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Bigger, Not Cleaner! Another Look at the Trade-Environment Nexus

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Abstract

In this paper, we use microdata from Chile to examine the relationship between export status and the environmental performance of firms. We proxy environmental performance by measures of emission intensity. We find that the correlation between export status and emission intensity depends on how the latter is measured. In particular, we find that export status is negatively correlated with emission intensity when we define emission intensity as emissions over sales, but it is uncorrelated when we use value added instead of sales. The difference between those two variables is that value added excludes the value of materials that the firm gets from other sources (outsourcing). Those intermediate inputs entail emissions that do not belong to the firm. Our data show that outsourcing is positively correlated with export status. Thus, using sales as an output measure overestimates firm activity, and, hence, exporters look cleaner than they actually are. We show, more formally, why the distinction between sales and value added is important, using a simple firm-level emission decomposition.

Keywords: Emission intensity, export status, foreign ownership, productivity, outsourcing.

JEL classification: F18, Q56.

1 Introduction

A growing body of literature studies the link between export status and the pollution emitted by firms. From a theoretical point of view, it is not clear whether exporting increases or decreases emission intensity. On one hand, when a firm becomes an exporter, its total scale increases, and so do its emissions. On the other hand, exporters are more productive and presumably more likely to invest in abatement or clean technology. From an empirical point of view, some evidence suggests that exporters are cleaner than non-exporters. (Batrakova and Davis, 2012; Jinji and Sakamoto, 2015; Holladay, 2016; Cui et al., 2016; Forslid et al., 2018). However,

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the results do not seem robust and depend on the type of industries considered, empirical specification, and the measure of environmental performance. In this paper, we pay close attention to this relationship and point out some important issues that need to be taken into the account.

With plant-level panel data from Chilean manufacturing sector, we test the effect of export status on firms' environmental performance. We estimate CO_2 emissions using emission coefficients of different types of fuels. We also use total energy input to proxy for emissions. To obtain emission intensity, we divide those variables by a measure of output (total sales or value added). We find that when we consider the firms' emission intensity, the distinction between total sales and value added becomes important. Because of a lack of data, some papers that study the link between exporters and firms' environmental performance rely on total sales to construct the emission intensity variable. However, considering total sales does not account for the intermediate material that firms buy from other sources. The production of those materials entails emissions that do not belong to the firm. Value added, on the other hand, is, by definition, total sales minus the intermediate inputs that firms get from other sources—i.e., outsourcing. If outsourcing is correlated with export status, then using total sales instead of value added might bias the results. We find that when we use value added to get emission intensity, being an exporter is not a significant predictor of emission intensity. However, when we use total sales to construct emission intensity, we find that exporters are less emission-intensive. If being an exporter is positively related to outsourcing, then sales overestimate firm activity, and, hence, exporters appear cleaner than they actually are. We check the data to determine whether outsourcing differs between exporter and non-exporters and find that exporting is associated with a significantly higher level of outsourcing.

We show formally why the choice of output measure used in emission intensity is important, using a simple version of the decomposition presented in Cherniwchan et al. (2017). The authors show when outsourcing is present, emissons per unit of sales will be smaller than emission per unit of value added. Firm-level markups and emission technology also affect emission intensities. We empirically show that once we control for outsourcing and markups the coefficient on export status becomes statistically insignificant regardless of the measure of output we use. Our results reveal that exporter are not any cleaner than non-exporters.

The literature that studies the relation between trade and the firms' environmental performance has grown rapidly as more micro-level data become available worldwide. One line of this literature focuses on the environmental performance of firms that engage in Foreign Direct Investment (Eskeland and Harrison, 2003; Cole et al., 2008; Dardati and Saygili, 2012).[1] More recently, a growing number of papers have attempted to test whether firms lower their emission rates by offshoring their dirty intermediate inputs abroad (Clark et al., 2000; Michel, 2013; Brunel, 2017; Li and Zhou, 2017; Cole et al., 2017b). The current study contributes to the strand of literature that studies the effect of exporting on the environmental performance of firms (Batrakova

[1] This is by no means an exhaustive list. See Cole et al., 2017a for a detailed survey.

and Davis, 2012; Jinji and Sakamoto, 2015; Girma and Hanley, 2015; Holladay, 2016; Cui et al., 2016; Forslid et al., 2018). Batrakova and Davis (2012) use data from Ireland to examine whether becoming an exporter affects a firm's energy use. Their measure of emission intensity is energy use divided by sales. They use a quantile regression and conclude that exporting increases energy intensity for low-energy-intensity firms, and reduces energy intensity for high-energy-intensity firms. Jinji and Sakamoto (2015), using data from Japanese manufacturing, conclude that exporting improves environmental performance in most industries, but actually increases CO2 emissions/energy intensity in the iron and steel industry. Forslid et al. (2018) use firm-level data from Sweden. They calculate CO_2 emissions exploiting data on energy usage and emissions coefficients. Unlike most other papers in the literature, they use value added to compute emissions intensity. Their results also show that the negative coefficient on export status disappears once firm-level fixed effects are included.

Holladay (2016) uses data from The National Establishment Time series (NETS) and the EPA Risk-Screening Environmental Indicators. He uses a hazard score as a proxy for environmental performance and finds that exporters emit less. However, when he performs the regression within each 2-digit industry, the exporter coefficient is negative and statistically significant in seven out of 20 industries. Moreover, the coefficient on exporters is positive and significant in four industries. The author does not include an explicit measure of firm productivity in regressions. As exporters are more productive, not controlling for productivity is likely to bias the results. Cui et al. (2016) also use data from NETS for facility characteristics. Additionally, they use information on four pollutants, SO_2, CO, O_3, and $TSPs$, from the National Emission Inventory of the EPA. They define emission intensity as the ratio of pollutants to sales and find a negative correlation between export status and emission intensity for the four considered pollutants.[2] However, when they include plant size as an additional control, the coefficient on export status is no longer significant.

We contribute to this literature by showing that the distinction between value added and sales is important: value added provides more reliable results, as it controls for outsourcing. In fact, once we control for these, we find that the superior environmental performance of exporters disappears. This result is at odds with the previous literature. Studies that find a negative relationship between export status and environmental performance rationalize their results by considering Melitz (2003) type models with heterogeneous firms and trade. Forslid et al. (2018), for example, consider investment in abatement and an environmental regulation in the form of a tax, while Batrakova and Davis (2012) use a model with technology adoption that reduces energy intensity. A very well established fact about exporters in the trade literature is that they are more productive and larger. When considered in the environmental context, the above models imply that

[2] The NETS data lack a measure of capital stock, but the authors compute total factor productivity (tfp) using a fixed-effect methodology assuming that plants in the same industry use the same technology and that a plant's productivity is time-invariant.

these large and more productive exporters are able to afford investment in clean technology or abatement and, hence, become cleaner than domestic firms. However, in a country that lacks strong environmental regulations, such as Chile, exporters may simply have no incentive to invest in abatement or clean technology to begin with.[3]

The paper is organized as follow. Section 2 describes the data and provides some descriptives. Section 3 presents the empirical analysis. Section 4 includes a series of robustness checks. Section 5 concludes.

2 Data and Descriptive Statistics

Our data are drawn from the "Encuesta Nacional Industrial Anual", (Annual National Industrial Survey), an annual survey of Chilean manufacturing plants with more than ten employees. The dataset is a panel with approximately 4,500 observations per year, covers the period 1995 to 2007 and has information on plant sales, value-added, employment, capital stock, fuel use, as well as export sales and the share of foreign ownership. The data also have 4-digit industry and geographic variables.[4]

We deflate our variables by appropriate price deflators to get real values. We deflate sales, value added, and wages by a 3-digit industry price deflator; and national and imported materials by an aggregate intermediate input deflator for domestic and imported goods, respectively.[5] Fuel and electricity are also deflated by the national input deflator. Finally, we use a capital deflator for capital stock.

The data set has information on capital stock for buildings, vehicles, and machinery separately, as well as on investment and depreciation for these categories. Therefore, our fixed capital is the sum of the book value of buildings, vehicles, and machinery. This variable is zero for some observations (about 5%). Some of these plants have zero capital stock in all years they appear in the survey. We leave capital stock at zero for the plants that also report zero sales. If they have zero capital in all the years but have non-zero sales, then we impute the mean capital stock of the plants with similar sales and number of workers within the same industry and year. Finally, if plants have non-zero capital values in at least one year in which they are observed, then we use the perpetual inventory method to fill in zero-capital values.

We construct a measure of total factor productivity (tfp) considering a Cobb-Douglas technology for firm

[3]According to the Global Competitiveness Report 2006-2007, Chile ranks 27th in the world in terms of stringency of environmental regulations, while, for example, the United States, the United Kingdom and Sweden rank 21st, 13th and 5th, respectively.

[4]Industries are based on International Standard Industrial Classifications (ISIC) Rev.2. Chile is divided into 15 geographic regions. Although the data set is plant-level, we use plant and firm interchangeably throughout the paper.

[5]The definition of value added in the data is very detailed. In general, it includes all sources of income and subtracts the value of inputs used. In addition to sales, income includes items such as the value of electricity sold or income from repairs. We construct an alternative measure of value added as total sales less the value of materials, electricity, and fuels. This measure, however, gives us a lot of negative values (about 20%). Therefore, we stick to the value added reported in the data.

i at time t of the following form:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it}$$

where y is the firm's output (value added); l is labor (variable input); and k is capital (state variable), all expressed in a natural logarithm.[6] The error term consists of two terms. The first term, ω_{it}, is unobserved productivity, while the second term, ϵ_{it}, is an idiosyncratic output shock. The problem with estimation is that, although econometricians do not observe the former, the firm does observe it, and hence, it is a state variable for the firm. An OLS estimation yields biased results because the unobserved productivity affects the firm's decision of optimal inputs, and it is omitted from the regression. An extensive literature on how to solve this issue and get consistent estimates has developed, starting with the canonical work by Olley and Pakes (1996). Levinsohn and Petrin (2003), Wooldridge (2009) and Ackerberg et al. (2015) modified and improved upon their method. The intuition behind all these studies involves the use of a proxy to control for unobserved heterogeneity.

We follow Wooldridge's two-step estimation procedure with a GMM. In particular, our free variable is the wage bill, and the state variable is the capital stock. We use electricity as the proxy. The choice of these particular variables reflects our effort to maximize our sample size. Some empirical studies employing the same data set as we do use the number of blue-collar and white-collar workers (or the wage bill for these) as free variables, and add fuels as an additional proxy. However, there are a lot of zeros for these variables, which result in a reduced sample size when the natural logarithm of the variables are taken. In addition, we notice that the categories of blue vs. white collar workers change across years. A particular worker might be classified as blue-collar in one year and as white-collar in the next. But either way, that person is included in the total labor count. So, we stick to totals as they tend to be more stable. Finally, we prefer to use the wage bill (in Chilean peso $\$'s$, CLP) rather than the number of workers because the distribution is close to normal, and all other variables are expressed in monetary terms, as well. We estimate the production function separately for each 2-digit industry (Mollisi and Rovigatti, 2017). As a robustness check, we also estimate the production functions using the well-known Levinsohn-Petrin method. The estimated productivities from both methods (Wooldridge and Levinsohn-Petrin) are similar.

We construct two measures of environmental performance for firms. The first measure is energy intensity, which is energy use (fuel and electricity) divided by a measure of output. Energy intensity has been used extensively as a measure of emission intensity in the literature when firm-level pollution data are not available. See Eskeland and Harrison (2003), Cole et al. (2008), and Batrakova and Davis (2012), among others. We drop the observations associated with the lowest and highest 0.1 percentile of the energy intensity distri-

[6] We have a small number of observation with negative value added (1%). We drop these, as we cannot calculate tfp with negative values of output.

bution.[7] We also estimate CO_2 emissions using fuel-specific CO_2 emission coefficients. (Forslid et al., 2018; Lyubich et al., 2018). This methodology is similar to the approach recommended by the Intergovernmental on Climate Change (IPCC).[8] Table 1 shows the CO_2 coefficients we used for different types of fuel. We consider only direct CO_2 emissions from fuel combustion by firms. Even though electricity generation itself may be an important source of emissions, use of electricity does not contribute to the firm's direct emissions. Our second measure is CO_2 intensity, which is the total estimated CO_2 emissions (KCO_2) divided by output (CLP $\$s$).

We use intermediate materials as the measure of outsourcing. Our data allow us to observe both imported materials and those purchased from other domestic firms. The latter captures domestic outsourcing and the former measures offshoring. However, imported materials are zero for many firms, possibly because most firms either do not import or they just do not report that they do. So, instead of considering domestic outsourcing and offshoring separately, we just use the value of total materials as a proxy for total outsourcing.

We follow De Loecker and Warzynski (2012) to estimate firm-level markups. Assume that firm i at time t produces with the following technology:

$$Q_{it} = Q_{it}(X_{it}^1, ..., X_{it}^V, K_{it}, \omega_{it})$$

where V represents variable inputs (labor, electricity); K is the dynamic input (capital); and ω_{it} is the firm productivity. The following expression comes from the cost-minimization problem of the firm:

$$\theta_{it}^X = \mu_{it} \frac{P_{it}^X X_{it}}{P_{it} Q_{it}}$$

where θ_{it}^X is the output elasticity of input X; and $\mu_{it} = \frac{P_{it}}{\psi_{it}}$ is the markup (ψ_{it} is the marginal cost of production; P_{it} and P_{it}^X are the prices of output and input X, respectively.) From this, De Loecker and Warzynski (2012) obtain the following expression for the markup, which forms the basis of the estimation:

$$\mu_{it} = \theta_{it}^X (\alpha_{it}^X)^{-1} \tag{1}$$

where α_{it}^X is the share of expenditures on input X in total sales, which is already observed in the data. The only thing needed to calculate firm-level markups is the output elasticity of the variable input. This is estimated from a production function. Note that we already estimated industry-level production functions to get firm-level tfps. The authors use the same framework to estimate tfps and markups at the same time. They consider both a general translog production function and the specific case of the Cobb Douglas. The latter is more restricted, in the sense that it implies a constant elasticity across producers within the same

[7] We see values as high as 295 and as low as 0, which would mean the firm uses 295 more times energy input than its output, or the firm does not use any energy input at all. These cases are likely to be a result of data misreport.

[8] See the link below for more details about the methodology:

`https://www.epa.gov/sites/production/files/2017-02/documents/2017_annex_2.pdf` industry and over time. However, the estimated markups from both production functions are close and produce qualitatively similar results. Therefore, we stick with the simpler case and use the labor coefficients that we already estimated while calculating tfps. These estimates give the output elasticity of labor. We calculate the labor share as the real wage bill divided by the real sales.

Our analysis controls for a number of plant characteristics. In particular, we define size as the number of total workers; skill intensity as the number of white-collar workers divided by the number of blue-collar workers; and capital intensity as the value of capital stock divided by the wage bill.[9]

The data allows us to identify and follow the export and foreign ownership status of firms over years. We label all firms reporting positive export sales as exporters. We consider any firm for which the share of foreign ownership exceeds 50% as foreign. Table 2 shows the summary statistics of all the variables. The average firm has 73 employees. About 19% of the plants are exporters, while 4% are foreign-owned. The data exclude the industries that depend heavily on natural resources: basic precious and non-ferrous metals, and basic chemicals, except for fertilizers and nitrogen compounds. [10]

Table 3 shows average firm statistics by export status. Exporters are significantly larger than non-exporters in terms of sales, value-added, and number of employees. They are also more capital- and skill-intensive. They have higher tfps and markups. In terms of emission intensities, they look cleaner than non-exporters. Exporters, on average, have lower energy and CO_2 intensities than non-exporters. The following section presents a thorough analysis of the impact of export status on emission intensity controlling for various plant characteristics.

3 Empirical Analysis

3.1 Performance of Exporters

We analyze the effect of export status on environmental performance using the following empirical model:

$$Z_{ijtk} = \beta_0 + \beta_1 exporter_{ijtk} + \beta_2 X_{ijtk} + \alpha_j + \gamma_t + \omega_k + \epsilon_{ijtk} \tag{2}$$

where Z_{ijtk} is a measure of emission intensity for plant i in industry j at time t in region k. $exporter$ is an indicator and equals one if the firm reports positive export sales in a particular year. The vector of plant characteristics, X, includes productivity, size, capital intensity, skill intensity, and foreign ownership status. Finally, α_j, γ_t and ω_k represent full sets of industry, time, and region dummies, respectively. All independent

[9]When we take the ratio of white-collar to blue-collar workers to calculate skill intensity, we add 1 to the denominator since a significant number of plants report zero for the number of blue- or white-collar workers.

[10]Chile is the largest copper exporter in the World. Therefore, studies that use this particular data set exclude these sectors. See, for example, Ramondo (2009) and Kohn et al. (2016). Still, we repeated our analysis by including all industries and our results are qualitatively the same.

variables, except for dummies, are in logs. We log transform energy intensity but estimate CO_2 intensity in levels since about 20% of observations are zero.[11]

We first estimate our empirical specification via ordinary least squares (OLS). We control for plant characteristics, including tfps. Controlling for plant productivity is important because the trade literature emphasizes productivity as the primary predictor of export behavior. In particular, exporters are significantly more productive than non-exporters. Productivity also affects energy intensity since, by definition, more productive plants are able to produce more output for a given level of input, including electricity and fuels. Therefore, any regression missing a productivity measure is likely to suffer from an omitted-variable bias. Even though we explicitly include a measure of total factor productivity in our regressions, we do not interpret our results as causal.

Table 4 shows the results for energy intensity. We include industry, year, and region dummies, and cluster standard errors at the plant level in the first column. We also add industry-year interactions in the second column to control for industry-specific aggregate trends. In the left panel, we normalize energy use by sales. Exporters seem 13% less energy-intensive than other plants. However, the results in the right panel where we use value added instead of sales to construct energy intensity, are different. Controlling for productivity and other plant characteristics, the coefficient on export status is not statistically significant. The results also suggest that more-productive and more-skill-intensive plants are less energy-intensive, while larger and more-capital-intensive plants are more energy-intensive. Foreign ownership does not seem to be significantly related to the emission intensity of firms.

Our data is a panel, which allows us to control for plant fixed-effects. The identification of export status in a fixed-effect regression is possible if there exits firms switching export status. We see that about 4% of plants switch status, suggesting some variation in export status is present. We run our baseline specification in Equation 2 with plant fixed effects. We omit industry and region dummies as plants are not very likely to change industry or location. We still keep year dummies to capture the influence of aggregate trends. The third column in Table 4 shows the results. Unlike the OLS results, the fixed effect results suggest that as firms get bigger and more capital intensive, they emit less. This difference may point to the existence of time-invariant firm-specific characteristics that affect energy intensity, size, and capital intensity at the same time. Not controlling for these firm-fixed effects causes bias in OLS outputs. The conclusions about export status, however, are similar. Exporting seems to reduce emissions per sales. But, emission per value added is positively related to export status.

Table 5 shows the results for CO_2 intensity. The first column on each panel reports the OLS results. When we use sales as our measure of output, export status is negatively correlated with CO_2 intensity, even

[11]Some empirical researchers use the trick of adding a very small number to zero values in the dependent variable to work around this issue. However, this is acceptable only if the number of zeros is relatively small (Wooldridge, 2016).

after controlling for productivity and other firm characteristics. However, export status is positively related to CO_2 intensity if we use value added instead of sales.

Even though the distribution of CO_2 intensity is highly skewed, we cannot log transform it because of the non-trivial number of zeros. Our sample size is big, and, thus, non-normality should not pose a problem for an OLS analysis. We still estimate Equation 2 via GLM with a log link as a robustness check. The GLM results in the second column of Table 5 are more consistent with the OLS results for energy intensity in Table 4. The export coefficient is negative when we use sales to construct emission intensity, but it is not statistically significant when we use value added. Bigger firms seem more CO_2 intensive, while more skill-intensive firms are less CO_2 intensive. Foreign ownership does not seem to be significantly related to the emission intensity of firms.

The final column in Table 5 shows the results with plant fixed-effects. The fixed-effect results for energy and CO_2 intensities are similar. Exporting has a negative impact on emission intensity if the latter is constructed using sales. When value added is used to get emission intensity, the coefficient on export status is not statistically significant.

We get conflicting results for export status, depending on the measure of output we use. Value added subtracts the value of materials and services received from other firms, as these are not directly produced by the firm. Nor do their emissions belong to the firm. Our empirical results can be reconciled if there is a positive correlation between exporting and outsourcing. In fact, Cole et al. (2014) find a positive relationship between export status and outsourcing using firm-level data from Japan. In this case, exporting increases both sales and value-added, but the latter increases less because of more outsourcing. Note that an increase in the scale of operations also raises emissions. Hence, whether emission intensity increases or decreases depends on the relative increase in emissions and output. If output increases more than emissions, the emission intensity decreases when a firm starts exporting.

We provide a more in-depth look into factors that explain our findings in the next section. In particular, we follow Cherniwchan et al. (2017) and focus on the decomposition of firm-level emission intensities.

3.2 Firm-Level Decomposition

In this section, we present a firm-level decomposition to understand why using value added is important when considering adjustments at the firm level, and firms are heterogeneous. We consider a simplified version of the framework presented in Cherniwchan et al. (2017). In particular, they consider production of goods consisting of multiple tasks that differ in terms of emission intensity. Substitution among different tasks offers another possible line of adjustment. This could also be interpreted as firms producing different goods, each of which has potentially different emissions intensities. However, our data contain no task-level or product-level information. All we see is the value of goods produced. Because of the nature of our data, we assume that each plant produces one good that consists of a single task. However, similar to Cherniwchan et al.'s (2017) model, we allow the partition of production. Assume that firm n produces $y_i(n)$ units of good i, $\lambda_i^I(n)$ is the fraction of output produced in-house; $\lambda_i^O(n)$ is the fraction outsourced.The latter includes domestic outsourcing as well as offshoring. By assumption, $\lambda_i^I(n) + \lambda_i^O(n) = 1$. Let $p_i(n)$ be the price that firm n charges for good i and $\omega_i(n)$ be the cost of the good.[12] Suppose that $\mu_i(n)$ is the rate at which the firm marks up the cost, which implies:

$$p_i(n)y_i(n) = (1 + \mu_i(n))\omega_i(n) \tag{3}$$

Then, the value added by firm n is:

$$v_i(n) = p_i(n)y_i(n) - (1 - \lambda_i^I(n))\omega_i(n) \tag{4}$$

Plugging equation (3) into (4) gives the following expression:

$$v_i(n) = [\lambda_i^I(n) + \mu_i(n)]\omega_i(n) \tag{5}$$

If good i is produced in-house and generates emissions $z_i(n)$, then we can define the emissions intensity of good i as

$$e_i(n) = \frac{z_i(n)}{\omega_i(n)}$$

If there is outsourcing, the emissions produced by firm n will be $\lambda_i^I(n)z_i(n) = \lambda_i^I(n)e_i(n)\omega_i(n)$. Hence, for firm n, emissions per dollar value added is:[13]

$$e_v(n) = \frac{\lambda_i^I(n)e_i(n)}{\lambda_i^I(n) + \mu_i(n)} \tag{6}$$

where $e_i(n)$, $\lambda_i^I(n)$, and $\mu_i(n)$ represent firm-level emission intensity, the fraction of in-house production, and the firm-level markup associated with good i. Emissions per sales, on the other hand, is:

$$e_s(n) = \frac{\lambda_i^I(n)e_i(n)}{1 + \mu_i(n)} \tag{7}$$

As long as there is outsourcing (i.e., $\lambda^I(n) < 1$), emissions per unit of sales will be smaller than emission per unit of value added. The factors affecting both of these measures are outsourcing, firm-level technique effect, and markups.[14] Consider a hypothetical case in which exporting only increases outsourcing (i.e., $\lambda^I(n)$) decreases), while emissions intensity and markups stay constant. Both expressions will decrease, but the

[12] We prefer to present a general version of the model by keeping the subscript i that represents different goods. Even though we have no product-level information, our empirical analysis controls for 3-digit ISIC Rev.2. industry codes. This, to some extent, controls for the fact that markups and outsourcing may depend on the nature of the goods produced.

[13] For multi-product firms, we would sum up emissions and value added from the production of all goods.

[14] An increase in markups reduces the firm's emissions intensity because the model assumes that the activities giving the firm the ability to charge markups do not generate pollution.

magnitude of the decrease will be larger for emissions per sales. It is possible to have a case in which the former increases while the latter decreases; for example, if outsourcing increases by a large amount, emission intensity increases only mildly, and markups do not change.

Proposition 1 *: Emissions per unit value added increase, while emissions per unit sales decrease if* $\Delta e_i > 0$, $\Delta\lambda_i^I < 0$, $\Delta\mu_i = 0$ *and*

$$1 > \frac{\%\Delta e_i}{|\%\Delta\lambda_i^I|} > \frac{\mu_i}{\lambda_i^I + \mu_i}$$

where $\%\Delta$ denotes percentage change. (See appendix for the proof.)

Exporting might potentially affect all three factors: outsourcing, markups, and the firm-level technique. Cole et al. (2014) find a positive relationship between export status and outsourcing using firm-level data from Japan. De Loecker and Warzynski (2012) find that exporters charge, on average, higher markups and that markups increase upon export entry. We check our data to see if outsourcing and markups differ significantly between exporters and non-exporters.

We estimate Equation (2) to analyze the effect of exporting on outsourcing and markups. Now, the dependent variable Z_{ijt} is the log of materials, which represents the volume of outsourcing or the log of estimated markups. We report both OLS and fixed effect results. The first case includes year, industry, industry-year, and region dummies and the latter includes year dummies only. The results in Table 6 confirm the positive correlation between exporting and outsourcing. Controlling for ownership, productivity, size, skill and capital intensity, we find that exporters outsource more than other firms. Our results also confirm the findings of De Loecker and Warzynski (2012). Controlling for plant characteristics, industry, year, and location, exporters have higher markups. Once a firm starts exporting, it charges a higher markup.

Now we go back to our initial question: Are exporters cleaner or less emission intensive than non-exporters? When we use sales to construct emission intensity, exporters seem less emission intensive. However, the simple decomposition we presented shows that using sales do not account for outsourcing, and hence, is likely to result in a bias. Taking the log of emission per sales in Equation 7 gives us an expression that is additively separable in three factors:

$$log(e_s) = log(\lambda_i^I) + log(e_i) - log(1 + \mu_i) \tag{8}$$

which shows that emission per sales decreases when offshoring $(1 - \lambda^I)$ or markups (μ) increase even if there is no change in firm-level emission technology. We reestimate our basic model in Equation 2. The independent variable is emissions per sales, and we control for outsourcing and markups this time in addition to foreign ownership, size, and skill- and capital-intensity. However, we do not include tfp. Note that markups can be defined as the price divided by the marginal cost—i.e., $(1 + \mu_{it}) = \frac{p_{it}}{mc_{it}}$. Taking logs gives $log(1 + \mu_{it}) = log(p_{it}) - log(mc_{it})$. If tfp picks up marginal costs, then it appears twice (embedded in log markups and on its own) in the regression. Firm-level markups capture the effects of average prices and productivities together. Whether a firm's markup is bigger because it charges a higher price or because it has a low marginal cost is not crucial for the purpose of this study. Thus, we estimate the model by including only markups and not tfps.[15] We also control for year, industry and location dummies. All independent variables, except for dummies, are in logs.

The results in Table 7 show that when we control for outsourcing and markups, export status becomes statistically insignificant. Table 6 reveals exporters outsource more and have higher markups. Thus, when we use emissions per sales as a measure of emission intensity, export status seems to have a negative impact on emission intensity. Equation 8, however, shows that an increase in outsourcing or markups reduces emissions per sales even though the firm does not get cleaner. Negative and significant coefficients on markups and outsourcing confirm the predictions of the simple model. Emission per sales is negatively related to size and positively related to capital intensity controlling for firm fixed-effects and year dummies. A 10% increase in size is associated with a 0.4% to 1% decrease in emission intensity.

For completeness, we repeat our analysis for emission per value added. Note that outsourcing is in both the numerator and denominator of Equation 6 for emission per value added. In addition, we cannot get an expression that is additively separable in outsourcing, markups, and firm-level technique effect as in the case of emission per sales (Equation 8). We still analyze the relationship between export status and emission per value added controlling for outsourcing and markups as well as other plant characteristics. Table 8 shows that emission per value added is not related to the export status of firms. Similar to emission per sales, emission per value added is negatively related to markups and size, and positively related to capital intensity. Outsourcing, however, has a positive coefficient.

We are able to reconcile our findings with different output measures (sales and value-added) once we control for outsourcing and markups. Now the results from both measures show that exporters are not less emission-intensive or cleaner than non-exporters. Normalizing emissions with firm sales without controlling for outsourcing and markups gives misleading results. Value-added provides more reliable results as it controls for outsourcing.

4 Conclusion

In this paper, we use firm-level data from Chile to study the relationship between export-status and firms' environmental performance. We find that exporting does not lower emission intensity. Our results differ from those of previous studies that find favorable effects of export status on firms' environmental performance.

[15] Our main results do not change if we include tfp explicitly in the regressions. However, we get results that look unintuitive at first look. For example, tfp comes out with positive and significant coefficients, which would suggest more productive plants being more emission intensive. But this happens because productivity is already embedded in markups.

Several points might explain this difference.

First, we observe that export status is not correlated with emission intensity when we define emission intensity as emissions over value added, but it is negatively correlated when we use total sales instead of value added. The difference between these two variables is that value added does not include the value of materials that the firm gets from other sources (outsourcing). Those intermediate inputs entail emissions that do not belong to the firm. The literature shows that outsourcing is positively correlated with export status. Thus, using total sales as an output measure biases the export coefficient downward, and exporters look cleaner than they actually are. We use a simple version of the model presented in Cherniwchan et al. (2017) and show that emission intensity captures the effect of outsourcing and markups as well as firm-level technique. In particular, emission per sales decreases if outsourcing or markups go up. Thus, if a firm starts outsourcing more or charging higher markups after an export entry, it looks less emission intensive even if it does not use any cleaner technology. We find that once we control for these two effects explicity, exporting has no significant impact on emission intensity regardless of the output measure used.

Second, the reason that researchers propose for why exporters might be cleaner is that these firms can afford to invest in cleaner technology. The idea is that exporting increases firm scale and, thus, rationalizes the investment in abatement or clean technology. Since a better technology usually requires a higher upfront fixed cost, only the firms that can spread this cost over a large scale find it profitable to adopt. Thus, large and more productive exporters invest in clean technology or abatement and, hence, become cleaner than domestic firms. However, the link between higher productivity and more abatement is broken if alternative demand structures are considered. In fact, Cao et al. (2016) consider linear demand and show that firms' abatement investment is an inverted U-shape with respect to productivity. They also show that more productive firms may invest less in abatement in response to tightening environmental regulations. Additionally, Cherniwchan et al. (2017) argue that abatement does not need to lower emission intensity. Instead, abatement will have two impacts on emission intensity: a direct effect that decreases emissions per unit of dirty fuel; and a classic rebound effect. The first effect reduces the pollution charges for dirty fuels and, hence, may cause firms to substitute towards the dirty input if the dirty and clean inputs are close substitutes. Finally, regardless of these caveats, if a country does not have strong environmental regulations, firms may not have incentives to invest in a cleaner technology in the first place, even if they can afford it. Taking into account that all of the studies we cite use data from developed countries, our results suggest that different dynamics might be at work in developing countries.

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5 Tables

Table 1: CO_2 Coefficients by Fuel

Fuel type	Kilogram CO_2
Coal (all types)	2316/ton
Petroleum	$3260/m_3$
Gasoline	$2348/m_3$
Paraffin Wax	$2830/m_3$
Liquid Gas	3000/ton
Natural Gas	$1.876/m_3$
Lubricants	$2832/m_3$
Wood	1783/ton

Table 2: Summary Statistics

Variables	mean	min	max	std	N
Sales	2,773,364	0	4.21e+08	1.08e+07	67411
Value added	1,770,237	0	4.70e+08	8712781	67411
Outsourcing	1,647,520	0	2.29e+08	6019721	67411
Size	73	0	5745	160	67411
Capital intensity	7.65	0	12215.5	126.4	67368
Skill intensity	4.09	0	3412	30.3	67411
Energy per sales	.043	3.79e-06	2.54	.085	64190
Energy per value added	.092	1.71e-06	7.28	.254	67409
CO_2 per sales	.387	0	109	1.41	64190
CO_2 per value added	.860	0	348.7	4.41	67409
Tfp	1.94	-5.49	9.40	1.16	66728
Markup	1.43	-6.24	9.37	.814	63932
Exporter	.195	0	1	.396	67411
Foreign	.042	0	1	.200	67411

This table presents the summary statistics of the main variables used throughout the paper. The data are drawn from the Annual National Industry Survey from Chile (ENIA) and covers the years 1995 to 2007. Energy use is constructed with fuel and electricity data. CO_2 emissions are estimated using emission coefficients for the different types of fuels provided in the data. All monetary variables are in real terms. Outsourcing is the value of materials. Size is the total number of workers. Capital intensity is the capital stock divided by the wage bill. Skill intensity is the ratio of white-collar workers to blue-collar workers. Tfp and markups (both in logs) are estimated following Woolridge (2009) and De Loecker and Warzynski (2012), respectively.

Table 3: Average Firm Characteristics by Export Status

Variables	Exporters	Non-exporters
Sales	9,412,481	1,165,304
Value added	5,749,226	806,487
Outsourcing	5,067,748	819,107
Size	192	45
Capital intensity	8.45	7.46
Skill intensity	5.33	3.80
Energy per sales	0.037	0.045
Energy per value added	0.089	0.093
CO_2 per sales	0.28	0.41
CO_2 per value added	0.77	0.88
Tfp	2.23	1.88
Markup	1.72	1.36

This table presents firm characteristics by export status. Exporters are firms that have a positive value of exports in a given period. All monetary variables are in real terms. Outsourcing is the value of materials. Size is the total number of workers. Capital intensity is the capital stock divided by the wage bill. Skill intensity is the ratio of white-collar workers to blue-collar workers. Tfp and markups (both in logs) are estimated following Woolridge (2009) and De Loecker and Warzynski (2012), respectively.

Table 4: Energy Intensity

	Energy per sales			Energy per value added		
	OLS	OLS	FE	OLS	OLS	FE
exporter	-0.131***	-0.129***	-0.061***	0.032	0.036	0.030*
	(0.027)	(0.027)	(0.018)	(0.026)	(0.026)	(0.016)
tfp	-0.371***	-0.371***	-0.245***	-0.699***	-0.699***	-0.841***
	(0.013)	(0.013)	(0.009)	(0.013)	(0.013)	(0.008)
foreign	-0.004	-0.005	-0.023	0.079	0.077	0.007
	(0.047)	(0.047)	(0.035)	(0.050)	(0.050)	(0.033)
size	0.037***	0.036***	-0.056***	0.030***	0.028***	-0.153***
	(0.011)	(0.011)	(0.015)	(0.010)	(0.010)	(0.015)
skill intensity	-0.016***	-0.015***	0.000	-0.003	-0.002	-0.003
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.003)
capital intensity	0.027***	0.027***	-0.015***	0.053***	0.054***	-0.018***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Plant FE	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	No	Yes	Yes	No
Industry FE	Yes	Yes	No	Yes	Yes	No
Industry-Year FE	No	Yes	No	No	Yes	No
Number of plants	9,848	9,848	9,848	9,848	9,848	9,848
Observations	62,717	62,717	62,717	62,717	62,717	62,717
Adjusted R-squared	0.223	0.225	0.057	0.376	0.378	0.349

This table shows the results from the regressions of energy intensity on export status and firm-level controls. The dependent variable, energy intensity, is energy use (fuel and electricity) over a measure of output: total sales for column (1) to (3) and value added for column (4) to (6). All specifications include a full set of year dummies. Column (1) and (4) include region and industry fixed effect. In addition to that, Column (2) and (4) include industry-year dummies. Column titles show estimation methods. OLS: Ordinary least squares, FE: (plant) Fixed-effects. Robust standard errors are in parentheses, clustered at plant level. * significant at 10%,** significant at 5%; *** significant at 1%.

Table 5: CO_2 Intensity

	CO_2 per sales			CO_2 per value added		
	OLS	GLM	FE	OLS	GLM	FE
exporter	-0.076***	-0.330***	-0.060***	0.232*	-0.019	0.021
	(0.029)	(0.056)	(0.015)	(0.132)	(0.062)	(0.082)
tfp	-0.145***	-0.343***	-0.100***	-1.060***	-0.717***	-1.622***
	(0.014)	(0.026)	(0.013)	(0.086)	(0.022)	(0.160)
foreign	0.020	-0.036	-0.024	0.316***	0.105	0.047
	(0.034)	(0.086)	(0.055)	(0.122)	(0.094)	(0.316)
size	0.014	0.094***	0.017	0.035	0.055***	-0.300***
	(0.010)	(0.021)	(0.021)	(0.024)	(0.021)	(0.062)
skill intensity	-0.007	-0.033***	-0.006	0.039***	-0.002	0.021*
	(0.006)	(0.010)	(0.006)	(0.014)	(0.010)	(0.011)
capital intensity	-0.020***	-0.013	-0.009	-0.011	0.021*	-0.004
	(0.007)	(0.013)	(0.008)	(0.026)	(0.012)	(0.021)
Plant FE	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	No	Yes	Yes	No
Industry FE	Yes	Yes	No	Yes	Yes	No
Industry-Year FE	Yes	Yes	No	Yes	Yes	No
Number of plants	9,848	9,848	9,848	9,848	9,848	9,848
Observations	62,717	62,717	62,717	62,717	62,717	62,717
Adjusted R-squared	0.065	-	0.004	0.069	-	0.050

This table shows the results from the regressions of CO_2 intensity on export status and firm-level controls. The dependent variable, CO_2 intensity, is CO_2 emissions over a measure of output: total sales for column (1) to (3) and value added for column (4) to (6). All specifications include a full set of year dummies. Column (1) and (4) also include region and industry fixed effect. In addition to that, Column (2) and (4) include industry-year dummies. Column titles show estimation methods. OLS: Ordinary least squares, GLM: Generalized linear model (with log link), FE: (plant) Fixed-effects. Robust standard errors are in parentheses, clustered at plant level. * significant at 10%,** significant at 5%; *** significant at 1%.

Table 6: Effect of Export Status on Outsourcing and Firm-level Markups

	Outsourcing		Markups	
	OLS	FE	OLS	FE
exporter	0.241***	0.102***	0.169***	0.086***
	(0.027)	(0.016)	(0.014)	(0.012)
foreign	0.502***	0.111***	0.053*	0.027
	(0.048)	(0.039)	(0.028)	(0.021)
tfp	0.550***	0.109***	0.642***	0.411***
	(0.014)	(0.008)	(0.008)	(0.008)
size	1.066***	0.665***	-0.106***	-0.167***
	(0.011)	(0.017)	(0.007)	(0.011)
skill intensity	0.056***	0.003	0.009***	-0.005**
	(0.005)	(0.003)	(0.003)	(0.002)
capital intensity	0.090***	0.009**	0.100***	0.079***
	(0.006)	(0.005)	(0.003)	(0.003)
Plant FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Industry-Year FE	Yes	No	Yes	No
Number of plants	9,825	9,825	9,848	9,848
Observations	62,392	62,392	62,717	62,717
Adjusted R-squared	0.704	0.198	0.480	0.298

This table shows the results from the regressions of outsourcing and markups on export status and firm-level controls. The dependent variable in Column (1) and (2), outsourcing, is the log of materials. The dependent variable in Column (3) and (4), markups, is estimated following De Loecker and Warzynski (2012). Column (1) and (3) are estimated with OLS and a full set of year, region, industry and industry-year dummies. Column (2) and (4) are estimated with plant fixed-effects and a full set of year dummies. Robust standard errors in parentheses, clustered at the plant level. * significant at 10%,** significant at 5%; *** significant at 1%.

Table 7: Emissions per Sales Controlling for Outsourcing and Markups

	Energy per sales		CO_2 per sales	
	OLS	FE	OLS	FE
exporter	-0.030	-0.009	-0.023	-0.017
	(0.025)	(0.015)	(0.028)	(0.014)
foreign	0.066	-0.009	0.053	-0.016
	(0.047)	(0.032)	(0.036)	(0.054)
size	0.081***	-0.102***	0.029	-0.042*
	(0.017)	(0.016)	(0.021)	(0.023)
skill intensity	-0.005	-0.002	-0.002	-0.009
	(0.005)	(0.003)	(0.005)	(0.006)
capital intensity	0.085***	0.030***	0.007	0.023**
	(0.006)	(0.006)	(0.008)	(0.009)
outsourcing	-0.090***	-0.076***	-0.033**	-0.020
	(0.012)	(0.010)	(0.016)	(0.022)
markup	-0.492***	-0.555***	-0.232***	-0.394***
	(0.018)	(0.014)	(0.032)	(0.063)
Plant FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Industry-Year FE	Yes	No	Yes	No
Number of plants	9,825	9,825	9,825	9,825
Observations	62,392	62,392	62,392	62,392
Adjusted R-squared	0.318	0.172	0.082	0.026

This table shows the results from the regressions of emissions per sales on export status controlling for outsourcing, markups and other firm-level controls. The dependent variable is energy per sales in column (1) and (2) and CO_2 per sales in column (3) and (4). Column (1) and (3) estimate the regression via OLS and include a full set of year, region, industry and industry-year dummies. Column (2) and (4) are estimated with plant fixed-effects and including a full set of year dummies. Robust standard errors are in parentheses, clustered at plant level. * significant at 10%,** significant at 5%; *** significant at 1%.

Table 8: Emissions per Value Added Controlling for Outsourcing and Markups

	Energy per value added		CO_2 per value added	
	OLS	FE	OLS	FE
exporter	-0.007	0.028	0.162	0.039
	(0.028)	(0.019)	(0.131)	(0.084)
foreign	-0.015	-0.008	0.180	0.023
	(0.056)	(0.041)	(0.128)	(0.326)
size	-0.115***	-0.255***	-0.131***	-0.362***
	(0.018)	(0.019)	(0.045)	(0.069)
skill intensity	-0.019***	-0.004	0.012	0.020*
	(0.005)	(0.004)	(0.015)	(0.012)
capital intensity	0.064***	0.015**	-0.012	0.042*
	(0.007)	(0.006)	(0.026)	(0.022)
outsourcing	0.035***	0.135***	0.010	0.153***
	(0.013)	(0.013)	(0.032)	(0.058)
markup	-0.213***	-0.326***	-0.177***	-0.393***
	(0.020)	(0.015)	(0.042)	(0.058)
Plant FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Industry-Year FE	Yes	No	Yes	No
Number of plants	9,825	9,825	9,825	9,825
Observations	62,392	62,392	62,392	62,392
Adjusted R-squared	0.223	0.044	0.036	0.003

This table shows the results from the regressions of emissions per value added on export status controlling for outsourcing, markups and other firm-level controls. The dependent variable is energy per value added in column (1) and (2) and CO_2 per value added in column (3) and (4). Column (1) and (3) estimate the regression via OLS and includes a full set of year, region, industry and industry-year dummies. Column (2) and (4) are estimated with plant fixed-effects and including a full set of year dummies. Robust standard errors are in parentheses, clustered at plant level. * significant at 10%,** significant at 5%; *** significant at 1%.

6 Appendix

Proof of proposition 1 Emissions per value added and emissions per sales are given in equations (6) and (7), respectively. We drop the firm subscript to simplify notations and get:

$$e_v = \frac{\lambda e}{\lambda + \mu} \tag{9}$$

$$e_s = \frac{\lambda e}{1 + \mu} \tag{10}$$

where λ is the share of in-house production (Hence, $(1 - \lambda)$ is the share of outsourcing); μ is firm's markup; and e is the firm's emissions intensity.

Given $\Delta\mu = 0$, totally differentiating these equations gives:

$$\Delta e_v = \frac{\lambda}{(\lambda + \mu)}\Delta e + \frac{e\mu}{(\lambda + \mu)^2}\Delta\lambda \tag{11}$$

$$\Delta e_s = \frac{\lambda}{(1 + \mu)}\Delta e + \frac{e}{(1 + \mu)}\Delta\lambda \tag{12}$$

$\Delta e_v > 0$ and $\Delta e_s < 0$ iff

$$\frac{\frac{\Delta e}{e}}{\frac{|\Delta\lambda|}{\lambda}} > \frac{\mu}{\lambda + \mu} \tag{13}$$

and

$$\frac{\frac{\Delta e}{e}}{\frac{|\Delta\lambda|}{\lambda}} < 1 \tag{14}$$

where $-\Delta\lambda = |\Delta\lambda|$.

Equations (13) and (14) together imply:

$$1 > \frac{\%\Delta e}{|\%\Delta\lambda|} > \frac{\mu}{\lambda + \mu} \tag{15}$$

where $\%\Delta e = \frac{\Delta e}{e}$ and $|\%\Delta\lambda| = \frac{|\Delta\lambda|}{\lambda}$.