Federal Reserve Bank of Dallas

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Globalization Institute Working Paper 393 **July 2020**

Research Department

https://doi.org/10.24149/gwp393

Exporting and Pollution Abatement Expenditure: Evidence from Firm-Level Data[*]

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June 30, 2020

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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[*]The authors thank Appalachian State University's Walker College of Business for a Dean's Club Research Grant and are very grateful to Matt Cole, two anonymous referees, Claire Brunel, and Daniel Millimet for helpful comments. The authors also wish to thank Jevan Cherniwchan, John Dalton, Scott Holladay, Tibor Besedes, seminar participants at Appalachian State University, Wake Forest University, and conference participants at the Fall 2017 Midwest Economic Theory and International Trade Meetings, the 2018 Southern Economic Association Meetings, the 2018 International Atlantic Economic Society Conference, the 2018 Pennsylvania Economic Association Conference, the 2018 Sustainability and Development Conference, and the 2020 Holshouser Ethics Lunch. The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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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. For example, García et al. (2007, p. 742-743) state: "Countries 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." 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, in keeping with contributions such as Kitzmueller and Shimshack (2012) and Chuang and Huang (2018), our topic relates to the increasingly important role of environmental protection as part of corporate social responsibility (CSR). According to Kitzmueller and Shimshack (2012, p. 79), "the international and especially developing country context is an interesting natural laboratory to explore CSR and its mechanisms."

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). As Distelhorst and Locke (2018, p. 697) note, "firms that observe higher standards - like offering higher wages or paying to mitigate their

[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.

environmental impacts - are at a competitive disadvantage in export markets. This view rests on two assumptions. The first assumption is that, other things equal, observing higher labor and environmental standards results in increased unit prices ... The second assumption is that customers (importers) are indifferent to the labor and environmental standards of their suppliers. They are unwilling to pay higher prices to do business with compliant exporters." 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). Again, Distelhorst and Locke (2018, p. 697) discuss how "[r]eputation-conscious importers may ... prefer to do business with exporters that comply with minimum standards in labor and environmental practices." 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 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. Similarly, political connections may influence firms' pollution discharges as well as exporting performance (Deng et al. 2020; Yasar 2013). Moreover, unobservables such as consumer preferences in overseas markets and plants' outsourcing and innovation behavior also qualify as potential confounders (Aghion et al. 2020; 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 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. The first approach begins by adjusting for differences in observed characteristics across exporters and non-exporters, and subsequently estimating the causal effect of interest for a subset of observations where the endogeneity bias is minimized. The second method extends this strategy by correcting for the bias arising from non-random selection into exporting. While both of these approaches are attributable to Millimet and Tchernis (2013), the remaining (IV-based) methods follow from Lewbel (2012) and Klein and Vella (2009) and 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 reviews the literature. Section 3 describes the empirical methodology. Section 4 discusses the data. Section 5 presents the results, while Section 6 concludes.

2 Literature Review

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. However, while the authors employ a difference-in-differences technique combined with propensity score matching in some of the specifications, they caution that this approach only accounts for selection bias attributable to time-invariant unobserved characteristics. In other words, to the extent that crucial unobservables such as outsourcing behavior or managerial quality vary over time, the coefficient estimates are potentially biased.

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 among Argentinean and Japanese firms, respectively. Focusing on Brazil, Da Motta (2006) also witnesses exporting to enhance environmental management. Among these studies, mainly Albornoz et al. (2009), Cole et al. (2006), and Cole et al. (2008) express concerns over endogeneity. While Cole et al. (2006) consider the issue to be less severe in case of firm-level studies, the time dimension of the data do not allow Cole et al. (2008) to control for time-invariant unobservables.

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] Here, despite controlling for firm fixed effects, the authors refrain from making a causal statement. It is worth noting that apart from failing to control for time-varying unobservables, the use of such fixed effects also rely on fairly strong assumptions such as strict exogeneity whereby exporting status in each time period is required to be uncorrelated with unobservables in every period. Next, Richter and Schiersch (2017) focus on German manufacturing and also 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. In addition, He and Wang (2020) employ plant-level data from China and assess how processing exports (whereby firms process imported raw materials and re-export finished products) affect sulfur dioxide and soot emissions.

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. However, the nature of the exporting status dummy prevents the use of facility fixed effects. Further, Cui et al. (2016) use facility-level data from the NETS and

[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.

[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).

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) resort to propensity score matching and 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. However, all of these studies are susceptible to plant-specific unobservables that vary over time. 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]

Overall, 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 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. Given the existing literature, we now proceed to our analysis.

3 Empirical Methodology

3.1 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

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

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

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

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, τ may still be identified by comparing firms' abatement activities after conditioning on such attributes. In such a scenario, conditioning on the propensity score, i.e., the conditional probability of exporting given the observables, is in fact sufficient (Rosenbaum and Rubin 1983).

As discussed below, our set of observables, X, includes firm-specific factors such as (log) capital-labor ratio, (log) labor productivity, (log) age, (log) total assets, (log) R&D expenditures, shares of imported raw materials, foreign ownership, and skilled employees, as well as industry and province fixed effects. Moreover, the propensity score for firm i is given by $P(X_i) = \Pr(EXP_i = 1|X_i)$. However, as noted above, selection into exporting is likely driven by unobserved attributes such as credit constraints, managerial quality, and political connections as well. Accordingly, exporting status is potentially endogenous and identification of the ATE is not trivial. Further, due to the paucity of valid instruments, a conventional IV strategy is not viable.

Given this framework, we resort to a number of approaches that attend to our concerns over endogeneity but circumvent the need for traditional instruments. The first estimator entails minimizing the selection bias by only including (in the estimation sample) observations with a propensity score value within a certain interval. However, to the extent that the effect of exporting on pollution abatement varies with X and thereby $P(X)$, this does not identify the ATE of exporting in the entire population. The second set of estimators build on this approach by also subtracting and thereby correcting for the minimized bias. Next, the final two estimators employ an IV approach where higher moments of the observed variables

[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.

are utilized to construct instruments. Before discussing these methods in greater detail, we obtain an expression for the bias due to selection on unobservables in τ.

3.2 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 (i.e., abatement behavior) and latent treatment assignment (i.e., exporting status) are additively separable in observed and unobserved variables

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

In other words, plant-level observed characteristics representing capital-labor ratio, labor productivity, R&D expenditures, and others, as well as unobservables such as credit constraints and managerial quality are assumed to be additively separable. This is in keeping with existing contributions such as Cole et al. (2006, 2008), Holladay (2016), Cui and Qian (2014), Cui et al. (2016), Forslid et al. (2018), and others. Moreover, EXP^* can be interpreted as a firm's net gain from exporting (Heckman et al. 2006). To the extent that firms benefit from exporting, they select into the treatment group.

Second, we assume

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

where

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

Here, the unobserved attributes are assumed to follow a normal distribution. Again, this is consistent with studies such as Batrakova and Davies (2012) and Girma and Hanley (2015) where probit specifications are employed to model participation in exporting activities or environmental innovation. Further, as noted towards the end of Section 3.4, we also consider deviations from normality. More importantly, unlike the majority of the literature, we attend to concerns over the correlation between unobservables influencing exporting and pollution abatement activities by considering non-zero values of the correlation parameters above.

Under these assumptions, following Heckman and Navarro-Lozano (2004) and Millimet and Tchernis (2013), 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, $B[P(X)]$ denotes the bias at some value of the propensity score, $P(X)$. Also, $\phi(\cdot)$ and $\Phi(\cdot)$ depict the standard normal density and cumulative distribution function, respectively. While $\delta = \varepsilon_1 - \varepsilon_0$ is the unobserved change in pollution abatement attributable to exporting, $\rho_{\delta u}$ denotes the correlation between δ and u. Thus, if firms sort into exporting status on the basis of some idea about δ, the correlation parameter is non-zero. σ_δ is the standard deviation of δ.

Before proceeding, note that Millimet and Tchernis (2013) highlight a few implausible scenarios under which the bias is zero. For instance, the bias clearly disappears if both ρ_{0u} and $\rho_{\delta u}$ are zero. In other words, if there is no selection into exporting on the basis of unobservables affecting abatement activities of non-exporters, or due to unobserved changes in abatement behavior, then $B[P(X)]$ is zero. As discussed above, due to unobserved attributes such as outsourcing, credit constraints, and management quality, this is unlikely. For example, plants that are likely to engage in less abatement perhaps due to outsourcing options may opt to export and thereby render $\rho_{0u} \neq 0$. Similarly, some notion about the difference in abatement activities attributable to varying levels of, say managerial quality, may encourage facilities to sort into the treatment group.

3.3 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

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

As discussed in contributions such as Hirano and Imbens (2001, p. 263), Morgan and Winship (2015), and Imbens and Rubin (2015), "adjusting for the propensity score removes the bias associated with differences in the observed covariates in the treated and control groups. One way to implement this approach is to reweight treated and control observations to make them representative of the population of interest." In other words, weighting exporters and non-exporters by the inverse of their assignment probabilities, i.e., $\hat{P}(X_i)$ and $1 - \hat{P}(X_i)$, respectively, adjusts for the observed characteristics across the two groups.[8]

[8] Note, while weighting simply by the inverse of $\hat{P}(X_i)$ and $1 - \hat{P}(X_i)$ corresponds to Horvitz and Thompson's (1952) unnormalized estimator, Hirano and Imbens (2001) propose the normalized estimator in (4). Moreover, Millimet and Tchernis

However, due to non-random selection (on unobservables) 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

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

where Ω depicts the set of observations with a propensity score close to P^*. Intuitively, while our objective is to estimate the ATE of exporting on pollution abatement, due to concerns over selection or endogeneity bias, the MB estimator ultimately compares the abatement behavior of exporters and non-exporters with propensity score values belonging to a subset of the unit interval. More specifically, we define Ω as the smallest neighborhood around P^* containing at least θ proportion of both exporters and non-exporters.[9] While we set θ as 0.05 and 0.25, observations with propensity scores above (below) 0.98 (0.02) 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 the terms involving the correlation parameters, i.e., $\rho_{0u}\sigma_0$ and $\rho_{\delta u}\sigma_\delta$ in (3). More precisely, suppose the relationship between (potential) abatement behavior and X is linear, and the causal effect of exporting on pollution abatement is homogeneous such that $g_0(X) = X\beta$ and $g_1(X) = \tau + X\beta$. Further, in the treatment assignment model, say $h(X) = X\gamma$. In such a scenario, if the unobservables influencing abatement as well as exporting behavior follow a bivariate normal distribution, τ may be identified from

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

Here, $\beta_{\lambda 0} = \rho_{0u}\sigma_0$ and $\beta_{\lambda 1} = \rho_{0u}\sigma_0 + \rho_{\delta u}\sigma_\delta$ and the corresponding terms involving $\phi(\cdot)$ and $\Phi(\cdot)$ account for selection into exporting. However, instead of resorting to the assumption of bivariate normality to identify our estimand of interest, the idea is to utilize (6) and ultimately estimate the correlation parameters. After replacing γ with a first-stage probit estimate, OLS estimation of equation (6) helps identify $\beta_{\lambda 0}$ and $\beta_{\lambda 1}$, and thereby $\rho_{0u}\sigma_0$ 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.

(2009), among others, find the normalized estimator to perform better.

[9] 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.

3.4 The Bias-Corrected Estimator

While the MB estimator focuses on observations with a propensity score in a neighborhood around P^* to examine the difference in pollution abatement behavior across exporters and non-exporters, the BMPS can be employed to calculate the value of minimized bias. Moreover, as Millimet and Tchernis (2013) explain, the minimized bias can then be subtracted from the MB and IPW estimators to obtain the corresponding bias-corrected (BC) estimators. To be more precise, from (3), the estimate of the bias at P^* is expressed as

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

Upon subtracting this bias from the MB estimator, we can arrive at the MB-BC estimator as

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

Now, 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 discussing the heteroskedasticity-based approaches, two comments are warranted. First, unlike the MB estimator, the BC approach does not alter the parameter being estimated. 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 23).

3.5 Lewbel (2012) Estimator

Turning to our first estimator based on higher moments, we assume the specification explaining pollution abatement activities to be represented as

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

This is essentially equation (6) without the selection correction terms. Moreover, in keeping with contributions such as Girma and Hanley (2015), the model depicting the determinants of exporting status is given by

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

As noted above, if unobserved firm-level attributes such as credit constraints, managerial quality, and political connections influence plants' exporting as well as abatement behavior, ν and ζ are likely correlated thereby rendering EXP endogenous in (10).

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 an IV strategy exploiting such heteroskedasticity helps identify τ, i.e., our ATE of interest. 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. Here, we resort to the Breusch-Pagan test for heteroskedasticity to determine the set of variables in Z. As detailed below, Z consists of variables depicting plant-level characteristics such as capital-labor ratio, labor productivity, total assets, and R&D expenditures. The strength of the (partial) correlation between the instruments and EXP is directly related to the degree of heteroskedasticity in equation (12). Moreover, from (13), the exclusion restrictions are uncorrelated with ν in (10), i.e., the unobservables in our outcome equation.

Lewbel (2012, 2018) provide additional details on the validity of the instruments. For instance, in case of a continuous abatement measure, Lewbel (2018) presents some sufficient conditions where the assumptions in (12) and (13) are satisfied. To be more precise, for linear specifications such as equations (10) and (11), one plausible scenario occurs when the error term in the outcome equation depends on exporting status along with idiosyncratic factors following specific distributions. Here, ν may be conceptualized as a composite index of unobservables such as innovation, consumer preferences, and outsourcing behavior attributable to exporting. Nonetheless, we employ a number of specification tests to assess the validity of our IV strategy. Our estimation is performed using Generalized Method of Moments (GMM).

3.6 Klein & Vella (2009) Estimator

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

$$\begin{aligned} EXP^* &= X\gamma - \widetilde{u} \\ EXP &= \begin{cases} 1 & \text{if } EXP^* > 0 \\ 0 & \text{otherwise} \end{cases}. \end{aligned} \tag{14}$$

As noted above, EXP^* can be conceptualized as a firm's net gain from exporting. To the extent that firms benefit from serving foreign markets, they select into exporting. However, $\widetilde{u} = \exp(Z\pi)u$. Here, u is assumed to be homoskedastic and drawn from a standard normal distribution with $Z \subseteq X$.[10] For example, u may represent an index of unobserved characteristics such as managerial quality and credit constraints that is correlated with ν in equation (10). Moreover, the variance of EXP^* may depend on attributes such as capital-labor ratio, productivity, R&D expenditures, and assets.

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).[11]

Prior to discussing the data used for our study, some comments pertaining to the performance of the various estimators are noteworthy. Based on the Monte Carlo results in Millimet and Tchernis (2013), the relative performance of the IPW, MB, MB-BC, BC, and KV estimators depends on factors such as the incidence of selection on unobservables into exporting, and knowledge of the correct functional forms in the probit specification along with the heteroskedasticity function in (15). For instance, in case of non-random selection accompanied by correct specification for the covariates in the probit models, the KV, MB-BC, and BC estimators are preferred. However, a traditional IV approach may outperform each of these. In practice, the functional forms are likely to be unknown and in fact under-specified. In such a scenario, the MB estimator is witnessed to outperform the others. Millimet and Tchernis (2013, p. 1000) note that "[w]hile the under-specified case is arguably the most important in practice," the MB-BC, BC, and KV estimators "perform extremely poorly" in case of under-specification (p. 1003). Accordingly, the authors particularly recommend the MB estimator "to become part of the applied researcher's toolkit in the absence of traditional exclusion restrictions (p. 1006)."

4 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

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

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

Bureau of Statistics of Indonesia.[12] 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. Thus, in case of the continuous abatement variable, we analyze how exporting affects overall abatement expenditure. For the binary measure, the impact of exporting on initiating firms' pollution abatement behavior is examined. This is similar to a number of contributions in the firm-level literature. For instance, while analyzing the effect of import competition on environmental performance using plant-level data from Mexico, Gutiérrez and Teshima (2018) consider binary as well as continuous measures of environmental and energy investment. Similarly, Rodrigue and Soumonni (2014) resort to continuous and binary indicators of abatement to assess the relationship between exporting and pollution abatement in Indonesian timber manufacturing firms.

Turning to the control variables, 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.[13] Some specifications also control for quadratic and interaction terms involving the continuous variables in X (detailed below). As Millimet and Tchernis (2009, p. 410) note, "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 survey does not provide additional information on the nature of pollution abatement activities. While employing plant-level data from Indonesia, Kaiser and Schulze (2003, p. 2) state: "Reliable estimates of industrial environmental costs - in particular for developing countries - are notoriously hard to come by." Focusing on Indonesian timber plants, Rodrigue and Soumonni (2014, p. 324) contend that although the abatement expenses are aimed at mitigating deforestation, one "cannot determine the total expenditure incurred on each type of expense within each plant." However, Dechezleprêtre et al. (2019) state: "Investments in pollution abatement technologies have been used as a proxy for firms' environmental performance, relying on the assumption that such investments result in actual pollution abatement."

Second, 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). Third, 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.[14] Fourth, since we control for (log) labor productivity, i.e., (log) output per labor, for

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

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

[14] Note, more precisely, the capital stock for 2006 is obtained as the sum of the (depreciated) stock from 2005 and any

our continuous dependent variable, abatement costs are not scaled by output (Borjas 1980). However, X includes (log) total assets to account for firm size.[15] Fifth, for (log) abatement costs, due to the 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 abatement 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. Moreover, for each of the variables in Table 1, t tests reject the equality of means across exporters and non-exporters at the 95% level of confidence. Accordingly, our concerns over non-random selection into exporting seem relevant.

5 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 the percentile method and 250 bootstrap repetitions. Further, the standard errors (in parentheses) are based on 250 bootstrap samples as well.[16]

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

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.

[15] 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.

[16] 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.

expenses by at least 63%.[17,18] 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.[19] 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%.[20] While the statistically significant estimates in case of the MB estimator are often 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.[21] 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. In fact, exporting is evidenced to increase abatement expenses by at least as much as 100%.[22] While the BC method produces an estimate of the unconditional ATE, the statistically significant estimates based on this strategy witness exporting to encourage pollution abatement costs by at least about 280%.[23] That said, as noted above, in the likely scenario of under-specifying the probit models, the MB estimator performs favorably relative to the BC approaches.

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 amidst concerns over non-random selection into exporting, our KV strategy is "highly sensitive to misspecification of the functional form." Second, if exporting status is endogenous, the Monte Carlo analysis in Millimet and Tchernis (2013) find a traditional IV strategy to outperform all estimators such as the MB,

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

[18] Note, as discussed in Bellemare and Wichman (2020), our elasticity interpretation is valid in spite of the inverse hyperbolic sine transformation.

[19] 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.

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

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

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

[23] 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.

MB-BC, BC, as well as KV. However, in case of heterogeneous treatment effects, the parameter identified by an IV estimator may differ from the ATE of interest (Imbens and Angrist 1994). Third, unlike our KV estimator, the Lewbel (2012) strategy entails an overidentified model, and thereby allows us to conduct additional tests to assess the validity of instruments.

Both estimators witness exporting to significantly encourage pollution abatement.[24] 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, 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 $\theta = 0.25$.[25] 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.

Further, 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.[26] 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.

Across all the estimators utilized, although we consistently find exporting to encourage pollution abate-

[24] 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.

[25] 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.

[26] 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.

ment behavior, a number of important issues merit further consideration. First, as discussed above, the survey does not specify the types of abatement activities that firms engage in. Accordingly, although abatement behavior may include measures such as removal or recycling of pollutants associated with production processes, adoption of end-of-pipe equipment to reduce pollution, use of less-polluting inputs, and associated employee training, we are unable to precisely estimate the impact of abatement in greater detail. Nonetheless, our analysis complements the existing literature analyzing the environmental implications of firm-level trade. For example, while contributions such as Cui et al. (2016), Holladay (2016), and Cherniwchan (2017) examine the effect of trade on firm-level emissions, others such as Batrakova and Davies (2012) and Cole et al. (2008) focus on energy use. Furthermore, although studies such as Cole et al. (2006), Martin-Tapia et al. (2008), and Albornoz et al. (2009) resort to various indicators of environmental management, Girma and Hanley (2015) employ self-reported measures of environmental innovation. In the context of Indonesia, while Roy and Yasar (2015) consider energy efficiency, Kaiser and Schulze (2003) and Rodrigue and Soumonni (2014) rely on abatement expenses. Interestingly, a few contributions such as Forslid et al. (2018) assess how exporting relates to abatement expenses as well as emissions. Thus, given the "very small" set of contributions assessing the crucial issue pertaining to the environmental consequences of firm-level trade, our findings are particularly relevant (Cherniwchan et al. 2017, p. 82).[27]

Second, our results are also consistent with some of the theoretical predictions in studies such as Forslid et al. (2018). For instance, Forslid et al. (2018) explain how firms' abatement activities are related to their production volumes and thereby exporting status. Intuitively, exporters are likely to engage in greater production which helps distribute the fixed costs of abatement investment over higher output. While the coefficient estimates in Forslid et al. (2018) witness exporting to encourage abatement expenses by up to 100%, the MB approach uncovers a causal effect to the tune of 125%. Moreover, while the authors witness a positive association between productivity and pollution abatement, our IV specifications based on Lewbel (2012) mostly uncover a positive effect of labor productivity on both our abatement measures. Further, in keeping with our results, Forslid et al. (2018, p. 169) find that "exporters invest more in abatement and they do so also after controlling for productivity, i.e., trade has an effect on abatement investments that is independent of productivity."

[27] Note, in keeping with contributions such as Brucal et al. (2019), we tried a few specifications with (log) total value of energy (i.e., fuels, lubricants, and electricity) use, as well as (log) energy intensity (i.e., the ratio of energy use to the value of output) as our measures of environmental performance. In these models, exporting is witnessed to encourage aggregate energy use but reduce energy intensity. Again, in case of energy intensity, we did not control for (log) labor productivity to avoid output from explicitly influencing our dependent and explanatory variables. The results are available upon request.

Third, due to concerns over selection into exporting attributable to unobservables such as plants' outsourcing behavior, we also account for the role of multi-plant firms despite their limited presence in the survey (see footnote 1). More precisely, we begin by defining a binary variable indicating whether a surveyed plant has a parent company. While there are less than 5% plants with such a parent organization, upon controlling for this characteristic, our results are qualitatively unchanged.[28]

Finally, as described above, concerns over the endogeneity of exporting status have received little attention among existing studies examining the environmental consequences of firm-level trade. While most contributions resort to panel data and only control for firm-specific time-invariant unobservables, very few resort to an IV strategy. This is partly attributable to the difficulty in obtaining a traditional instrument. According to Cherniwchan et al. (2017, p. 82), "[a]lthough some researchers have adopted clever strategies to identify the causal impact of trade, others have been less careful. Despite these limitations, this research agenda is extremely valuable and should be pursued vigorously." Thus, recognizing the significance of the topic as well as the challenges involved in identifying the causal effect of interest, we utilize a number of novel approaches. While each of the methods rely on certain assumptions, they advance the literature in a number of ways. For example, the MB and BC estimators do not rely exclusively on a linear specification of the outcome equation. Although the MB estimator may ultimately be relevant for a subset of observations, it does not restrict crucial unobservables to be, say time-invariant. Next, despite the paucity of traditional exclusion restrictions, the Lewbel (2012) and KV strategies discuss some instruments based on higher moments of the data.

6 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. As He and Wang (2020, p. 9) note in the context of China, "given that exporters can generate more value with lower emissions than non-exporters, encouraging firms to engage in foreign markets can facilitate both economic growth and environmental progress." Moreover, the issue 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.

[28] Note, the results are available upon request.

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. 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 accounts for the differences in observed characteristics across exporting and non-exporting plants, and subsequently estimates the ATE for a subset of observations where the endogeneity bias is minimized, the BC methodology additionally corrects for such bias. 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 N	Exporters Mean	Exporters Standard Deviation	Non-exporters N	Non-exporters Mean	Non-exporters Standard Deviation	Difference in Means
Abatement Expenditure	4546	65890.560	536174.200	18206	10031.490	296331.300	55859.060
Abatement Expenditure (1=Yes)	4546	0.191	0.393	18206	0.098	0.297	0.093
Capital-Labor Ratio	2734	977333.400	39500000.000	9327	96050.220	3815198.000	881283.200
Labor Productivity	4546	265794.800	1184958.000	18206	100901.700	669565.000	164893.100
Total Assets	4546	37900000000.000	424000000000.000	18206	3900000000.000	52300000000.000	34000000000.000
R&D Expenditure	4546	37613.640	439339.500	18206	3979.835	113730.800	33633.800
Age	4546	14.420	12.020	18206	14.928	11.575	-0.508
Share of Imported Raw Materials	4384	0.140	0.298	17443	0.035	0.159	0.105
Share of Foreign Ownership	4546	0.195	0.377	18206	0.024	0.145	0.171
Share of Skilled Employees	4546	0.155	0.159	18206	0.128	0.164	0.027

Notes: For each variable, 'Difference in Means' corresponds to the difference in sample means between exporters and non-expoters. Each difference is statistically significant at the 95% level of confidence.

Table 2. Effect of Exporting on Pollution Abatement Expenditure.

	Spec (1)	Spec (2)	Spec (3)
τ_{OLS}	0.538	0.492	0.503
	(0.123)	(0.131)	(0.124)
	[0.348, 0.758]	[0.301, 0.713]	[0.299, 0.715]
τ_{IPW}	0.416	0.449	0.435
	(0.144)	(0.161)	(0.153)
	[0.183, 0.673]	[0.160, 0.679]	[0.223, 0.696]
$\tau_{MB,\ 0.05}$	0.447	0.398	0.472
	(0.566)	(0.455)	(0.439)
	[-0.067, 1.774]	[-0.224, 1.425]	[-0.132, 1.464]
$\tau_{MB,\ 0.25}$	0.751	0.604	0.825
	(0.204)	(0.221)	(0.214)
	[0.401, 1.013]	[0.223, 0.926]	[0.316, 1.027]
$\tau_{MB\text{-}BC,\ 0.05}$	1.952	0.719	1.096
	(0.953)	(0.887)	(0.743)
	[0.604, 3.785]	[-0.362, 2.542]	[0.124, 2.601]
$\tau_{MB\text{-}BC,\ 0.25}$	2.256	0.926	1.449
	(0.730)	(0.732)	(0.668)
	[0.947, 3.343]	[-0.169, 2.129]	[0.276, 2.478]
τ_{BC}	2.189	0.957	1.347
	(0.704)	(0.750)	(0.700)
	[1.072, 3.261]	[-0.331, 2.163]	[0.283, 2.598]
$P*$	0.399	0.793	0.728
	(0.190)	(0.271)	(0.273)
	[0.170, 0.838]	[0.027, 0.933]	[0.092, 0.950]
τ_{L}	0.821	0.806	0.867
	(0.174)	(0.190)	(0.191)
	[0.591, 1.253]	[0.581, 1.269]	[0.649, 1.236]
τ_{KV}	2.209	1.143	1.496
	(0.638)	(0.678)	(0.577)
	[1.065, 3.172]	[0.070, 2.286]	[0.414, 2.586]

Notes: 90% confidence intervals in brackets are obtained using 250 bootstrap repetitions. Standard errors in parentheses are also based on 250 bootstrap samples. 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.

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
	(0.012)	(0.012)	(0.012)
	[0.016, 0.057]	[0.015, 0.054]	[0.015, 0.054]
τ_{IPW}	0.025	0.027	0.028
	(0.015)	(0.015)	(0.014)
	[0.006, 0.050]	[-0.000, 0.056]	[0.009, 0.055]
$\tau_{MB,\ 0.05}$	0.049	0.008	0.016
	(0.057)	(0.046)	(0.043)
	[-0.030, 0.151]	[-0.032, 0.125]	[-0.038, 0.135]
$\tau_{MB,\ 0.25}$	0.059	0.042	0.062
	(0.021)	(0.020)	(0.021)
	[0.020, 0.086]	[0.011, 0.077]	[0.013, 0.084]
$\tau_{MB\text{-}BC,\ 0.05}$	0.169	0.046	0.072
	(0.092)	(0.081)	(0.073)
	[0.042, 0.313]	[-0.059, 0.207]	[-0.017, 0.228]
$\tau_{MB\text{-}BC,\ 0.25}$	0.178	0.080	0.118
	(0.070)	(0.066)	(0.065)
	[0.065, 0.267]	[-0.031, 0.191]	[0.005, 0.205]
τ_{BC}	0.163	0.076	0.107
	(0.067)	(0.065)	(0.069)
	[0.065, 0.262]	[-0.048, 0.184]	[-0.003, 0.202]
P^*	0.328	0.601	0.693
	(0.197)	(0.277)	(0.276)
	[0.078, 0.679]	[0.032, 0.930]	[0.074, 0.962]
τ_{L}	0.046	0.047	0.052
	(0.019)	(0.017)	(0.018)
	[0.024, 0.079]	[0.024, 0.075]	[0.036, 0.089]
τ_{KV}	0.177	0.073	0.117
	(0.064)	(0.060)	(0.063)
	[0.064, 0.289]	[-0.008, 0.174]	[0.001, 0.198]

Notes: 90% confidence intervals in brackets are obtained using 250 bootstrap repetitions. Standard errors in parentheses are also based on 250 bootstrap samples. 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.