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Does Exporting Improve Firms' CO_2 Emissions Intensity and Energy Intensity? Evidence from Japanese manufacturing[*]

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Abstract

Using Japanese firm-level data, we investigate the firm-level relationship between export status and environmental performance in terms of carbon dioxide (CO_2) emissions intensity and energy intensity. As in previous studies, we first find that exporting firms have significantly lower CO_2 emissions/energy intensity. We then investigate the effects of exporting on CO_2 emissions/energy intensity by employing the propensity score matching (PSM) method, and find that the effects significantly vary across industries. Whereas exporting significantly improves environmental performance in most industries, exporting actually increases CO_2 emissions/energy intensity in the iron & steel industry. This finding suggests that the effect of exporting varies across industries.

Keywords: Trade and the environment, Environmental performance, CO_2 emissions, Energy intensity
JEL classification: F14, F18, Q56

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1 Introduction

The issue of trade and the environment has been getting increased attention in economics in the last two decades (Copeland and Taylor, 2003, 2004). A number of empirical studies have investigated the environmental effects of trade openness (Antweiler et al., 2001; Cole and Elliot, 2003; Managi et al., 2009). Antweiler et al. (2001) find that sulfur dioxide (SO_2) concentrations decrease as trade openness rises. Cole and Elliot (2003) support the finding by Antweiler et al. (2001) for SO_2 but do not find similar results for other pollutants such as nitrogen oxides (NO_x) and biochemical oxygen demand (BOD). Managi et al. (2009) address the endogeneity issue and find a somewhat mixed result: whereas trade is beneficial to the environment in OECD countries for SO_2, CO_2, and BOD, it has detrimental effects on SO_2 and CO_2 in non-OECD countries.

Recently, the focus of the research has shifted to the micro-level relationship between trade and environment. In particular, the firm-level (or plant-level) relationship between export status and the environmental performance has been examined by several recent studies (Batrakova and Davies, 2012; Cui et al., 2012; Forslid et al., 2011; Holladay, 2010). Using a panel of firm-level data for Irish manufacturing industries for 1991–2007, Batrakova and Davies (2012) find that export status is associated with an increase in energy intensity (i.e., total fuel and power purchase per sales) for low-energy-intensity firms and with a decrease in energy intensity for high-energy-intensity firms. Holladay (2010) employs a panel of establishment-level data for US manufacturing industries during 1990–2006 and estimates the export premium on environmental performance as measured by toxic pollution emissions. He provides evidence that exporters emit less toxic emissions than non-exporters when controlling for establishment output and industry characteristics. Moreover, Cui et al. (2012) use facility-level data of the US manufacturing industry for the years 2002, 2005, and 2008, and analyze the relationship between export status and emissions intensity for air pollutants. They find a significantly negative correlation between export status and emission intensity. Finally, using Swedish firm-level data for CO_2 emissions during 2000–2007, Forslid et al. (2011) test predictions from the model they develop in which emissions from production are incorporated into a Melitz (2003) type model. They find that exporters have, on average, lower emissions intensity than non-exporters.

In this paper, we examine the firm-level relationship between export status and environmental performance in terms of CO_2 emissions intensity and energy intensity, using Japanese manufacturing data. We address two important issues, which have rarely been examined by previous studies. First, we estimate whether exporting increases or decreases CO_2 emissions/energy intensity by employing the propensity score matching (PSM) method developed by Rubin (1974) and Rosenbaum and Rubin (1983). Second, we pay attention to sectoral variations in the relationship between exporting and CO_2 emissions/energy intensity. Previous studies (Forslid et al., 2011; Cui et al., 2012) assume that the same mechanism can be applied to all manufacturing industries. However, the effects of exporting on environmental performance may depend on production technique, product composition, or industrial structure.

To examine the above issues, we employ Japanese firm-level data from two data sources for the period 2006–2011. The first data source is Mandatory Greenhouse Gas Accounting and Reporting System, which is provided jointly by the Ministry of Economy, Trade, and Industry (METI) and the Ministry of Environment (MOE). This data set includes plant-level emission data for major greenhouse gases (GHGs). The second data source is the Basic Survey of Japanese Business Structure and Activities, which is an annual survey conducted by METI. This survey data contain various firm-level information including export values. We aggregate the plant-level GHG data to firm-level data, and match the two data sets mentioned above. As for our empirical strategy, we first estimate the firm-level relationship between exporting and CO_2 emissions/energy intensity by ordinary least square (OLS), and then estimate the causal effects of exporting on CO_2 emissions/energy intensity by PSM method.

The main findings in this paper are as follows. First, we find from the OLS regressions that exporting firms have significantly lower CO_2 emissions/energy intensity than non-exporting firms. This finding is consistent with those in previous studies (Cui et al., 2012; Forslid et al., 2011; Holladay, 2010). Second, from the PSM analysis, we find that the effects of exporting on CO_2 emissions/energy intensity significantly vary across industries. In most industries, we find that exporting significantly reduces CO_2 emissions/energy intensity, though the magnitude of the effects substantially varies with industries. For some industries, however, such as paper and metal products, the effects are statistically insignificant. Surprisingly, there is an industry, namely the iron and steel industry, in which exporting actually *increases* CO_2 emissions/energy intensity. We suspect a change in product composition upon exporting may affect CO_2 emissions and energy intensity in the iron and steel industry.

Our findings have important policy implications. In the literature on trade and the environment, it has been well known that the environmental effect of trade liberalization can be decomposed into three effects: *scale*, *composition*, and *technique* (Grossman and Krueger, 1993; Copeland and Taylor, 1994). (1) Trade increases real income, or the economy's scale, which in turn increases total emissions; this is the scale effect. (2) Trade also induces countries to specialize in industries in which they have a comparative advantage, and the consequent changes in the shares of dirtier and cleaner industries affects total emissions; this is the composition effect. (3) Finally, if the environment is a "normal good," an increase in real income increases the demand for the environment and hence the demand for more stringent environmental regulation, which in turn reduces the emissions intensity of production; this reduction in emissions intensity is called the technique effect. Whereas the technique effect is a key for trade to be good for the environment, how the technique effect works has not been investigated much. The findings of this study reveal one possible mechanism of the technique effect: we confirm that, on average, firms reduce CO_2 emissions/energy intensity when they start exporting, and that this mechanism does not actually require any change in environmental regulation. Thus, our findings suggest that the trade-induced technique effect may work in favor of the environment without any change in the economy-wide environmental policy. However, we found that the environmental effects of exporting significantly vary across industries. Therefore, some policy measures should be implemented to deal with the heterogeneity in the effects across industries.

The remainder of the paper is organized as follows. Section 2 discusses the theoretical background of our empirical analysis. Section 3 explains our data and reports the results of our preliminary analysis. In section 4, we explain our empirical strategy to analyze the effects of exporting on environmental performance. Section 5 reports our empirical results from the PSM analysis. Section 6 discusses our results, and section 7 concludes.

2 Theoretical Background

In this section, we briefly explain theoretical the background of our empirical analysis. We do not construct a new model here but instead explain the essence of the models developed by previous related studies.

The issue is whether there is any systematic relationship at the firm-level between export status and environmental performance. Cui et al. (2012) present a model of heterogeneous firms based on Melitz (2003). They focus on a single monopolistically competitive industry, and in their model, technology adoption is a key factor to determining the relationship between export status and environmental performance. Pollution is generated as a byproduct of output. The government regulates emissions by implementing a domestic emission permit cap-and-trade program. Thus, expenditure on emission permits is part of the firms' variable production costs. Two types of production technologies are available: clean and dirty. The adoption of clean technology requires extra fixed costs but reduces marginal costs by decreasing emissions per unit of output. Moreover, as in Melitz (2003), exporting requires additional fixed costs and iceberg trade costs. Then, firms decide whether to stay in the market, which technology to adopt, and whether to export to the foreign market. As in Melitz (2003), only the most productive firms have an incentive to engage in exporting. In addition, more productive firms have a higher incentive to adopt the clean technology because those firms benefit more from reducing marginal costs. Cui et al. (2012) impose certain assumptions on the parameters and cost structure so that all firms that choose to adopt the clean technology choose to export and that some of the firms choosing the dirty technology too export.

Batrakova and Davies (2012) present a model with a similar structure, but include energy as a production factor, instead of emissions. In their model, technology choice is associated with the effectiveness of energy usage. That is, a higher technology increases the energy efficiency of production. Firms differ in both productivity and energy intensity in production. Then, they show that more productive firms are more likely to export and also more likely to adopt the energy-efficient technology.

Forslid et al. (2011) consider investment in pollution abatement. Emission taxes are imposed by the government. Firms can reduce their emissions intensity by two types of abatement activities. The first type of abatement involves the share of labor devoted to abatement activities, which incurs variable abatement costs. The second type of abatement is attained by investments in machines and equipment, which require fixed costs. Firms optimally choose the fraction of labor devoted to abatement. Then, Forslid et al. (2011) show that for any given level of productivity, exporters invest more in abatement than non-exporters and hence exporters have lower emissions intensity than non-exporters.

Barrows and Ollivier (2014) argue that in addition to technology upgradation, measured emissions intensity may change through changes in prices or product-mix. This is mainly because emissions intensity is usually measured in value due to data limitations. If exporters and non-exporters charge different prices, then the difference in emissions intensity between exporters and non-exporters may simply reflect the price differential without any difference in emissions per output. Similarly, if exporters and non-exporters have a different product-mix, then their average emissions intensity will differ even though they use the same technology. Therefore, caution is needed to interpret the empirical finding of lower emissions intensity for exporters. The view of technology upgrading upon exporting may be misleading. We take this possibility into account in our empirical analysis.

3 Data and preliminary analysis

To investigate the relationship between exporting and environmental performance, we combine the two data sets available to analyze the Japanese manufacturing sector. The first is the Mandatory Greenhouse Gas Accounting and Reporting System provided jointly by METI and MOE, or the MOE survey. Under the Act on Promotion of Global Warming Countermeasures, major emitters of GHGs are obliged to report the amounts of GHG emissions to the government. Firms that use more than 1,500 kl/year of oil equivalent energy or emit more than 3,000 t/year of CO_2 equivalent have to file their details. Contained in the MOE survey is plant-level emission data for every major GHG. The second data set is the Basic Survey of Japanese Business Structure and Activities provided by METI, which we hereafter refer to as the METI survey. This is a mandatory annual survey for all firms with 50 or more employees and paid-up capital or investment funds exceeding 30 million yen. The METI survey covers mining, manufacturing, wholesale/retail trade, and service industries, and approximately 32,000 firms responded to the survey in 2012. In this study, we use data for only the manufacturing industries. The METI survey contains firm-level information for a number of important variables, including sales, employment, capital stock, and exporting.

For each plant appearing in the MOE survey, we search for the associated firm registered in the METI survey and match them if any. This matching procedure, conducted over the period of 2006–2011, leaves us with a six-year balanced panel of 1,740 firms.[1]

Table 1 presents the number of exporting firms and non-exporting firms in each

[1] The procedure we have employed inevitably restricts our analysis to the balanced panel because otherwise one firm would be associated with different number of plants in different points in time.

Table 1: Exporting firms and non-exporting firms (2006–2011)

	obs.	# of firms	non-exporters	exporters
Food	1650	275	200	75
Textile	408	68	46	22
Paper	336	56	40	16
Chemical	2250	375	136	239
Ceramic and cement	630	105	48	57
Iron and steel	762	127	73	54
Non-ferrous metal	522	87	38	49
Metal product	432	72	37	35
Machinery	588	98	25	73
Electronics	1338	223	104	119
Transportation equipment	1266	211	76	135
Precision instrument	258	43	12	31

Source: Authors' calculations from the data of the METI survey.
Note: Non-exporters here are the firms that had no exports in the six-year period.

2-digit industry we consider in the following analysis. Exporting is quite prevalent in many industries, especially in the machinery and transportation equipment industries. In some industries such as the food industry, on the other hand, exporters are not in the majority.

3.1 Intensity measure

The focus of our study is on two distinct, but closely related measures of firm-level environmental performance: CO_2 emissions intensity and energy intensity. We define CO_2 emissions intensity as CO_2 emissions (including non-energy-related emissions) per value added.[2] Energy intensity, on the other hand, is defined as energy consumption per value added.[3] The former intensity measure directly captures firms' environmental performance whereas the latter puts more emphasis on their production efficiency, which indirectly influences the environment as well. Alternative definitions of intensity measure are possible. For instance, one could divide CO_2 emissions and energy consumption by sales instead of value added. Later in the paper, we will discuss if and how the definition of intensity measure matters.

Figure 1 depicts the histograms of CO_2 emissions intensity for exporting firms

[2] In the process of calculating value added, we transformed sales and purchases into real values using deflators taken from Japanese SNA.

[3] Energy consumption is calculated based on the reported CO_2 emissions from energy consumption together with the energy-source-specific conversion coefficients set by the government.

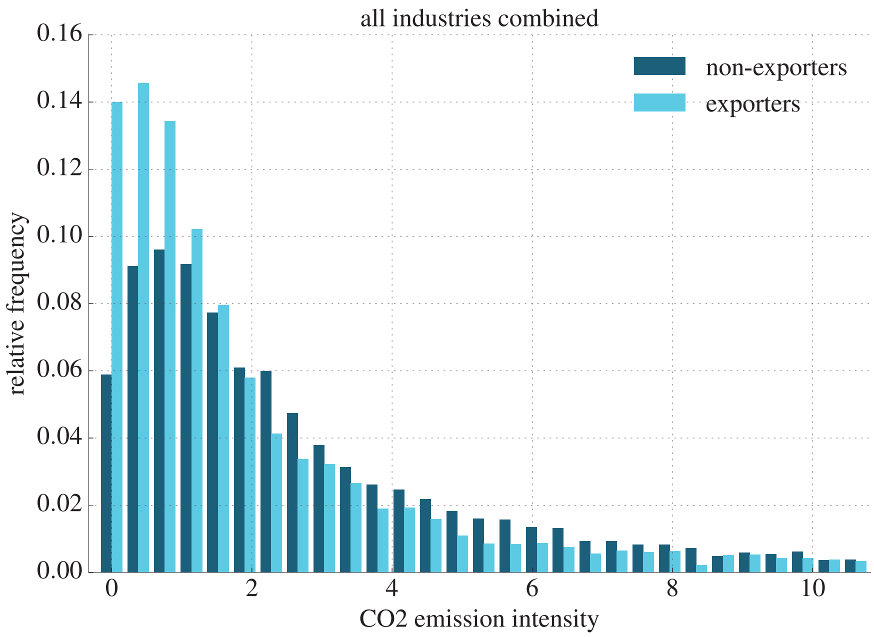

Figure 1: Exporters vs. non-exporters

Source: Authors' calculations from the data of the MOE and METI surveys.

and non-exporting ones observed during the entire sample period. Obviously, the two groups have different distributions.[4] The distribution for exporters is more concentrated in the low levels of CO_2 emissions intensity. The distribution for non-exporters, on the other hand, has a fatter tail in the high levels of CO_2 emissions intensity. Figure 2 compares the two groups by year. From this figure, it should be easy to see that exporting firms are relatively less CO_2 emission intensive and that this fact is stable over time. Hence, similar to the empirical evidence provided by Forslid et al. (2011) for the Swedish manufacturing sector, our data set of Japanese manufacturing indicates that exporters are, on average, consistently cleaner.[5] In general, however, more productive firms are likely to show higher environmental performance, and at the same time, have a better chance of starting exports. Therefore, the observed correlation between exporting and high environmental performance might be a logical consequence of self-selection. The question of interest then is if and to what extent the apparent

[4]In fact, the Kolmogorov–Smirnov test result shows that the distribution for exporters is located to the left of that for non-exporters.

[5]Although an explicit carbon tax is absent in the Japanese market, energy price in effect works as an implicit tax for CO_2 emissions since CO_2 emissions is closely connected to energy consumption.

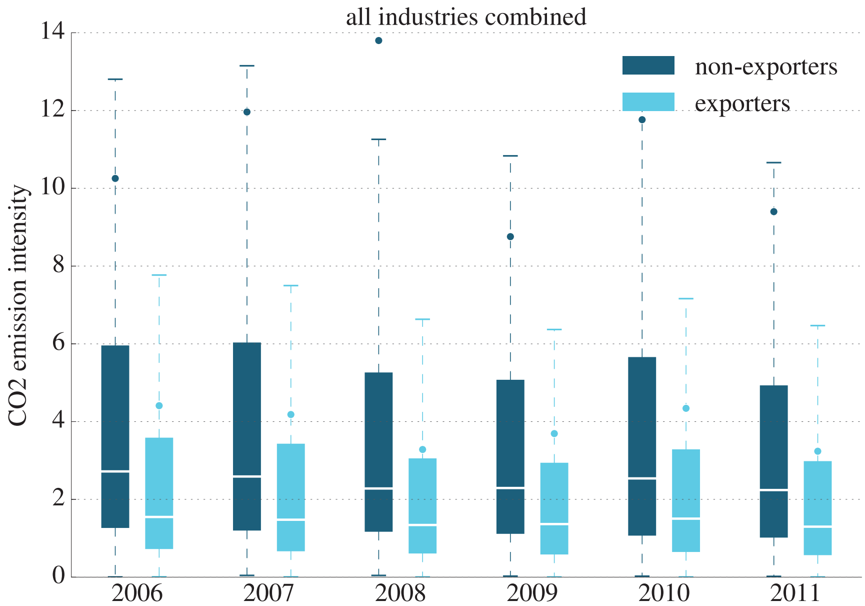

Figure 2: Comparison over time

Source: Authors' calculations from the data of the MOE and METI surveys.

high performance of exporters is actually attributed to exporting.

Another important fact we can see in our data set is that there exists large industry-level heterogeneity. Table 2 provides the industry-level descriptive statistics on CO_2 emissions intensity in our data set. As the table shows, average CO_2 emissions intensity significantly varies across different industries. Some industries such as the ceramic and cement industry are highly CO_2 intensive while others such as the transportation equipment industry are not really so. As expected from the preceding discussion, exporting firms are, on average, cleaner in many industries. In the iron and steel industry, however, exporters are relatively more CO_2 emissions intensive. This already suggests that aggregation over industries may omit some important aspects of the trade–environment interplay. Further, it can be seen from the table that the distributions too are quite heterogeneous. In the chemical industry, for instance, non-exporters have very diverse emissions intensity values whereas the distribution for exporters is much more concentrated. The opposite is true for the textile industry, where the distribution for non-exporters has relatively small variance. A similar observation can be made if we use energy intensity instead of CO_2 emissions intensity. With this industry-level heterogeneity in mind, we separately analyze the effect of exporting on

Table 2: CO_2 emissions intensity by industry (2006–2011)

	mean		standard deviation	
	non-exporters	exporters	non-exporters	exporters
Food	3.70	1.78	12.35	2.43
Textile	8.02	4.81	8.73	23.51
Paper	10.93	7.30	12.05	10.75
Chemical	35.62	4.53	265.52	9.48
Ceramic and cement	38.79	13.31	71.05	52.22
Iron and steel	6.94	8.62	8.27	15.15
Non-ferrous metal	16.28	7.86	49.88	47.10
Metal product	3.96	2.31	6.95	3.73
Machinery	4.87	1.02	13.94	0.92
Electronics	3.90	1.77	7.40	3.06
Transportation equipment	2.55	1.60	3.16	2.12
Precision instrument	3.48	1.07	5.61	1.34

Source: Authors' calculations from the data of the MOE and METI surveys.

CO_2 emissions/energy intensity for each industry.

3.2 Preliminary analysis

As background for the analysis we conduct later in this paper, we first perform a preliminary analysis on the firm-level relationship between exporting and environmental performance. Letting $\text{INTENS}_{i,t}$ be the intensity measure of firm i at year t, we run the following OLS regression:

$$\ln \text{INTENS}_{i,t} = \alpha + \beta \text{EXPORTER}_{i,t} + \gamma x_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $\text{EXPORTER}_{i,t}$ is an export dummy which is equal to one when firm i is exporting at year t. Covariates $x_{i,t}$ contain other relevant characteristics such as productivity measured by total factor productivity ($\text{TFP}_{i,t}$), firm size measured by labor ($\text{LABOR}_{i,t}$), and R&D intensity measured by labor share of R&D division within each firm ($\text{RDINT}_{i,t}$). Our productivity estimates are obtained from the method developed by De Loecker and Warzynski (2013).[6] We also control for industry and year effects. Our primary interest lies in coefficient β, which tells us whether exporting firms and non-exporting ones have significantly different environmental performance. Table 3 and Table 4 show the estimation results for (1) for four different specifications of the model.

[6] See Appendix A.1 for more details.

Table 3: OLS on log CO_2 emissions intensity (all industries combined)

	(1)	(2)	(3)	(4)
EXPORTER	-0.303^{***}			-0.280^{***}
	(0.025)			(0.027)
EXPSHARE		-0.646^{***}		-0.027
		(0.093)		(0.101)
$\ln$ TFP			-0.309^{***}	-0.303^{***}
			(0.014)	(0.014)
$\ln$ LABOR	-0.374^{***}	-0.399^{***}	-0.409^{***}	-0.374^{***}
	(0.013)	(0.013)	(0.013)	(0.013)
RDINT	-0.410^{***}	-0.441^{***}	-0.445^{***}	-0.379^{***}
	(0.050)	(0.050)	(0.048)	(0.048)
YEAR	yes	yes	yes	yes
IND	yes	yes	yes	yes
Observation	7662	7662	7662	7662
R squared	0.442	0.434	0.465	0.474

Note: The values in parentheses are standard errors. Observations with missing values are dropped. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

It is clear from the tables that exporters do differ from non-exporters. To be more precise, there is a significant negative correlation between exporting and intensity measure. Column 1 of Table 3, for example, shows that exporters have on average 30% lower CO_2 emissions intensity. This estimate is statistically significant at 1% level. One might argue that this reflects the effect of the intensive margin, that is, change in the share of exports in sales ($\text{EXPSHARE}_{i,t}$). Column 2 of the table suggests this possibility because a larger export share apparently implies a lower emissions intensity. As column 4 of the table reports, however, the influence of export share becomes very small and statistically insignificant once export status and export share are simultaneously taken into account. Hence, the observed negative correlation between exporting and emissions intensity is likely to be the effect of the extensive margin, that is, from becoming an exporter. Further, it is worth mentioning here that productivity and emissions intensity are negatively correlated. We find in column 3 of Table 3 that a 1% increase in total factor productivity lowers emissions intensity by 30%. This correlation remains unaffected even after relevant covariates are controlled for.

The fact that exporters are significantly cleaner than non-exporters does not necessarily imply a causal effect of exporting on CO_2 emissions/energy intensity. As

Table 4: OLS on log energy intensity (all industries combined)

	(1)	(2)	(3)	(4)
EXPORTER	-0.275^{***}			-0.247^{***}
	(0.024)			(0.026)
EXPSHARE		-0.629^{***}		-0.057
		(0.090)		(0.097)
ln TFP			-0.324^{***}	-0.318^{***}
			(0.013)	(0.013)
ln LABOR	-0.365^{***}	-0.387^{***}	-0.396^{***}	-0.365^{***}
	(0.013)	(0.013)	(0.012)	(0.013)
RDINT	-0.374^{***}	-0.400^{***}	-0.400^{***}	-0.340^{***}
	(0.048)	(0.048)	(0.046)	(0.047)
YEAR	yes	yes	yes	yes
IND	yes	yes	yes	yes
Observation	7662	7662	7662	7662
R squared	0.429	0.423	0.460	0.469

Note: The values in parentheses are standard errors. Observations with missing values are dropped. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

discussed in the preceding section, one possible mechanism behind this result is self-selection. Theoretical models in trade literature such as the one by Melitz (2003) suggest that the more productive firms are, the more likely they are to engage in export activities. In fact, in our data set, we find that exporting firms are more productive than non-exporting ones. Combined with the productivity–intensity correlation reported in the tables above, this self-selection mechanism makes it difficult to disentangle the effect of exporting on firm-level environmental performance. It may be the case that exporters are cleaner not because they started exporting, but rather because they were more productive in the first place.

As already suggested by Table 2, another issue that requires careful investigation is industry-level heterogeneity. Table 11 and Table 12 report the industry-wise OLS estimates for CO_2 emissions/energy intensity, respectively.

Table 11 and Table 12 are around here

We find from the tables that there exists a large variation in the estimated effect of exporting on CO_2 emissions/energy intensity. Exporting firms in the textile industry, for example, are as much as 57% less CO_2 emissions intensive than non-exporting ones. In the transportation equipment industry, on the other hand, the estimated performance improvement is only 15%. Moreover, for the paper industry, iron and steel industry, and precision instruments industry, the correlation between exporting and environmental performance becomes statistically insignificant once the other covariates are controlled for. The correlation is even positive in the metal products industry, although it is not statistically significant. Comparing Table 11 and Table 12, we also notice that the effect of exporting in the ceramic and cement industry is evident for CO_2 emissions intensity, but not statistically significant for energy intensity. Although these estimates might be confounded by the well-known correlation between export status and productivity, our preliminary analysis suggests that the effects of the decision to start exporting depend on industry.

To examine if the observed differences between exporters and non-exporters are actually attributed to exporting, and how the effects of exporting on CO_2 emissions/energy intensity differ across industries, we need a counterfactual scenario in which the exporting firms did not start exporting. If we could find a counterfactual substitute for each exporting firm, we would be able to identify, at least on average, the effects of exporting by comparing exporters and their counterfactual counterparts. For this purpose, the present paper employs the matching technique discussed below.

4 Empirical strategy

The econometric method we use in this paper is the propensity score matching (PSM) method developed by Rubin (1974) and Rosenbaum and Rubin (1983). In essence, PSM reduces the dimensionality problem in matching firms with multidimensional characteristics. By constructing a single-dimensional criterion called the propensity score, it allows us to match an exporter (treated) with a non-exporter (control) based on the proximity of the score.

4.1 Propensity score

The propensity score is the probability of firms switching from remaining a non-exporter to becoming an exporter conditional on relevant firm characteristics. To compute the propensity score for each firm at each point in time, we first specify the propensity score function as

$$\Pr(\mathrm{START}_{i,t} = 1 \mid x_{i,t-1}) = \Phi(\gamma x_{i,t-1}), \tag{2}$$

Table 5: Estimated propensity score function

	(1)	(2)	(3)
$\ln$ LABOR	0.13553^{**}	0.95820^{**}	0.91274^{**}
	(0.05400)	(0.46391)	(0.46322)
$(\ln \text{LABOR})^2$		-0.06891^{*}	-0.06429^{*}
		(0.03811)	(0.03809)
RDINT	0.60381^{***}	1.59904^{**}	1.60104^{**}
	(0.20233)	(0.63730)	(0.63751)
$(\text{RDINT})^2$		-1.87967^{*}	-1.89118^{*}
		(1.07815)	(1.07894)
$\ln$ TFP	0.01358	-0.23375^{*}	-0.22347
	(0.07660)	(0.13841)	(0.13884)
$(\ln \text{TFP})^2$		0.02539^{**}	0.02409^{**}
		(0.01213)	(0.01218)
FDI	0.58750^{***}	0.59822^{***}	0.59581^{***}
	(0.11583)	(0.11618)	(0.11631)
CAPINT			-0.00131
			(0.00159)
$\ln$ AGE			-0.03333
			(0.07067)
YEAR	yes	yes	yes
IND	yes	yes	yes
LOCATION	yes	yes	yes
Observation	4105	4105	4105
AIC	1281	1275	1277
Pseudo R squared	0.159	0.169	0.170

Note: The values in parentheses are standard errors. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

where Φ is the normal cumulative distribution function. Here, $\text{START}_{i,t}$ is an export-starting dummy that is 1 if firm i starts exporting at period t. In our data set, there are 151 firms that started exporting during the period 2006–2011. Combining these with those firms that did not export at any point in the same sample period, we estimated (2) where covariates $x_{i,t}$ include a foreign direct investment dummy ($\text{FDI}_{i,t}$), capital–labor ratio ($\text{CAPINT}_{i,t}$), and firm age ($\text{AGE}_{i,t}$), as well as $\text{LABOR}_{i,t}$, $\text{RDINT}_{i,t}$, and $\text{TFP}_{i,t}$. Firm location is controlled for. The results are presented in Table 5.

As expected, firm size ($\text{LABOR}_{i,t}$) and R&D intensity ($\text{RDINT}_{i,t}$) have consistently large impacts on the decision to start exporting. Larger firms that actively invest in R&D are more likely to switch from remaining a non-exporter to becoming an exporter. In all three specifications, a higher productivity ($\text{TFP}_{i,t}$) positively influences the propensity score although it is not statistically significant for the linear specification. While the insignificant coefficient of productivity is not entirely consistent with the prediction of theoretical models in the literature, our estimation result is largely in line with the existing empirical studies. Tanaka (2013), for instance, uses the same METI survey (for a different sample period) and reports a similar finding for the entire manufacturing sector. Further, Table 5 indicates that the FDI dummy plays an important role as well. The experience of foreign direct investment therefore facilitates the decision to export. Out of the three models listed in the table, we use model 2 for the analysis that follows.

4.2 Matching

The estimated propensity score function yields the propensity score $P_{i,t} = \Phi(\hat{\gamma} x_{i,t})$ of firm i at year t. For each exporting firm, we then search for a single non-exporting counterpart based on the nearest-neighbor matching method with replacement. Denote by J_i the set of all non-exporters categorized in the same industry as exporter i and by T the set of years contained in the sample period. Non-exporter $j_{i,t} \in J_i$ at year $s_{i,t} \in T$ is matched with exporter i at year t if

$$|P_{i,t} - P_{j_{i,t},s_{i,t}}| = \min_{(k,\tau)\in J_i \times T} |P_{i,t} - P_{k,\tau}| = \Delta P_{i,t}. \tag{3}$$

Alternatively, one could use different matching algorithms such as radius matching or kernel matching. The radius matching algorithm is a variant of nearest-neighbor matching, which considers each match as successful only when the minimum distance $\Delta P_{i,t}$ is smaller than a predetermined radius. Kernel matching, on the other hand, uses the distance to construct a weight for each non-exporter and employs the weighted average of non-exporters as a counterfactual of each exporter. We now discuss how sensitive the estimated causal effects are to the choice of the matching algorithm.

Once we have assembled appropriate exporter and non-exporter pairs, it is straightforward to estimate the effect of exporting. What we are interested in here is the average effect of the treatment on the treated (ATT). Conceptually, ATT compares the average CO_2 emissions/energy intensity among exporters with what the average would have been had these same firms remained non-exporters. To this end, we substitute the matched non-exporter for each exporter's unobservable counterfactual. The estimate

Table 6: Effects of exporting on CO_2 emissions intensity

	ATT	t-value	% change	# matched
Food	-1.11^{***}	-2.81	-42.5	199
Textile	-1.67^{***}	-3.71	-38.7	65
Paper	-6.69^{***}	-3.06	-54.5	59
Chemical	-8.95^{**}	-1.98	-69.8	716
Ceramic & cement	-18.60^{***}	-4.86	-73.0	163
Iron & steel	2.35^{***}	3.29	48.0	179
Non-ferrous metal	-4.92^{***}	-3.69	-58.8	159
Metal product	-0.25	-0.59	-9.4	124
Machinery	-1.22^{***}	-6.04	-49.6	234
Electronics	-2.74^{***}	-6.32	-62.7	341
Transportation equipment	-0.63^{***}	-3.68	-27.7	430
Precision instrument	-3.06^{***}	-4.48	-73.8	90
All industries combined	-4.47^{***}	-3.71	-59.2	2759

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

of the ATT is accordingly calculated as

$$\text{ATT} = \frac{\sum_{i,t}(\text{INTENS}_{i,t} - \text{INTENS}_{j_{i,t},s_{i,t}})}{N}, \tag{4}$$

where N is the number of successfully matched pairs. To shed light on industry-level heterogeneity, we separately estimate the ATT for each industry.

5 Results

This section reports the effects of exporting on CO_2 emissions/energy intensity. We first present the benchmark results and compare them with the OLS estimates. The robustness of our findings is then briefly discussed by analyzing the sensitivity to the matching algorithm and intensity measure.

5.1 Benchmark estimates

Our main results are summarized in Table 6 and Table 7. First, considering all industries, a considerable improvement is observed in the environmental performance of exporters. The last row of Table 6 shows that exporting firms achieve a 59% reduction in CO_2 emissions intensity. Similarly, the last row of Table 7 shows that firms become

Table 7: Effects of exporting on energy intensity

	ATT	t-value	% change	# matched
Food	-1.95^{***}	-2.86	-41.8	199
Textile	-2.55^{***}	-3.36	-35.9	65
Paper	-10.61^{***}	-3.30	-53.1	59
Chemical	-14.76^{**}	-1.98	-69.2	716
Ceramic & cement	-5.99^{**}	-2.13	-32.2	163
Iron & steel	2.68^{***}	2.64	32.2	179
Non-ferrous metal	-7.80^{***}	-3.50	-55.8	159
Metal product	-0.49	-0.60	-10.0	124
Machinery	-1.97^{***}	-6.56	-47.5	234
Electronics	-4.66^{***}	-6.21	-62.0	341
Transportation equipment	-1.00^{***}	-3.49	-25.9	430
Precision instrument	-6.10^{***}	-4.62	-76.6	90
All industries combined	-6.01^{***}	-3.08	-53.3	2759

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

53% more efficient in terms of energy consumption per value added by becoming exporters. Both results are statistically significant at the 1% level. Moreover, the effects of exporting identified here are stronger than those reported in Table 3 and Table 4, where the estimated reduction in intensity measures is about 30%. This indicates that the OLS estimates, which are confounded by the endogenous export-starting decision, underestimate the causal effect of exporting on firms' environmental performance. We therefore conclude that, at least on average, exporting does improve environmental performance at the firm level and this effect is likely to be greater than one might expect from the observed correlation.

As is clear from the same tables, however, the estimated effects vary quantitatively and qualitatively across industries. In Chemical industry, for instance, the decision to start exporting causes as much as 70% drop in CO_2 emission and energy intensities. Firms in Transportation Equipment industry, on the other hand, only experience a modest improvement (about 27%) in both intensity measures. The numbers reported here are much larger than the OLS estimates (34% for Chemical and 15% for Transportation Equipment). For some industries, the OLS estimate is rather an overestimation. In Textile industry, for which the OLS estimate is about 60% reduction in both intensity measures, a relatively small impact (about 41%) is reported here. Hence, in this case, the actual effect caused by exporting is weaker than the observed correlation.

While Table 3 and Table 4 both report a sizable performance improvement in most industries, there are two notable exceptions. First, for the metal products industry, we find no statistically significant effect of exporting on CO_2 emissions/energy intensity. Although consistent with the associated OLS estimate, this finding is remarkable since exporting firms in this industry are cleaner than non-exporting ones on average (Table 2). This, therefore, indicates that at least for the metal products industry, the self-selection mechanism completely explains the observed higher environmental performance of exporters. Second, somewhat surprisingly, firms in the iron and steel industry experience a 48% increase in CO_2 emissions intensity from exporting. This counterintuitive result is statistically significant at the 1% level, exhibiting a striking contrast to our preliminary analysis, where the OLS regression suggests the opposite.

Moreover, a closer inspection of Table 6 and Table 7 reveals that for some industries, the effects of exporting are substantially different in CO_2 emissions/energy intensity. The estimated improvement of firm-level environmental performance in the ceramic and cement industry, for example, is much larger for CO_2 emissions intensity (73%) than for energy intensity (32%). This suggests that for exporting firms in this industry, a sizable portion of the environmental gain materializes as a reduction in non-energy-related CO_2 emission per value added. Similarly, the performance-worsening effect in the iron and steel industry is much less pronounced (32%) and is statistically less significant when the intensity is measured by energy consumption instead of CO_2 emissions. This is an indication that a major part of the additional CO_2 emissions resulting from exporting in this industry is not energy-related.

5.2 Robustness

Before further discussions on the implications of our findings, let us check if the main results are sufficiently robust. In particular, we verify to what extent the results depend on the matching algorithm and the definition of intensity measure.

5.2.1 Alternative matching algorithms

The benchmark estimates presented above are obtained based on the nearest-neighbor matching method. As a robustness check, we also used radius matching and kernel matching and computed the associated ATT estimates.[7] The first three columns of

[7]For radius matching, we set the radius to 0.01. For kernel matching, we use the Gaussian kernel with bandwidth 0.001.

Table 8: Robustness check: ATT (% change) on CO_2 emissions intensity

	neighbor	radius	kernel	per sale
Food	-42.5^{***}	-42.0^{***}	-45.6^{***}	-23.8
Textile	-38.7^{***}	-33.1^{***}	-52.8^{***}	-55.4^{***}
Paper	-54.5^{***}	-52.8^{**}	-53.2^{***}	-48.3^{***}
Chemical	-69.8^{**}	-70.6^{**}	-79.2^{***}	-33.6^{***}
Ceramic & cement	-73.0^{***}	-71.5^{***}	-75.8^{***}	-78.2^{***}
Iron & steel	48.0^{***}	40.3^{***}	15.9	43.6^{***}
Non-ferrous metal	-58.8^{***}	-66.2^{***}	-63.2^{***}	-65.7^{***}
Metal product	-9.4	16.3	-19.2	-10.0
Machinery	-49.6^{***}	-36.5^{***}	-66.6^{***}	-49.7^{***}
Electronics	-62.7^{***}	-63.8^{***}	-58.1^{***}	-62.0^{***}
Transportation equipment	-27.7^{***}	-27.1^{***}	-27.2^{***}	-20.3^{***}
Precision instrument	-73.8^{***}	-68.0^{**}	-76.6^{***}	-64.7^{***}
All industries combined	-59.2^{***}	-59.5^{***}	-67.5^{***}	-51.1^{***}

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8 and Table 9 compare the three alternative matching algorithms. In the tables, ATTs are expressed in terms of percent changes so that the results can be easily compared with each other.

For many industries, the benchmark results are fairly robust. In particular, we find no significant difference between nearest-neighbor matching and radius matching. The only exception is the metal products industry, where the sign is reversed. This may be an indication that the nearest-neighbor matching causes some ill-matched pairs in this industry. The corresponding estimate under kernel matching, however, again has a negative sign. On the whole, we should conclude that in this industry the decision to start exporting does not have a significant influence on the firm's environmental performance. We should also mention that when the kernel matching method is used, the influence of the decision to export on the iron and steel industry becomes statistically insignificant. Although the sign of the coefficient is preserved, this result suggests that the performance-worsening effect observed in the benchmark result should be carefully interpreted.

5.2.2 Alternative intensity measure

The last columns of Table 8 and Table 9 present a robustness check of a different kind. For this extra analysis, the CO_2 emissions/energy intensity is defined by CO_2

Table 9: Robustness check: ATT (% change) on energy intensity

	neighbor	radius	kernel	per sale
Food	-41.8^{***}	-41.4^{***}	-43.8^{***}	-21.4
Textile	-35.9^{***}	-29.5^{***}	-50.4^{***}	-53.1^{***}
Paper	-53.1^{***}	-52.3^{***}	-50.2^{***}	-47.5^{***}
Chemical	-69.2^{**}	-69.9^{**}	-77.2^{***}	-28.9^{***}
Ceramic & cement	-32.2^{**}	-31.8^{*}	-42.7^{***}	-43.0^{***}
Iron & steel	32.2^{***}	28.6^{**}	2.7	24.7^{***}
Non-ferrous metal	-55.8^{***}	-63.8^{***}	-60.5^{***}	-62.8^{***}
Metal product	-10.0	18.2	-19.9	-9.9
Machinery	-47.5^{***}	-36.7^{***}	-64.1^{***}	-48.7^{***}
Electronics	-62.0^{***}	-63.1^{***}	-56.9^{***}	-62.1^{***}
Transportation equipment	-25.9^{***}	-25.7^{***}	-25.8^{***}	-17.2^{**}
Precision instrument	-76.6^{***}	-71.0^{**}	-79.0^{***}	-68.5^{***}
All industries combined	-53.3^{***}	-54.0^{***}	-61.9^{***}	-36.7^{***}

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

emissions and energy consumption per sale instead of per value added. We rerun the same estimation procedure (with nearest-neighbor matching) as the benchmark result. Since a different definition of intensity measure is used, the estimates listed in the last column cannot be directly compared with those in the other columns. Nevertheless, as the tables show, the results are qualitatively the same. Food industry is a notable exception, for which the estimate is insignificant here. The overall impression is that our benchmark estimates are not really sensitive to the definition of intensity measure.

6 Discussion

For many industries, we find robust evidence that exporting improves environmental performance at the firm level. On average, firms are likely to become less CO_2 emissions/energy intensive once they decide to start exporting. This empirical finding is consistent with the theoretical predictions provided by previous studies such as Cui et al. (2012), Batrakova and Davies (2012), and Forslid et al. (2011).

A closer look at industry-level heterogeneity, however, yields that the magnitude of the effect significantly varies across industries. Moreover, in some industries, our empirical results suggest that exporting has no positive effect and may even worsen firms' environmental performance. In particular, firms in the iron and steel industry become more CO_2 emissions/energy intensive when they engage in exporting, indicating that a different mechanism exists for this industry. Upon brief inspection of the profile of the iron and steel industry, we realize that this is probably due to the production process specific to this industry.[8] Typically, the production of iron or steel products can be divided into two distinct steps. In the first step, raw iron or steel is produced using a (blast or electric) furnace, which is then processed into some intermediate iron or steel products. This process involves a huge amount of CO_2 emissions and energy consumption but the products, if sold at this stage, usually have a low market value. In the second step, the intermediate products are further processed into finished iron or steel products, which often have a much higher market value. If firms mainly export the products of the first step, which is actually the case for Japanese firms, exporters will become, on the surface, more CO_2 emissions/energy intensive than non-exporters.

This discussion, although informal, suggests that if the effect of exporting on environmental performance is to be accurately measured, a careful examination of industry-specific production process is crucial. As Barrows and Ollivier (2014) point out, exporting may change the firm's product mix. For some industries, such a change in product mix matters a lot since CO_2 emissions/energy intensity can differ much with product choice. If the decision to start exporting changes a firm's product mix in favor of emissions-intensive products, it partially offsets (or even completely masks) the expected technology-upgrading effect. This is the possible underlying mechanism for the iron and steel industry. Unfortunately, however, we are not able to disentangle the technology-upgrading effect from the product-mix effect because our data set does not allow us to control for the latter. The product-mix effect can work in the opposite direction, too, if the firm's product mix is rather tilted in favor of low-intensity products. In fact, using a detailed data set of Indian manufacturing firms, Barrows and Ollivier (2014) find that the technology-upgrading effect might not be as large as it initially looks if changes in a firm's product profile are appropriately controlled for.

Therefore, an important caveat to our empirical results is that the estimated effects are not solely attributed to the technology upgradation facilitated by exporting. They only capture the net impact of exporting, including the influence of possible changes in the firm's product mix.

[8] Our matching procedure is implemented based on the 2-digit industry code. We first suspected that there are some ill-matched pairs in this industry where, for example, firms with a blast furnace and those with an electric furnace are compared. However, this is not the case. In reality, in Japan, there are only four firms which own one or more blast furnaces, and these firms were omitted from our data set due to missing values.

7 Conclusions

In this paper, we examined the firm-level relationship between export status and the environmental performance in terms of CO_2 emissions/energy intensity. We employed Japanese firm-level data for the period 2006–2011. Using the PSM method, we rigorously analyzed whether exporting *does* improve CO_2 emissions/energy intensity. We then found that on average exporting actually improves CO_2 emissions/energy intensity significantly. However, we also observed a large degree of heterogeneity in this effect of exporting across industries. Whereas exporting improves CO_2 emissions/energy intensity in most industries, the PSM analysis resulted in an insignificant average effect of the treatment on the treated (ATT) in the metal products industry. Moreover, in the iron & steel industry, exporting actually *increases* CO_2 emissions/energy intensity., which we suspect is due to a change in product composition upon exporting.

Due to data limitations, we were unable to identify the mechanism behind the above heterogeneity. Thus, in the future, we intend to further investigate the reason why the relationship between export status and environmental performance differs across industries.

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A Appendix

A.1 Productivity estimation

To estimate the total factor productivity, we consider a translog production function of the form

$$y_{i,t} = \omega_{i,t} + \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_{ll} l_{i,t}^2 + \beta_{kk} k_{i,t}^2 + \beta_{lk} l_{i,t} k_{i,t}, \tag{5}$$

where $y_{i,t}$ is value added, $l_{i,t}$ is labor, and $k_{i,t}$ is capital, all in logarithmic value. Following De Loecker and Warzynski (2013), we first run the OLS regression on

$$y_{i,t} = \phi_t(l_{i,t}, k_{i,t}, e_{i,t}, d_{i,t}, , r_{i,t}) + \epsilon_{i,t}, \tag{6}$$

where $e_{i,t}$ is energy consumption, $d_{i,t}$ is an export dummy, and $r_{i,t}$ is R&D intensity. We approximate $\phi_t(\cdot)$ with a second-order polynomial series. Having obtained estimates $\hat{\phi}_{i,t}$ of expected output, we can compute

$$\omega_{i,t}(\beta) = \hat{\phi}_{i,t} - \beta_l l_{i,t} - \beta_k k_{i,t} - \beta_{ll} l_{i,t}^2 - \beta_{kk} k_{i,t}^2 - \beta_{lk} l_{i,t} k_{i,t} \tag{7}$$

for any candidate value $\beta = (\beta_l, \beta_k, \beta_{ll}, \beta_{kk}, \beta_{lk})$. We then run the regression

$$\omega_{i,t}(\beta) = g_t(\omega_{i,t-1}(\beta)) + \xi_{i,t}, \tag{8}$$

where $g_t(\cdot)$ is approximated with a third-order polynomial. This in turn allows us to recover the associated estimates $\hat{\xi}_{i,t}(\beta)$ of innovation as

$$\hat{\xi}_{i,t}(\beta) = \omega_{i,t}(\beta) - \hat{g}_{i,t}(\beta). \tag{9}$$

The estimate of β for the production function is obtained by the standard GMM technique with the moment condition

$$\mathbb{E}\left[\hat{\xi}_{i,t}(\beta) z_{i,t}\right] = 0, \tag{10}$$

Table 10: Estimated translog production function

	$\hat{\beta}_l$	$\hat{\beta}_{ll}$	$\hat{\beta}_k$	$\hat{\beta}_{kk}$	$\hat{\beta}_{lk}$
Food	0.76	−0.05	−1.44	0.11	0.04
Textile	0.68	0.08	−0.96	0.09	−0.07
Paper	1.79	0.13	0.13	0.08	−0.24
Chemical	0.52	0.04	−0.29	0.06	−0.05
Ceramic & cement	0.75	0.06	0.25	0.04	−0.09
Iron & steel	1.10	−0.07	−0.55	0.05	0.03
Non-ferrous metal	0.24	0.14	0.86	0.01	−0.15
Metal product	0.62	0.06	0.11	0.04	−0.08
Machinery	1.21	0.01	−0.91	0.08	−0.06
Electronics	0.49	0.11	0.13	0.06	−0.14
Trans. eqpt	0.78	0.13	0.27	0.09	−0.22
Precision inst.	−1.30	0.30	−0.93	0.16	−0.25

where

$$z_{i,t} = (l_{i,t-1}, k_{i,t}, l_{i,t-1}^2, k_{i,t}^2, k_{i,t} l_{i,t-1})^T. \tag{11}$$

Table 10 reports the estimation results. Once estimate $\hat{\beta}$ is obtained, the estimated total factor productivity in logarithmic value is given by

$$\hat{\omega}_{i,t} = y_{i,t} - \hat{\beta}_l l_{i,t} - \hat{\beta}_k k_{i,t} - \hat{\beta}_{ll} l_{i,t}^2 - \hat{\beta}_{kk} k_{i,t}^2 - \hat{\beta}_{lk} l_{i,t} k_{i,t}. \tag{12}$$

Table 11: OLS on log CO_2 emission intensity (industry-wise decomposition)

	Food	Textile	Paper	Chemical
EXPORTER	-0.374^{***}	-0.573^{***}	-0.266	-0.344^{***}
	(0.058)	(0.097)	(0.187)	(0.061)
EXPSHARE	0.227	2.285^{***}	1.938	0.645^{**}
	(0.456)	(0.812)	(1.561)	(0.273)
ln TFP	-0.883^{***}	-0.405^{***}	-0.033	-0.809^{***}
	(0.032)	(0.061)	(0.114)	(0.044)
ln LABOR	-0.476^{***}	-0.095	-0.038	-0.384^{***}
	(0.022)	(0.068)	(0.065)	(0.032)
RDINT	-0.220^{**}	-0.331^{**}	-0.666^{**}	-0.586^{***}
	(0.093)	(0.135)	(0.329)	(0.108)
Observation	1266	324	294	1554
R squared	0.541	0.554	0.345	0.537
	Ceramic & cement	**Iron & Steel**	**Non-ferrous metal**	**Metal product**
EXPORTER	-0.365^{**}	-0.017	-0.481^{***}	0.108
	(0.145)	(0.091)	(0.103)	(0.096)
EXPSHARE	-0.083	0.935^{**}	-0.890^{**}	-1.227^{**}
	(0.565)	(0.430)	(0.400)	(0.506)
ln TFP	0.013	-0.490^{***}	-0.621^{***}	-0.765^{***}
	(0.107)	(0.073)	(0.084)	(0.070)
ln LABOR	-0.531^{***}	-0.023	-0.137^{**}	-0.671^{***}
	(0.090)	(0.053)	(0.059)	(0.049)
RDINT	-0.945^{***}	-0.452	0.541^{**}	0.112
	(0.298)	(0.279)	(0.215)	(0.208)
Observation	468	618	378	312
R squared	0.286	0.128	0.444	0.601
	Machinery	**Electronics**	**Trans. eqpt**	**Precision inst.**
EXPORTER	-0.235^{***}	-0.445^{***}	-0.149^{**}	-0.215
	(0.087)	(0.068)	(0.062)	(0.153)
EXPSHARE	-0.529^{***}	-0.125	0.483^{**}	0.123
	(0.164)	(0.213)	(0.230)	(0.348)
ln TFP	-0.947^{***}	-0.524^{***}	-0.829^{***}	-0.833^{***}
	(0.075)	(0.048)	(0.053)	(0.135)
ln LABOR	-0.521^{***}	-0.256^{***}	-0.158^{***}	-0.698^{***}
	(0.044)	(0.028)	(0.033)	(0.096)
RDINT	-0.234	-0.454^{***}	-0.336^{***}	0.391
	(0.144)	(0.102)	(0.117)	(0.272)
Observation	390	966	924	168
R squared	0.666	0.377	0.294	0.753

Note: The values in parentheses are standard errors. Observations with missing values are dropped. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: OLS on log energy intensity (industry-wise decomposition)

	Food	Textile	Paper	Chemical
EXPORTER	-0.367^{***}	-0.604^{***}	-0.269	-0.293^{***}
	(0.058)	(0.097)	(0.183)	(0.059)
EXPSHARE	0.336	3.262^{***}	2.025	0.580^{**}
	(0.453)	(0.807)	(1.528)	(0.265)
ln TFP	-0.868^{***}	-0.405^{***}	-0.034	-0.821^{***}
	(0.032)	(0.061)	(0.112)	(0.042)
ln LABOR	-0.456^{***}	-0.148^{**}	-0.015	-0.364^{***}
	(0.022)	(0.068)	(0.063)	(0.031)
RDINT	-0.215^{**}	-0.234^{*}	-0.543^{*}	-0.527^{***}
	(0.093)	(0.134)	(0.322)	(0.105)
Observation	1266	324	294	1554
R squared	0.532	0.573	0.341	0.533
	Ceramic & cement	**Iron & Steel**	**Non-ferrous metal**	**Metal product**
EXPORTER	-0.115	-0.037	-0.477^{***}	0.100
	(0.116)	(0.087)	(0.102)	(0.096)
EXPSHARE	-0.328	0.823^{**}	-0.914^{**}	-1.231^{**}
	(0.453)	(0.409)	(0.398)	(0.506)
ln TFP	-0.252^{***}	-0.516^{***}	-0.597^{***}	-0.805^{***}
	(0.086)	(0.070)	(0.083)	(0.070)
ln LABOR	-0.482^{***}	-0.041	-0.153^{***}	-0.669^{***}
	(0.072)	(0.050)	(0.058)	(0.049)
RDINT	-0.861^{***}	-0.426	0.619^{***}	0.160
	(0.239)	(0.266)	(0.214)	(0.208)
Observation	468	618	378	312
R squared	0.263	0.146	0.429	0.607
	Machinery	**Electronics**	**Trans. eqpt**	**Precision inst.**
EXPORTER	-0.262^{***}	-0.422^{***}	-0.150^{**}	-0.220
	(0.087)	(0.067)	(0.061)	(0.153)
EXPSHARE	-0.467^{***}	-0.117	0.412^{*}	0.189
	(0.164)	(0.209)	(0.227)	(0.347)
ln TFP	-0.945^{***}	-0.531^{***}	-0.822^{***}	-0.864^{***}
	(0.074)	(0.047)	(0.052)	(0.134)
ln LABOR	-0.495^{***}	-0.268^{***}	-0.150^{***}	-0.694^{***}
	(0.044)	(0.027)	(0.033)	(0.096)
RDINT	-0.245^{*}	-0.437^{***}	-0.274^{**}	0.466^{*}
	(0.143)	(0.100)	(0.116)	(0.271)
Observation	390	966	924	168
R squared	0.663	0.378	0.294	0.754

Note: The values in parentheses are standard errors. Observations with missing values are dropped. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.