0.05$ or 0.25; BC is the unconditional bias-corrected estimator; L is the Lewbel (2012) estimator; KV is the Klein and Vella (2009) estimator; and, P* is the bias-minimizing propensity score.

Table 3. Effect of Exporting on the Probability of Pollution Abatement.

	Spec (1)	Spec (2)	Spec (3)
τ_{OLS}	0.036	0.033	0.034
	[0.016, 0.057]	[0.015, 0.054]	[0.015, 0.054]
τ_{IPW}	0.025	0.027	0.028
	[0.006, 0.050]	[-0.000, 0.056]	[0.009, 0.055]
$\tau_{MB,\ 0.05}$	0.049	0.008	0.016
	[-0.030, 0.151]	[-0.032, 0.125]	[-0.038, 0.135]
$\tau_{MB,\ 0.25}$	0.059	0.042	0.062
	[0.020, 0.086]	[0.011, 0.077]	[0.013, 0.084]
$\tau_{MB\text{-}BC,\ 0.05}$	0.169	0.046	0.072
	[0.042, 0.313]	[-0.059, 0.207]	[-0.017, 0.228]
$\tau_{MB\text{-}BC,\ 0.25}$	0.178	0.080	0.118
	[0.065, 0.267]	[-0.031, 0.191]	[0.005, 0.205]
τ_{BC}	0.163	0.076	0.107
	[0.065, 0.262]	[-0.048, 0.184]	[-0.003, 0.202]
$P*$	0.328	0.601	0.693
	[0.078, 0.679]	[0.032, 0.930]	[0.074, 0.962]
τ_{L}	0.046	0.047	0.052
	[0.024, 0.079]	[0.024, 0.075]	[0.036, 0.089]
τ_{KV}	0.177	0.073	0.117
	[0.064, 0.289]	[-0.008, 0.174]	[0.001, 0.198]

Notes: 90% confidence intervals in brackets are obtained using 250 bootstrap repetitions. IPW is the inverse probability weighted estimator; MB is the minimum-biased estimator using θ = 0.05 or 0.25; MB-BC is the minimum-biased bias-corrected estimator using θ = 0.05 or 0.25; BC is the unconditional bias-corrected estimator; L is the Lewbel (2012) estimator; KV is the Klein and Vella (2009) estimator; and, P* is the bias-minimizing propensity score.