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Is there an environmental benefit to being an exporter? Evidence from firm level data*

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Abstract

One of the greatest concerns over globalisation is its impact on the environment. This paper contributes to this debate by analysing the consequences of becoming an exporter on a firm's energy consumption. We show both theoretically and empirically that for low fuel intensity firms exporting status is associated with higher fuel consumption while for high fuel intensity firms exporting is results in decreased fuel consumption. Further analysis reveals that higher fuel consumption of low fuel intensity firms occurs after exporting, perhaps as a response to increased production. In contrast, firms using relatively large quantities of fuel decrease their energy use after exporting, perhaps by adopting more fuel-efficient technology. These results indicate that the use of aggregate data, as is the case in almost all studies of trade and the environment, is likely to conceal important connections between the two.

Keywords: Exporting, Energy, Heterogeneity, Quantiles, Matching
JEL Classifications: F18, L23, Q56, C21

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1 Introduction

With international trade now comprising half of world GDP (World Bank (various years)), the impact of international trade on the environment is a subject of growing concern by economists, environmentalists, and policy makers. The pollution haven hypothesis is now a cornerstone of the debate on globalisation and the environment. As formulated by Pethig (1976) and McGuire (1982) this hypothesis postulates that opening up to trade allows pollution-intensive industries to move to countries with weaker environmental regulations. This results in a race to the bottom in overall environmental standards and increased pollution levels. With this in mind, most of the attention has concentrated on foreign direct investment (FDI), plant location, and multinationals' impact on the overall level of environmental standards and pollution. However, more recent theoretic finds the effect is not as straightforward when environmental policy is endogenised (Copeland and Taylor (1994) and Copeland and Taylor (1995)), pollution is local (Markusen et al. (1995)), factor endowments are taken into consideration (Copeland and Taylor (1997) and Antweiler et al. (2001)), or when governments have other strategic considerations (Barrett (1994)). The empirical evidence has likewise cast doubt on the pollution haven hypothesis. Studies using aggregate data, such as Antweiler et al. (2001), Dean and Lovely (2010), Javorcik and Wei (2004) and Ederington et al. (2004), generally fail to find support for increased FDI leading to increased pollution. In addition, recent firm-level studies including Cole et al. (2008), Cole et al. (2006), and Kaiser and Schulze (2003) have uncovered a positive effect of foreign ownership on the environmental performance of firms in the host country. This should not be taken to imply that there is no evidence for a shift in activities as a result of differences in environmental standards, since Levinson and Taylor (2008) and Ederington et al. (2005) find evidence of increased net imports in response to increased abatement costs. Rather, as discussed by Levinson (2009), these effects are quantitatively small compared to other factors such as the effect of advances in technology.

This paper contributes to the debate by considering the impact of exporting status on fuel use by firms. Since fuel use is correlated with pollution, this is our measure of environmental performance.[1] We begin with a theoretical model borrowing from the heterogeneous firms literature popularised by Melitz (2003).[2] When a firm begins exporting, its output will tend to rise, increasing its demand for energy and the pollution it is responsible for. However, this greater scale increases the return from investment in fuel-efficiency enhancing technologies which would reduce fuel use. This latter effect is likely to be particularly large for big firms (i.e. more productive firms) and those that are fuel intensive. Therefore the net effect of exporting on fuel use is ambiguous and varies across different firms, with low fuel intensity firms increasing fuel use when exporting and high fuel intensity firms reducing fuel use when exporting.

We then test this using firm-level data on Irish firms from 1991 to 2007. Looking at just the mean effect of exporting on a firm's use of fuel hides differences between

[1] This is similar to the aggregate data studies Eskeland and Harrison (2003) and Cole et al. (2008). The existing firm-level work of Kaiser and Schulze (2003) and Girma et al. (2008) consider the impact of exporting status on firms' adoption of pollution abatement technology, an alternative measure of environmental performance. In contrast, we examine the impact of exporting on actual fuel use.

[2] For an overview of the empirical findings see Wagner (2007).

low and high fuel intensity firms, resulting in an overall neutral effect. Distinguishing between different fuel intensities, we find that exporting status is associated with an increase in fuel use for low fuel intensity firms and with a decrease in fuel use for high fuel intensity firms.[3] Thus, mean effects mask important variation in the data since such analysis restricts both low fuel intensity firms (those for whom the increased output effect dominates) and high fuel intensity firms (those most likely to adopt more fuel efficient technologies) to have the same estimated coefficients.

We further establish that these differences arise after firms begin exporting, not before. By employing matching and difference-in-differences estimations we show that low fuel intensity firms increase their fuel use as a result of output expansion due to exporting.[4] Likewise, high fuel intensity firms decrease their fuel use following the commencement of exporting, in line with our model's prediction. In addition, we find that for low fuel intensity firms that cease exporting, there is no difference between them and comparable non-exporters immediately following the cessation of exporting. For high fuel intensity firms, there is a lasting reduction in fuel usage even after exporting stops. If the scale effect disappears immediately but newly adopted technology remains when exporting stops, this is exactly the pattern one would expect to see. Thus, as highlighted by Levinson (2009), there is an important interplay between globalisation, technology adoption, and the environment.

Looking at the role of exporters is a relatively new terrain with only a few studies examining the issue. Kaiser and Schulze (2003) find that among Indonesian manufacturing plants those engaging in export activities are significantly more likely to report spending on environmental protection, with magnitudes at least on a par with spending by the non-exporting plants. Girma et al. (2008) analyze environmental performance of firms in a heterogeneous setting. Extending the Melitz (2003) model, they show that compared to non-exporters, more productive exporting firms will adopt newer and, therefore, more advanced and more environmentally-efficient technologies because they can afford them. Further, using the UK survey data Girma et al. (2008) empirically confirm their theoretical prediction by showing that exporters are more likely to report their innovations to be more environmentally- and energy-efficient. Our paper complements these by looking at fuel use, rather than just the adoption of environmentally friendly technologies. Since exporting has a pollution-generating scale effect even for firms that do adopt new technologies, examining fuel use is critical to understanding the link between exporting and the environment. In particular, it raises the possibility that targeting export promotion policies towards high fuel intensity firms may be much more successful in persuading them to adopt greener technologies than when such policies are adopted at their low fuel intensity counterparts.

The remainder of the paper is structured as follows. Section 2 outlines simple theoretic model designed to illustrate the competing scale and technology adoption effects of exporting status with a particular eye for how these vary across fuel intensities. Section 3 describes the data and provides some descriptive statistics. Section 4 presents our em-

[3] Here we rely on quantile regression technique as used before in some trade literature, such as Yasar et al. (2006) and Girma and Görg (2005).

[4] Matching in combination with difference-in-differences has been widely used. Amongst the studies used to analyze an effect of exporter on productivity using matching and difference-in-differences are Girma et al. (2004) and Wagner (2002).

pirical methodology and findings for the exporter effects on environmental performance. Section 5 distinguishes between pre- and post-exporting dynamics of energy use, outlining both the empirical methodology and key findings. Section 6 gives a brief summary of some robustness checks. Section 7 concludes.

2 Theory

In this section, we present a simple theory of the decision to export and environmentally-friendly technology adoption. The purpose of this is to illustrate how technology adoption, and thus fuel usage, can depend on both the firm's productivity, the firm's intensity of fuel usage, and export costs. Our basis begins with the well-known Melitz (2003) model of heterogeneous firms. Since our data is at the firm level, where in the theory many factors are taken as given by the firm, we focus on a partial equilibrium analysis to focus our discussion.

There exists a continuum of firms which, as in Melitz (2003), are distinguished by a productivity parameter $a(i)$, which we assume is increasing in i. Unlike Melitz (2003), firms use two factors of production, labour (l) and fuel (f). The price of labour is given by w while the price of fuel is r. Each firm's production function is Cobb-Douglas in these two inputs, where the exponent on fuel ($\alpha(i)$) varies with i.[5] Note that we do not assume a particular relationship between the distributions of $a(.)$ and $\alpha(.)$. In addition, the firm chooses a level of technology $t_j = t_H, t_L$ where $t_H > t_L$. This technology choice augments the effectiveness of fuel usage, i.e. higher technology for a given amount of fuel increases the efficiency units of fuel in production. Combining these elements yields the production function for firm i: $a(i)l^{1-\alpha_i}(t_j f)^{\alpha_i}$. Taking the firms technology and factor prices as given, the cost minimising unit cost function for firm i:

$$c(i, t_j) = t_j^{-\alpha_i} a(i)^{-1} \alpha_i^{-\alpha_i} (1-\alpha_i)^{\alpha_i - 1} r^{\alpha_i} w^{(1-\alpha_i)}. \tag{2.1}$$

In addition to these production costs, the firm faces three types of fixed costs. First, should it choose to produce at all, it incurs F.[6] Second, it faces beachhead costs F_X if it chooses to serve the foreign market in addition to the home market.[7] In addition, if it exports, it incurs unit iceberg costs such that if q^* units are to reach the foreign market, it must export $(1+\tau)q^*$ units. The firm's final fixed cost is $\gamma(t_j)$, which is the cost of its technology choice. We assume that $F_X > F$ and $\gamma(t_H) > \gamma(t_L)$.

The continuum of firms compete monopolistically competitively, with each facing a domestic inverse demand function of

$$q(i) = p(i)^{-\sigma} P^{(\sigma-1)} I \tag{2.2}$$

[5] This is akin to the multi-factor model of Bernard et al. (2007).

[6] In addition, it is common to assume a cost to learning one's $a(i)$ and $\alpha(i)$. Since this does not affect relative payoffs from the different choices, we ignore it here.

[7] In line with the heterogeneous firms literature, we assume that parameters are such that any exporting firm also chooses to serve the domestic market. Assuming positive transport costs and/or that $F_X > F$ are sufficient for this.

and

$$q^*(i) = p^*(i)^{-\sigma} P^{*(\sigma-1)} I^* \tag{2.3}$$

where σ is the elasticity of substitution, $p(i)$ ($p^*(i)$) is the domestic (foreign) price of firm i, P (P^*) is the home (foreign) price index (a weighted average of firm prices), and I is the amount of income spent on the differentiated product industry. These latter two terms are endogenous in general equilibrium (see Melitz (2003)), however individual firms treat them as given under monopolistic competition. Since our goal is to describe individual firm behaviour to motivate our regressions, we will also treat them as parameters. Under profit maximisation, prices will be constant markups over unit costs. Thus the domestic and foreign prices for firm i with technology t_j will be:

$$p(i,t) = \frac{\sigma}{\sigma-1} c(i,t) \tag{2.4}$$

and

$$p^*(i) = \frac{\sigma}{\sigma-1} (1+\tau)\, c(i,t) \tag{2.5}$$

which yield quantities of

$$q(i) = \left(\frac{\sigma}{(\sigma-1)} c(i,t) \right)^{-\sigma} P^{(\sigma-1)} I \tag{2.6}$$

and a foreign inverse demand equation of

$$q^*(i) = \left(\frac{\sigma}{(\sigma-1)} (1+\tau) c(i,t) \right)^{-\sigma} P^{*(\sigma-1)} I^*. \tag{2.7}$$

Thus, the profit for firm i if it only serves the domestic market with low technology is:

$$\begin{aligned}\pi_D(i,t_L) = {} & \Omega a(i)^{\sigma-1} t_L^{\alpha_i(\sigma-1)} \alpha_i^{\alpha_i(\sigma-1)} (1-\alpha_i)^{(1-\alpha_i)(\sigma-1)} r^{-\alpha_i(\sigma-1)} w^{-(1-\alpha_i)(\sigma-1)} \left[P^{(\sigma-1)} I \right] \\ & - F - \gamma(t_L)\end{aligned}$$

where $\Omega = (\sigma-1)^{\sigma-1} \sigma^{-\sigma}$.

Compare this to the profits of a firm that only serves the domestic market but uses the high technology:

$$\begin{aligned}\pi_D(i,t_H) = {} & \Omega a(i)^{\sigma-1} t_H^{\alpha_i(\sigma-1)} \alpha_i^{\alpha_i(\sigma-1)} (1-\alpha_i)^{(1-\alpha_i)(\sigma-1)} r^{-\alpha_i(\sigma-1)} w^{-(1-\alpha_i)(\sigma-1)} \left[P^{(\sigma-1)} I \right] \\ & - F - \gamma(t_H).\end{aligned}$$

In contrast, an exporter with low technology will earn:

$$\pi_{EX}(i,t_L) = \Omega a(i)^{\sigma-1} t_L^{\alpha_i(\sigma-1)} \alpha_i^{\alpha_i(\sigma-1)} (1-\alpha_i)^{(1-\alpha_i)(\sigma-1)} r^{-\alpha_i(\sigma-1)} w^{-(1-\alpha_i)(\sigma-1)} \\ \left[P^{(\sigma-1)} I + (1+\tau)^{1-\sigma} P^{*(\sigma-1)} I^*\right] - F - F_X - \gamma(t_L)$$

while an exporter with high technology will earn:

$$\pi_{EX}(i,t_H) = \Omega a(i)^{\sigma-1} t_H^{\alpha_i(\sigma-1)} \alpha_i^{\alpha_i(\sigma-1)} (1-\alpha_i)^{(1-\alpha_i)(\sigma-1)} r^{-\alpha_i(\sigma-1)} w^{-(1-\alpha_i)(\sigma-1)} \\ \left[P^{(\sigma-1)} I + (1+\tau)^{1-\sigma} P^{*(\sigma-1)} I^*\right] - F - F_X - \gamma(t_H).$$

Finally, if the maximum of these four is negative, a firm can simply decide not to enter at all and earn zero profits.

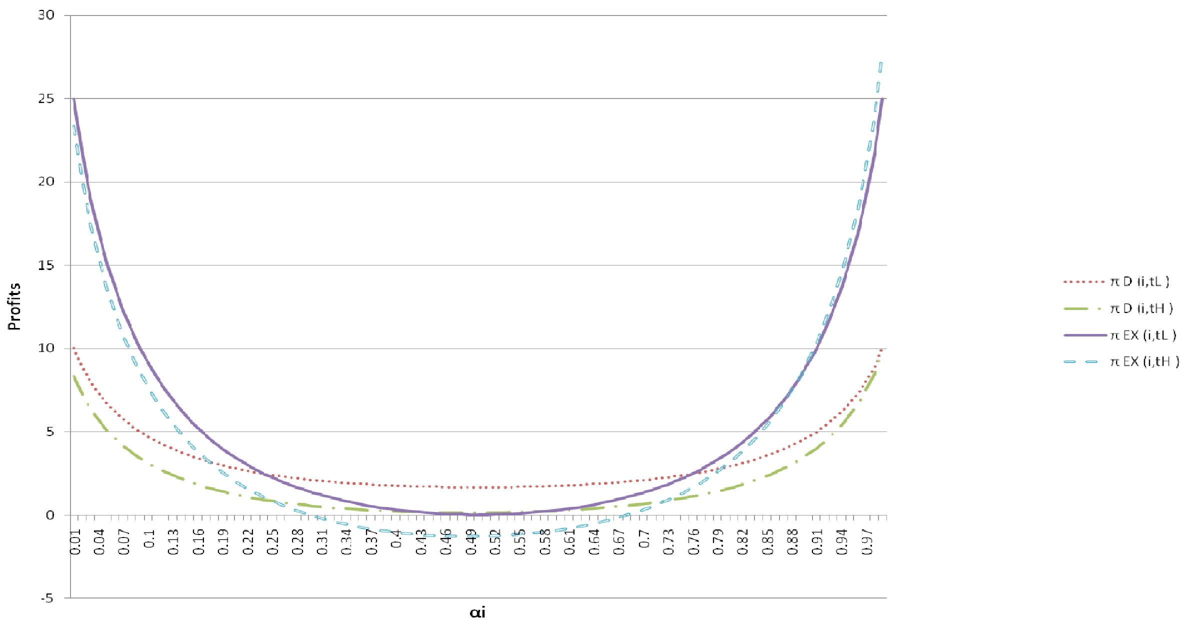

Figure 1: Profits Across Entry Modes

In order to most easily compare these four profit levels, consider Figure 1 which illustrates the profit level as it varies across $\alpha(i)$. Values for the various parameters are found in Table 8 in Appendix A. Three main results can be seen. First, there is a link between fuel intensity ($\alpha(i)$) and technology adoption. For low levels of α, low technology choices dominate high technology choices for a given export status (i.e. domestic only or exporting). Since these firms use relatively little fuel in production, the increased productivity of fuel use is outweighed by the added cost of installing this technology. For the highest αs, the reverse is true.

Second, there is a link between fuel intensity and exporting. Firms that have extreme values of α benefit more from exporting. This is because under the Cobb-Douglas production technology, unit costs are greatest when $\alpha = .5$, all else equal.[8] Thus firms with mid-range α have the highest cost and generate the least profits overseas. Therefore these firms will not choose to export.

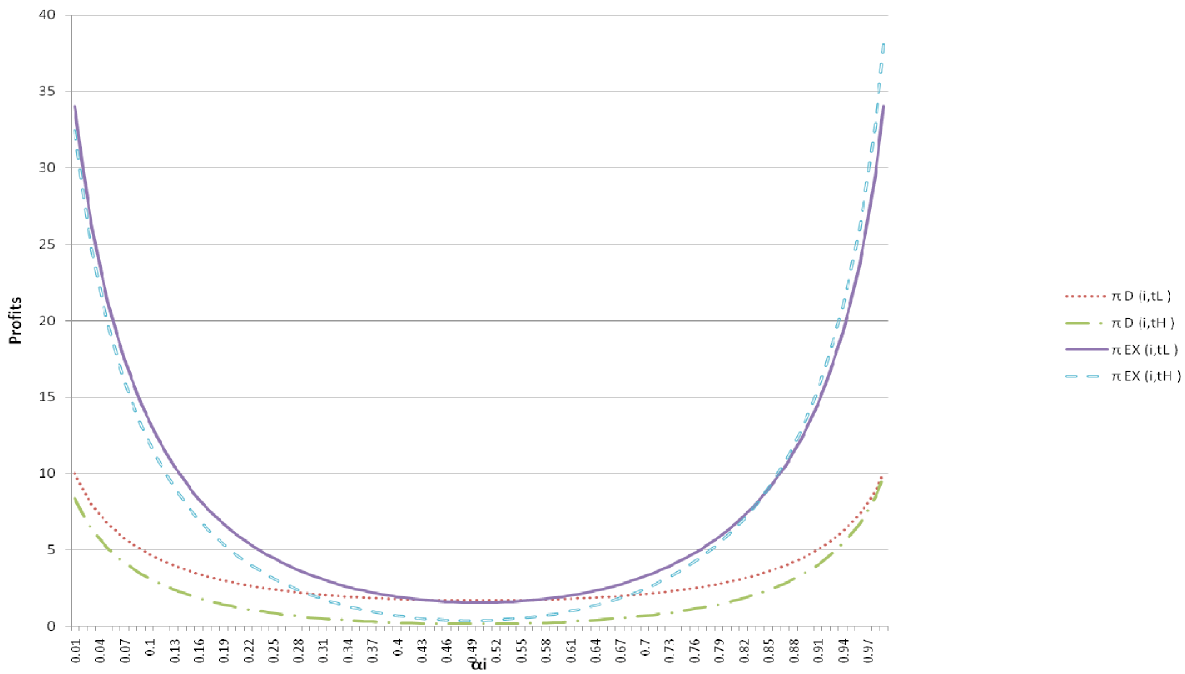

Figure 2: Profits Across Entry Modes with Reduced Trade Costs

Third, and most important for the current study, there is a link between exporting status and technology adoption. This can be seen for firms with moderately high $\alpha(i)$s. When they do not export, the low technology is the profit maximizing choice. When, exporting, however, the reverse is true. This is because the rate of return from installing the high technology is rising in output and firms that export produce more than firms that do not. As such, for these firms, the more fuel-efficient technology is only worth the added cost when they are serving a larger (international) market. For further insight, consider Figure 2, which repeats this set of simulations but imposes a 25 percent reduction in trade costs τ. Two key differences are seen between the figures. First, more firms choose to export. Second, the set of exporters that choose to install the high technology grows. This is because with reduced trade costs, exporters increase overseas sales and therefore benefit more from the cost savings of the high technology. Thus there is a positive correlation between exporting status and technology adoption. Figure 3 reverts to the original trade cost, but increases productivity by 50 percent. Again, we see that more firms export (and under this productivity rise, all firms do so) and that more firms choose the high technology. Thus not only do we see the Melitz (2003) result that more productive firms are more apt to export, be we also find that more productive firms are more likely to

[8]Similar figures are found if we alter the production function to be $a(i)\alpha_i^{-\alpha_i}(1-\alpha_i)^{\alpha_i-1}l^{1-\alpha_i}(t_j f)^{\alpha_i}$, a production function in which the cost function depends on α only in the exponents on wages and fuel prices. When these prices are equal, this alternative production function yields profits that are linear in α. However, the relative ranking of technology choices remains the same, i.e. high α firms are more likely to use the high technology than low α firms regardless of export status, and exporters are more likely to adopt the high technology than non-exporters for a given α.

adopt the fuel-efficient technology.[9] Finally, note that return on investment depends on total production, $q(i) + (1 + \tau)q^*(i)$, not on the amount sold which is only $q(i) + q^*(i)$, i.e. what remains after transport costs are taken into account. Because of this, in our data analysis it will be important to control both for sales and for exporting status.

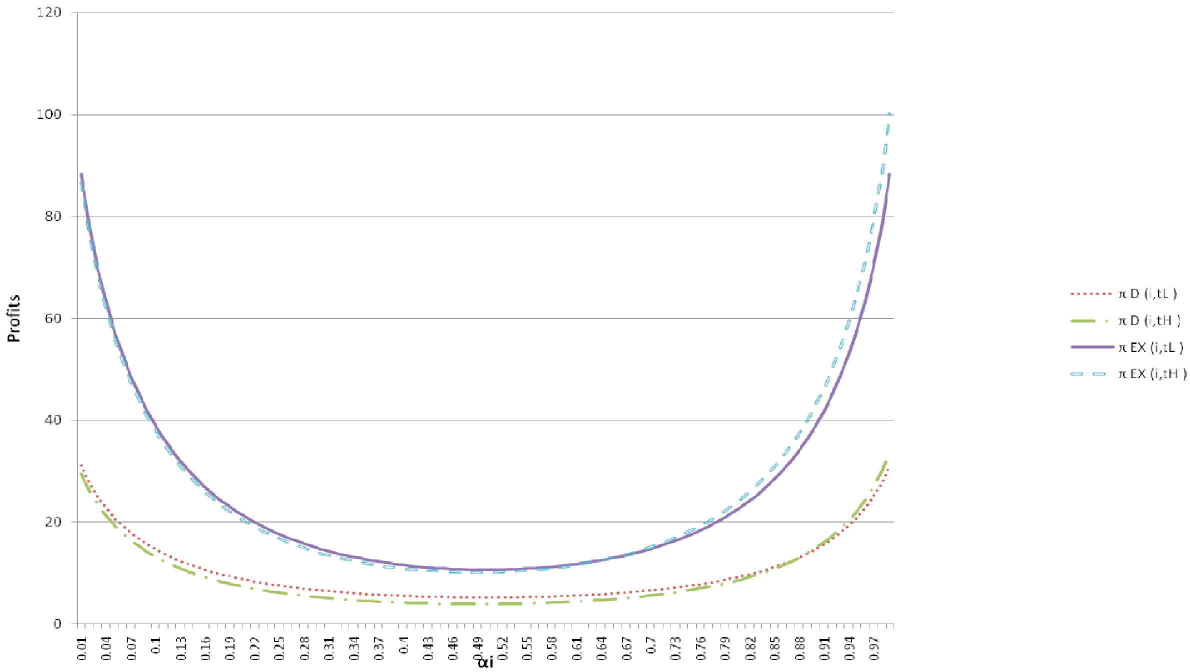

Figure 3: Profits Across Entry Modes with Higher Productivity

What then of total fuel expenditures? Where Q is total output, fuel use for a firm i with technology j is:

$$rf = Qa(i)^{-1}t_j^{-\alpha_i}\left[\frac{(1-\alpha_i)r}{\alpha_i w}\right]^{\alpha_i - 1} \tag{2.8}$$

which is increasing in total quantity and lower for a high technology firm for a given Q. As discussed above, when a firm begins to export, two changes occur. First, output rises. *Ceteris paribus*, this will increase fuel use. Second, for high fuel intensity firms, the firm will adopt a more efficient technology. For a given output, this reduces fuel usage.

Given the discussion above, we expect that for when a low fuel intensity firms begins exporting, only this first effect will be present, i.e. there will be a positive correlation between exporting status and fuel expenditures. For high fuel intensity firms, however, both effects are present. Thus, for these firms we expect either a smaller positive correlation or possibly even a negative correlation between exporting status and fuel expenditures. This is the main prediction we will test. One item to keep in mind is the converse of this story. When a firm stops exporting, its scale declines as does its fuel use. If technology

[9]This provides a potential benefit to the environment from trade since highly productive exporters drive out low productivity domestic firms. If this results in a greater percentage of firms using a more environmentally friendly technology, this could lead to a positive correlation between international trade and the environment. We leave a thorough treatment of this issue to future research.

is partially irreversible, or at least does not immediately depreciate, however, the effect of choosing the high technology will persist even after exporting ceases. Thus, we expect that low fuel intensity firms that stop exporting see their fuel use revert to that of comparable firms that never exported while high fuel intensity firms that stop exporting will still use less fuel than their counterparts because of the technology they adopted while exporting.

3 Data, Descriptive Statistics

3.1 Data

The panel of firm level data used in this study comes from the Irish Census of Industrial Production (CIP), an annual census of manufacturing, mining and utilities. The Census is conducted by the Central Statistics Office (CSO) at both enterprise and plant level. The CIP covers all enterprises or plants with three or more employees. The CIP data covers the period 1991 to 2007. Industries covered by the CIP are in classes 10 to 41 of the NACE Revision 1.1 (European Statistical Classification System), however we concentrate solely on manufacturing (NACE classes 15-36).[10] In this paper we concentrate solely on manufacturing (NACE classes 15-36). This leaves us with an unbalanced panel of 11,245 unique firms.

Our dependent variable is relative fuel use, i.e. fuel use divided by sales, which is a measure environmental performance.[11]We use this because there are no data available on pollution at the firm level. This approach is similar to Eskeland and Harrison (2003) and Cole et al. (2008). As the questions on fuel and power used were asked on the enterprise rather than plant level, we use the enterprise dataset of the CIP. Most enterprises (more than 90%) in the Census are single-plant firms. Fuel purchases include purchases of solid fuels, petroleum products, natural and derived gas, renewable energy sources, heat, and electricity. In addition, in our robustness checks, we add relative freight charges, i.e. firm expenditures on shipping, to relative fuel use. This is to account for the likelihood that firms that ship overseas may be outsourcing their transportation, and hence a portion of their fuel use.

Our main variable of interest is a dummy variable "Exporter" which is equal to one if a firm exports in year t and is zero otherwise. We expect this to be greater for firms that have low fuel intensity as compared to firms with high fuel intensities (for whom the coefficient may well be negative). Again, as discussed in the theory section, it is important to control for exports as well as sales since the latter will not equal output (the true scale effect) in the presence of transportation costs. In our data, 57% of all firms export at some point during the sample.

Since the theory suggests that more productive firms produce more and are more likely to install fuel-efficient technologies, we include labour productivity (measured turnover per employee). To control for other aspects of a firm's technology, we include the firm's capital stock and skill level, with the idea that firms using a good deal of capital may require more energy while those with more white-collar workers may use less. In addition,

[10]The list of industries is given in Table 9 in Appendix A.

[11]For the rest of the paper we will be using terms fuel intensity and relative fuel use interchangeably.

we control for R&D expenses which may be particularly important when focusing on technology changes. Earlier studies suggest that foreign ownership increases a firm's environmental performance, as might be the case if the parent provides the subsidiary with better technology. With this in mind, we include an ownership variable equal to one if a firm is foreign-owned. Since our dependent variable is fuel use relative to sales, this should control for scale effects assuming constant returns to scale. Nevertheless, as a safeguard against non-constant returns, we include both the size (measured as total earnings) and size squared of a firm.

Finally, we include 3-digit industry classification dummies, and year dummies. It is important to recognise that year dummies control for variations in the price of fuel over time. Table 10 in Appendix A presents a list of variables used and their definitions for the purpose of this analysis. Table 11 in Appendix A provides summary statistics for the main variables used in the subsequent analysis. [12]

3.2 Descriptive Statistics

Table 1 provides a brief overview of the distribution of exporters in manufacturing. Exporters comprise 57% of firms. The average share of exports in sales for all exporters is 45%. Amongst the exporters, 86% are domestic firms and 14% are foreign-owned. Almost all (97%) of the non-exporters are domestic firms.

Table 1: Exporting status and Ownership

	% Total	% Foreign-owned	% Domestic
Exporter	57	14	86
Non-exporter	43	3	97

Table 2 shows how the mean of relative fuel use compares between exporters and non-exporters alongside the means of other firm characteristics.

Table 2: Exporters vs non-exporters

Exporter	Fuel per turnover	Productivity	Total Earnings	Employment	% High-Skilled	Capital
Yes	0.0153	185.41	2017.08	72.29	26.88	24.49
No	0.0151	106.12	495.72	20.89	22.66	14.37

Reported are mean values over the period of 1991-2007. All monetary values are in EUR thousands.

Similar to what has been found in previous research, exporting firms are larger, more productive and capital-intensive, employ more people in general and more skilled people

[12]Monetary values are deflated using Industrial Producer Price Indices with year 2000 as a base, provided by the CSO. Energy variables are deflated using the CSO Wholesale Price Indices for Energy Products with year 1995 as a base.

in particular.[13] Their fuel use, however, is almost indistinguishable from that of non-exporters.[14] An important caveat to these comparisons is that they use unconditional means and do not account for other important characteristics of a firm. As we show in the next Section the mean values in table 2 mask important heterogeneity in the effect of exporter on a firm's fuel use.

4 Exporting and fuel use

This section estimates the effect exporting has on fuel use in manufacturing. As suggested in Section 2 it is important to concentrate on firm's fuel intensity, which we hereby measure as firm's fuel use relative to its total turnover.[15]

We start off with estimating a mean effect exporting has on relative fuel use. The results are shown in Table 3. Note that these results include both firm and industry fixed effects, which is possible as some firms' industries are reclassified by the CSO. Also, The mean exporter effect on the changes in fuel intensity is not significantly different from zero. In fact, only labour productivity and skill intensity are significant. However, as suggested by the theory, the mean effect across all firms might hide important heterogeneity of the exporter effects. Therefore we set aside discussion of the other controls for the moment.

To check whether the exporter effect varies along the distribution of fuel consumption we employ quantile regressions as they allow us to study the impact of exporter at different points (conditional quantiles) of relative fuel use distribution and not just conditional mean.

Quantile regression method as first introduced by Koenker and Bassett (1978) estimates conditional quantile functions: models in which quantiles of the dependent variable are conditioned on the observed covariates (Koenker and Hallock (2001)). The advantage of using quantile regression is that it provides a more complete picture about the effect of the control variables (X) on the dependent variables (Y) as it allows us to study the impact of X along the full conditional distribution, or at different points (quantiles), of Y. When the impact of a control variable varies across the range of the dependent variable, this can give a much better picture of the underlying data than when looking at just the conditional mean. Since we expect the dynamics of the relationship between exporting and relative fuel use to vary with relative fuel use, quantile regression is an optimal technique for our study. In particular, we expect the coefficient on exporting to be greater for low quantiles of relative fuel use than for high quantiles.

The quantile regression model can be written as:

$$Quantile_\theta(Fuel_{it}|X_{it}) = X'_{it}\beta_\theta \tag{4.1}$$

[13] Although not reported here, exporters are also on average more R&D intensive.

[14] Further breakdown of exporters reveals that foreign exporters use less fuel relative to sales when compared to either domestic exporters or non-exporters.

[15] The same results are obtained when using fuel relative to total costs as an alternative measure of a firm's fuel intensity.

Table 3: Mean exporter effect on relative fuel use: fixed effect panel estimation

Exporter	-0.00227
	(0.00965)
Ownership	-0.00384
	(0.02755)
Labour Productivity	-0.06322***
	(0.00594)
Size	-0.00341
	(0.01152)
Size^2	0.00708
	(0.00860)
Skill	0.02556***
	(0.00501)
Capital	0.00758
	(0.00645)
R&D	0.00627
	(0.00409)
Observations	74257
Number of id	10725
R-squared	0.06

Standard errors in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
The model includes firm, year, and 3 digit industry dummies and intercept, which are not reported.
All coefficients are standardised.

where $Quant_\theta(Fuel_{it}|X_{it})$ denotes a conditional quantile of fuel use and X_{it} represent control covariates.

Koenker and Bassett (1978) show that the θth regression quantile, where $0 < \theta < 1$, can be computed by:

$$min_\beta \Big[\sum_{i,t:Fuel>X'\beta_\theta} \theta |Fuel_{it} - X'_{it}\beta_\theta| + \sum_{i,t:Fuel<X'\beta_\theta} (1-\theta)|Fuel_{it} - X'_{it}\beta_\theta| \Big] \qquad (4.2)$$

where β will be estimated differently at different quantiles θ, with θ and $1-\theta$ used as weights and X are the set of variables as discussed in Section 3 and used above, in the fixed effects panel estimation.

The results of estimations in (4.2) are presented in Table 4. Indeed, as predicted by the theory, there is a heterogeneity in the effect of exporter on fuel use. The results in Table 4 show that as one moves from low fuel intensity towards high fuel intensity, the coefficient on exporting declines. In fact, for the eighth conditional quantile there is no longer a significant effect, while for the most fuel intensive firms (the ninth quantile and higher), switching into exporting lowers relative fuel use. This is consistent with the theory, which suggested that when becoming an exporter, there is a positive scale effect that increases fuel use for all firms, however, this is at least somewhat offset for high fuel intensity firms because they adopt more fuel efficient technologies.

Looking to our other controls, we see much more significance in the quantile regressions than in the panel regression. Labour productivity is significantly negative in all cases. As the theory indicates, more productive firms are more apt to invest in fuel-efficiency enhancing technologies, therefore this too is in line with our priors. Also in line with

Table 4: Quantile Estimations of exporter effects on relative fuel use

	.20	.50	.70	.80	.90	.95
Exporter	0.05087***	0.04550***	0.01804***	-0.00099	-0.02722***	-0.06952***
	(0.00213)	(0.00236)	(0.00392)	(0.00573)	(0.01046)	(0.01899)
Ownership	-0.01649***	-0.00192	0.02697***	0.06698***	0.10622***	0.11870***
	(0.00339)	(0.00368)	(0.00608)	(0.00886)	(0.01603)	(0.02903)
Labour	-0.04861***	-0.05459***	-0.05292***	-0.05894***	-0.06852***	-0.07333***
Productivity	(0.00082)	(0.00122)	(0.00254)	(0.00423)	(0.00906)	(0.01977)
Size	-0.00198	-0.01521***	-0.02233***	-0.03102***	-0.05687***	-0.07305***
	(0.00176)	(0.00186)	(0.00301)	(0.00439)	(0.00829)	(0.01578)
Size^2	0.00019	0.01084***	0.01267***	0.01584***	0.02867***	0.03615***
	(0.00131)	(0.00174)	(0.00257)	(0.00363)	(0.00543)	(0.00877)
Capital	0.00839***	0.01285***	0.02153***	0.02839***	0.04570***	0.05957***
	(0.00167)	(0.00138)	(0.00186)	(0.00245)	(0.00346)	(0.00468)
Skill	-0.02631***	-0.02718***	-0.02882***	-0.03281***	-0.02361***	-0.01671
	(0.00118)	(0.00125)	(0.00210)	(0.00312)	(0.00580)	(0.01088)
R&D	0.00816***	0.01412***	0.01270***	0.01425***	0.01729***	0.00617
	(0.00099)	(0.00107)	(0.00191)	(0.00249)	(0.00451)	(0.00708)
Constant	-0.38265***	-0.03708***	0.31409***	0.59334***	1.22525***	2.33197***
	(0.00672)	(0.00737)	(0.01218)	(0.01784)	(0.03235)	(0.05902)
Observations	74257	74257	74257	74257	74257	74257
Pseudo R^2	0.11	0.17	0.19	0.20	0.22	0.24

Standard errors in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
Dependent variable: total fuel and power purchase per turnover, all coefficients are standardised.
The model includes year and 3 digit industry dummies, which are not reported.

our priors, we find that firms with more capital and less skill use more fuel relative to sales. Firms that spend more on R&D also use more fuel. Looking to the size variables, we find that increased size seems to reduce relative fuel use for small firms, but that the effect is reduced for large ones. Finally, we find heterogeneity across quantiles for the ownership variable. Unlike the exporter variable, this is negative for low fuel intensity firms, suggesting that in the lower quantiles foreign ownership reduces fuel intensity. For higher quantiles, however, the reverse is true and the effect grows as one moves towards the most fuel intensive firms. This suggests that previous studies finding an environmental benefit from foreign ownership may be primarily driven by FDI in low fuel intensity firms.

5 Pre- and post-exporter dynamics

The above results find that there is a significant difference between the fuel use of exporters and non-exporters and that this difference varies according to fuel intensity. As a next step of the analysis we would like to see whether the exporter effect observed above can be attributed to pre- or post-exporter differences in relative fuel use. It is reasonable to expect that similar to the observations that most productive firms self-select into exporting, firms may adopt newer, more energy-efficient technologies before becoming exporters. Alternatively, as Section 2 suggests, upon becoming exporters more fuel-intensive firms may find it more profitable to adopt a higher level of technology. In order to disentangle these two effect, we employ matching and difference-in-differences technique as suggested by Heckman et al. (1997) and Blundell and Dias (2000) to establish a causal effect of becoming an exporter on a firm's fuel consumption. Propensity score matching and difference-in-differences techniques allow us to deal with selection bias and any differences in time invariant unobserved characteristics of firms that matching alone was unable to control for.

5.1 Empirical Strategy

According to Blundell and Dias (2000), matching is a way of re-creating the conditions of a natural experiment where none is realistically available. Matching uses non-experimental data by assuming that selection into treatment, in our case exporting, is completely determined by observed variables and, conditional on these observed variables, the assignment to treatment is random. This is known as conditional independence assumption (CIA) and can be written as:

$$(Y_1, Y_0) \perp\!\!\!\perp D|X \tag{5.1}$$

where $\perp\!\!\!\perp$ denotes independence, D - treatment (=1) or control (=0) group, (Y_1, Y_0) denote outcomes and X - observed covariates.

Conditioning on a large number of covariates X, however, can present a serious dimensionality problem. The solution to this was proposed by Rosenbaum and Rubin (1983) who suggested to use propensity score which measures the probability of receiving a treatment given the observed variables. Propensity score therefore allows to match the treated and the control on one number rather than across a whole range of covariates. Here we select a number of variables that predict a probability of becoming an exporter and calculate propensity scores based on those observable variables.

We do this by running probit estimations of predicting a probability of becoming exporter to see what characteristics make a firm more likely to start exporting (based on Wooldridge (2002), p.482):

$$P(Y_{it} = 1|X_{it-1}) = G(X_{it-1}\beta) \tag{5.2}$$

where Y equals one for an exporting firm and zero otherwise and X are a set of one year lagged covariates used to predict a probability of becoming an exporter at a year t. We additionally control for industry (at NACE 3 digit) and year effects.[16] The probit estimations are also used to calculate propensity scores for matching.

We then match firms from treatment group (exporters) with firms from control group (non-exporters) based on their respective propensity scores. As it is impossible to match the scores exactly, the Nearest Neighbor Matching (NNM) method with one neighbour

[16]We cannot include firm-level fixed effects in a probit estimation as it leads to inconsistent estimates, see Wooldridge (2002), p.484.

and with replacement is used. Nearest Neighbor Matching chooses a firm from the control group of non-exporters that is closest in terms of propensity score to a firm in the treatment group of exporters.

Common support is also imposed to ensure there are no regions where the support of X does not overlap for the $D = 1$ and $D = 0$ (Smith and Todd (2005)), in other words we exclude those firms for whom a match could not be found or whose propensity scores are too far apart from each other.

When performing matching a careful balance needs to be established between the CIA and the common support. Selecting a large number of covariates might introduce a bias due to the weakness of the common support, while adhering to a minimal number of explanatory variable will ensure the common support is not a problem but the plausibility of the CIA becomes questionable.[17] In Section 5.2 we try and strike a balance between both common support and the CIA to ensure a good quality of matching.

The conditional independence assumption, however, is quite strong and it is possible some unobserved, time-invariant characteristics may influence the selection into treatment (e.g. geographic location, among other things). We therefore use a difference-in-differences estimator to remove such temporally-invariant components of bias (Heckman et al. (1997)).

Therefore (based on Angrist and Pischke (2009)),

$$E(Y_{1t} - Y_{0t}|X, D = exporters) - E(Y_{1t} - Y_{0t}|X, D = non - exporters) = \delta \quad (5.3)$$

is the causal effect of interest, or difference-in-differences estimator.

where Y is the outcome of firm's relative fuel use among exporters and non-exporters. Y_{0t} represents fuel use one year before a firm switches to exporting. Y_{1t} represents the outcomes of fuel use after the switch to exporting. We utilise three specifications for this latter variable: at the first year a firm exports, at the second year of exporting and at the third year of exporting.

To establish how exporting matters for fuel use we need to single out firms that change their exporting status from non-exporter to exporter to be able to see the causal effect of that change on their fuel use. We therefore leave out all firms that always export during the sample since we do not have any pre-export information on fuel use. We also need those firms that switch to exporting to stay exporters for some time if we are to examine effects that "phase in" over time. We thus require firms to stay exporters for at least three years to be classified as such. To eliminate firms that switch more than once in our sample we require firms not to export for at least three years before they switch to exporting. Therefore, we focus on those firms that do not export three years prior to switching to exporting and then export for at least three years (years t to $t + 2$). We contrast these firms with those that have never exported (our control group).

The procedure is then to first match firms on a number of characteristics that make them likely to become exporter in a year t, select firms that have the most similar characteristics in a year $t - 1$ from exporter and non-exporter groups and then examine how fuel use of firms that become exporters diverges from those that stay non-exporters.

[17] See Caliendo and Kopeinig (2005) for further details on the quality of matching.

5.2 Results

To establish pre-exporter effect in relative fuel use we run probit estimation that measures a probability a firm exports in year t based on its characteristics in $t-1$, as in (5.2). Table 5, column (1) presents these results.[18] We find no evidence that more fuel-efficient firms self-select into becoming exporters. We do find that firms with more capital are more likely to become exporters. Additionally, given the range of values for size, the probability of exporting is a decreasing as size increases. Similar to McCann (2009) who also uses Irish firm level data, we do not find that more productive firms self-select into exporting. This is in contrast to studies such as Bernard and Jensen (1999) who find that more productive firms self-select into exporting. As such, this may represent an unusual feature of the Irish data.

To establish what happens after a firm begins exporting, we compare the subsequent fuel use of matched exporters and non-exporters as defined in (5.3) in Table 6. The pattern afterwards is mixed and shows no significant differences in fuel consumption of exporters compared to non-exporters.

However, as shown in Section 2, the patterns of fuel expenditures of exporters may vary depending on a fuel intensity of a firm. To test this, we divide the sample into two groups, based on their fuel intensity, which we measure as fuel purchases relative to total turnover. Division is based on unconditional quantiles of relative fuel use. We can't directly apply any insights from the quantile regressions since they give conditional on other covariates quantile functions that do not directly translate into unconditional quantiles. We therefore try out several divisions, starting with the one at the median. After splitting the sample, we find that there is a clear difference in the pattern of fuel consumption of exporters based on their initial fuel intensity. This difference is most plainly seen when we contrast two groups: firms in up to and including the median quantile of relative fuel use, which we refer to as low fuel intensity firms, and firms with relative fuel use from the .6th quantile of relative fuel use, who we refer to as high fuel intensity firms.[19] In terms of the relative importance of these groups, the low fuel intensity firms account for 80% of total sales but just over 30% of all fuel used. Low fuel intensity firms also account for about half of all people employed. Further, 53% of these firms export with the average export share exceeding 50%. In contrast, the high fuel intensity firms account for over 60% of all fuel used but just about 14% of total sales. They employ over 30% of all people and although the share of exporters is somewhat higher - 57% of high fuel intensity firms export - their average export share is lower at just around 40%.

With this split in hand, we repeat the same matching and difference-in-differences estimations for these low and high fuel intensity firms. The results for the propensity to export are found in columns 2 and 3 of Table 5 while the changes in subsequent fuel use are in the lower two panels of Table 6.

While there aren't any big variations between the two groups in their pre-exporting patterns, their post-exporting behaviour is clearly different, as shown in table 6. Low

[18] The choice of variables used is a combination of their significance and quality of matching. Tables 12 to 14 in Appendix A assess the quality of matching by reporting t-tests that indicate that there are no statistically significant differences in the means of variables used to calculate the propensity scores.

[19] The same dynamics is also observed when we limit the last group to fuel intensity starting at the .7th quantile of relative fuel use; see Table 15 in Appendix A.

Table 5: Selection into exporting

	All firms (1)	Low fuel intensity firms (2)	High fuel intensity firms (3)
Relative Fuel Use$_{t-1}$	-0.0394	-0.0488	-0.0022
	(0.0387)	(0.0701)	(0.0759)
Labour Productivity$_{t-1}$	0.0213	0.0241	-0.0047
	(0.0400)	(0.1602)	(0.1983)
Size$_{t-1}$	0.1283**	0.8298***	0.7667*
	(0.0604)	(0.1921)	(0.4203)
Size$^2_{t-1}$	-0.2226***	-1.6535***	-3.2195*
	(0.0730)	(0.5232)	(1.8305)
Ownership$_{t-1}$	0.1908	0.8026*	
	(0.2554)	(0.4635)	
Capital$_{t-1}$	0.2104***	0.1819	0.8735
	(0.0665)	(0.1386)	(0.5470)
Skill$_{t-1}$	0.0311	0.0744	-0.1595
	(0.0323)	(0.0726)	(0.0985)
R&D$_{t-1}$			0.2306
			(0.3815)
Observations	5275	1853	1511
Chi^2	282.10	136.84	77.17
Prob > Chi^2	0.0000	0.0000	0.0000
Pseudo R^2	0.10	0.23	0.15

Probit estimations. Standard errors in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
Fuel intensity: low in up to and median quantile of relative fuel use; high - from .6th upwards.
The models include year and 3 digit industry dummies and an intercept, which are not reported.
The reported coefficients are standardised. Matching is performed on non-standardised values.

fuel intensity firms that start exporting increase their fuel use relative to comparable non-exporters and this difference persists across time. This would be expected if their fuel use rises due to increased production. On average, we observe about 20% increase in relative fuel use compared to the pre-exporting year.

For high fuel intensity firms that start to export we observe a decrease in fuel use compared to comparable non-exporters, which is statistically significant in the first and the second year of exporting and of slightly higher magnitude than the increase in fuel consumption of low fuel intensity firms. This difference, however, becomes insignificant in the third year after exporting. This would be consistent with a setting in which high fuel intensity, exporting firms experience a scale effect increasing fuel use but also choose to adopt greener technology, resulting in a net negative effect. If this technology either depreciates or becomes cheaper over time, in which case even non-exporters adopt it, this difference would gradually disappear. This is consistent with the observed dynamics of fuel use of high fuel intensity non-exporters.

An additional way of testing whether the observed outcome differences can indeed be attributed to technology effects, we invert the focus and examine what happens when firms stop exporting as compared to firms that have never exported. Our theoretical predictions would suggest that scale effect would cease immediately when a firm stops

Table 6: Comparing relative fuel use of exporters and non-exporters: Difference-in-Differences results on the matched sample

	One year before exporting	1st year of exporting	2nd year of exporting	3rd year of exporting
All firms				
Treated	0.0155	0.0137	0.0141	0.0135
Control	0.0161	0.0154	0.0137	0.0132
DiD		**-0.0011**	**0.0009**	**0.0008**
		(0.0010)	(0.0011)	(0.0013)
No. of matched pairs	375	375	375	375
Low fuel intensity firms				
Treated	0.0052	0.0054	0.0052	0.0050
Control	0.0056	0.0047	0.0046	0.0042
DiD		**0.0011*****	**0.0010****	**0.0012****
		(0.0003)	(0.0005)	(0.0005)
		+20%	**+19%**	**+22%**
No. of matched pairs	60	60	59	58
High fuel intensity firms				
Treated	0.0325	0.0259	0.0259	0.0254
Control	0.0324	0.0343	0.0329	0.0283
DiD		**-0.0085*****	**-0.0071****	**-0.0031**
		(0.0029)	(0.0034)	(0.0034)
		-26%	**-22%**	
No. of matched pairs	58	58	58	58

Standard errors in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
Fuel intensity: low in up to and median quantile of relative fuel use; high - from .6th upwards.
% indicates change relative to the average level of fuel intensity before exporting.

exporting. Technology adoption, however, would have a longer lasting effect since once the fixed cost of adoption is paid a firm would continue to utilise it. By replicating the estimations used to derive the results of the last two rows of Table 6 for firms that stop rather than start exporting, as shown in Table 7 this is exactly what we find.

As expected, the scale effect observed above for the low fuel intensity firms disappears as soon as a firm stops exporting. In contrast, the technology effect is still observed for high fuel intensity firms that stop exporting for at least two years after exporting ceases.

Before concluding, a caveat should be mentioned. As this division into groups is arbitrary, we check whether other quantiles of fuel use can be used to divide firms into low or high fuel intensity groups. Results for the .7th and the .8th quantiles of relative fuel use as dividing points are shown in Table 15 in Appendix A. They reveal that although similar dynamics holds if we limit high fuel intensive firms to higher quantiles of relative fuel use, the low fuel intensive firms results are primarily driven by those up to and including the median fuel intensity.

In summary, our estimates reveal an important heterogeneity in a way exporter status affects fuel use depending on a firm's fuel intensity. We empirically confirm the theoretical

Table 7: Comparing relative fuel use of firms that stop exporting and non-exporters: Difference-in-Differences results on the matched sample

	One year before exporting	1st year of exporting	2nd year of exporting	3rd year of exporting
Low fuel intensity firms				
Treated	0.0059	0.0050	0.0054	0.0050
Control	0.0060	0.0055	0.0052	0.0043
DiD		**-0.0004**	**0.0003**	**0.0008**
		(0.0004)	(0.0004)	(0.0005)
No. of matched pairs	66	66	66	64
High fuel intensity firms				
Treated	0.0275	0.0247	0.0251	0.0271
Control	0.0244	0.0258	0.0274	0.0294
DiD		**-0.0042****	**-0.0054*****	**-0.0054**
		(0.0016)	(0.0019)	(0.0038)
		-16%	**-21%**	
No. of matched pairs	81	81	81	81

Standard errors in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
Fuel intensity: low in up to and median quantile of relative fuel use; high - from .6th upwards.
% indicates change relative to the average level of fuel intensity before quitting to export.

predictions of a positive correlation between exporting status and fuel expenditures for low fuel intensity firms and negative correlation for high fuel intensity firms. These observed effects stem from differences in which firms adopt more fuel efficient technologies when they become exporters.

6 Robustness Checks

In order to test the veracity of our primary conclusions, we performed a number of robustness checks on both quantile regression estimations and on propensity score matching with difference-in-differences estimations. Some of these findings are summarised below.

Outsourcing of Transportation

Upon becoming an exporter a firm might be more likely to outsource transportation of its goods due to the added difficulty of reaching overseas markets. In this case, the firm's direct fuel purchases would understate their actual energy usage (and thus the pollution for which they are responsible). The CIP dataset provides additional information on firm's spending on freight charges which we added to the expenses on fuel to account for any potential outsourcing influence. When doing so, for the quantile regressions, we find that the effect of exporting status on fuel and freight charges is positive throughout. This is because high fuel intensity firms also spend more on freight charges relative to turnover. In the propensity score matching and the differences-in-differences analysis using this alternative measure of environmental performance, we find that the results are qualitatively unchanged for the lower quantiles but the negative dynamics of exporters' fuel use becomes insignificant in the higher quantiles.[20] Thus, although we do not find the reductions for high fuel intensity firms we find that, unlike low fuel intensity firms, they do not increase expenditures on fuel and shipping when they begin exporting. Since the theory only implies that the rise in total expenditures should fall as fuel intensity rises, not that it be negative, this is again consistent with our model.

Electricity

Electricity might be perceived as the cleanest source of energy amongst all available. In addition, for many firms, it is the largest component of their fuel expenditures. To see whether the same heterogeneity would be observed for the electricity consumption quantile regression estimations are re-run for firms' electricity use relative to turnover. As in the presented results using all fuel expenditures, the exporter effect is positive and decreasing for the higher quantiles of relative electricity use.

Foreign vs Domestic Exporters

When the quantile estimations are performed to distinguish explicitly between foreign and domestic exporters, they show that domestic exporters drive the dynamics observed in table 4. This may suggest that, consistent with Cole et al. (2008), Cole et al. (2006), and Kaiser and Schulze (2003) a foreign parent may transfer technology to its subsidiary. Alternatively, this may result from the fact that nearly all foreign owned firms in our sample export for the entire period, eliminating the necessary variation to obtain significant results in that sample.

Absolute fuel use

In the above analysis, we use fuel use relative to sales as our dependent variable. As an alternative, we repeated our estimation using absolute, rather than relative, fuel use. When doing so, we found comparable results: i.e. exporting increases fuel use for firms that use small amounts of fuel, reduces it for firms using large quantities of fuel, and that these changes are largely driven by changes while exporting. The only distinction is that we observe a self-selection effect of more fuel-efficient firms into exporting among big energy users.

Influential Observations

Although we restrict our sample to only manufacturing firms, thereby eliminating variations in terms of fuel use patterns that exist between manufacturing and other activities, there is still a large degree of heterogeneity within manufacturing. For example, publishing and furniture manufacturing activities use very little fuel whereas the manufacture of basic metals accounts for some of the largest fuel use values reported in the CIP. In order to assess the impact of these extreme values on our results, we repeat the analysis on the data with the top 1% of fuel use observations removed from the sample. This does not impact any our results qualitatively.[21]

[20] Note that here firms are divided into lower and upper quantiles of the sum of fuel and freight costs relative to turnover rather than fuel costs alone.

[21] Exploiting the underlying heterogeneity in manufacturing in detail is beyond the scope of this paper and is something to be left for future work.

7 Conclusions

One of the greatest concerns over globalisation and trade openness is the impact on the environment. This paper contributes to this debate by examining the relationship between firm's decision to export and its energy use. Our theoretical model predicts a positive correlation between exporting and fuel expenditures for low fuel intensity firms and a smaller or even a negative correlation for high fuel intensity firms. This is because for low fuel intensity firms exporting creates only a scale effect through which increased production increases fuel use. For high fuel intensity firms, this is at least partially offset by the adoption of greener technology made profitable because of the increased market size. We confirm this empirically using a panel firm-level data set on Irish manufacturing firms for 1991 to 2007. This suggests that studies using aggregated data or firm level data with a focus entirely on mean effects may miss important links between globalisation, fuel use, and the environment.

Although neither our model nor our estimates speak directly to policy implications, it is worth considering what our results might suggest. Since the environmental benefits of exporting accrue primarily to those firms that use a lot of fuel relative to sales, our results provide some justification for targeted export promotion policies. However, since doing so increases output by firms that are on the high end of the fuel use distribution, it is by no means clear that from an environmental perspective, these firms should be encouraged. Alternatively, a policy that subsidizes technology adoption may be both more cost effective and environmentally beneficial. Thus, although such analysis is beyond the scope of this paper, we hope that our estimates provide a useful framework for the continuing debate.

A Appendix

Table 8: Baseline Values for Simulations

Variable	Interpretation	Baseline Value
F	Fixed Cost of a Domestic Plant	0
F_x	Fixed Cost of Exporting	5
P	Domestic Price Index	2
I	Domestic Income	15
P^*	Foreign Price Index	4
I^*	Foreign Income	30
σ	Elasticity of Substitution	3.8
τ	Iceberg Transport Cost	1
$a(i)$	Productivity Parameter	1
r	Cost of Fuel	1
w	Wage Rate	1
t_H	High Technology Parameter	1.05
t_L	Low Technology Parameter	1
$\gamma(t_H)$	High Technology Cost	1.65375
$\gamma(t_L)$	Low Technology Cost	0

Datawork

To prepare the data prior to analysis, we were required to clean the data. All of the changes are described below.

In a few instances, the CIP data reported negative or missing values of fuel and/or export share and/or zero values of employment, earnings and/or turnover. When possible, these were replaced using values from adjacent years. When this was not possible, the observation was dropped. For instances of export shares bigger than 100 their values were replaced using values from previous and later years. Export share values that could not have been replaced were treated as follows. Firms which did not have export share equal to 100 in any other years were dropped from the sample. If a firm had at least one occurrence of export share equal to 100 in other years the value of export share larger than 100 was set to 100.

Table 9: List of NACE 2 digit industries in the Census of Industrial Production (CIP)

NACE Code	Description
15	Manufacture of food products and beverages
16	Manufacture of tobacco products
17	Manufacture of textiles
18	Manufacture of wearing apparel; dressing and dyeing of fur
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
21	Manufacture of pulp, paper and paper products
22	Publishing, printing and reproduction of recorded media
23	Manufacture of coke, refined petroleum products and nuclear fuel
24	Manufacture of chemicals and chemical products
25	Manufacture of rubber and plastic products
26	Manufacture of other non-metallic mineral products
27	Manufacture of basic metals
28	Manufacture of fabricated metal products, except machinery and equipment
29	Manufacture of machinery and equipment n.e.c.
30	Manufacture of office machinery and computers
31	Manufacture of electrical machinery and apparatus n.e.c.
32	Manufacture of radio, television and communication equipment and apparatus
33	Manufacture of medical, precision and optical instruments, watches and clocks
34	Manufacture of motor vehicles, trailers and semi-trailers
35	Manufacture of other transport equipment
36	Manufacture of furniture; manufacturing n.e.c.

Table 10: Definition of variables

Variable	Description
Relative fuel use	Total fuel and power purchase as declared by firms in the CIP, scaled down by total turnover.
Exporter	Dummy variable equal to 1 if a firm exports in any given year and 0 otherwise. For matching estimations exporters are defined as firms that switch to and stay exporting: firms that do not export 3 years prior to switching to exporting and then export for at least 3 years.
Ownership	Dummy variable equal to 1 if a firms is foreign-owned and 0 if it is a domestic firm.
Labour Productivity	Total turnover divided by the number of employees.
Size	Total earnings (in constant thousand of Euros).
Skill	% of managerial/technical and clerical personnel in total employment.
R&D	Research and development services supplied to the enterprise.
Freight costs	Freight charges for transport of the firm's products.
Capital	Firm's capital additions built over the whole period minus sales of capitals assets, assuming 10% yearly depreciation rate overall.

Table 11: Summary Statistics, Manufacturing

Variable	Mean	Std. Dev.	Min	Max
Total fuel use	120.72	853.57	0	66043.99
Fuel per turnover	0.015	0.021	0	1.356
Export share	25.86	36.48	0	100
Total Turnover	18240.99	203343.73	0	12670647
Size	1370.54	5144.87	0	257530.28
Total Employed	50.42	143.66	0	4554
Labour Productivity	151.71	373.58	0	16062.42
% High-Skilled	25.09	18.87	0	100
Capital	2726.69	38761.71	-93586.49	4326626.5
R&D	384.16	12639.16	0	1386157
Fuel and freight charges	330.84	2087.33	0	195178.77
Fuel and freight per turnover	0.033	0.037	0	1.935

All monetary values are in EUR thousands.

T-Tests for Section 5.2 comparing sample means of the treated and control groups to assess the quality of propensity score matching performed. Both tables indicate that there is no statistically significant difference in the means of variables used to calculate the propensity score.

Table 12: T-test, all manufacturing firms

	Treated	Control	T-test
Relative Fuel Use$_{t-1}$	0.01553	0.01611	-0.52
Labour Productivity$_{t-1}$	101.73	101.42	0.03
Size$_{t-1}$	611.55	710.87	-0.94
Size$^2_{t-1}$	1.9e+06	3.2e+06	-1.01
Capital$_{t-1}$	672.92	865.16	-0.80
Ownership$_{t-1}$	.01867	.02133	-0.26
Skill$_{t-1}$	25.215	24.827	0.30

Table 13: T-test, low fuel intensity firms

	Treated	Control	T-test
Relative Fuel Use$_{t-1}$	0.00521	0.00558	-0.81
Labour Productivity$_{t-1}$	113.06	123.32	-0.57
Size$_{t-1}$	694.89	541.81	1.04
Size$^2_{t-1}$	1.2e+06	8.4e+05	0.64
Capital$_{t-1}$	404.76	514.23	-0.65
Ownership$_{t-1}$	0.05	0.08333	-0.73
Skill$_{t-1}$	30.646	33.572	-0.65

Low fuel intensity firms - firms in up to and including median quantile of relative fuel use.

Table 14: T-test, high fuel intensity firms

	Treated	Control	T-test
Relative Fuel Use$_{t-1}$	0.03249	0.03235	0.03
Size$_{t-1}$	444.58	414.22	0.34
Size$^2_{t-1}$	4.4e+05	3.8e+05	0.34
Capital$_{t-1}$	506.4	416.7	0.40
Labour Productivity$_{t-1}$	73.171	82.007	-0.72
Skill$_{t-1}$	18.27	17.32	0.46
R&D$_{t-1}$	2.1859	0.56206	1.43

High fuel intensity firms - firms from .6th quantile of relative fuel use upwards.

Table 15: Changing definitions of low and high fuel intensity firms

Dividing point		1st year of exporting	2nd year of exporting	3rd year of exporting
.7th quantile	**Low fuel intensity firms**	**0**	**0.0005**	**0.0007**
		(0.0004)	(0.0005)	(0.0004)
	High fuel intensity firms	**-0.0122*****	**-0.0128****	**-0.0060**
		(0.0034)	(0.0048)	(0.0044)
.8th quantile	**Low fuel intensity firms**	**-0.0001**	**0.0004**	**0.0004**
		(0.0004)	(0.0004)	(0.0004)
	High fuel intensity firms	**-0.0121****	**-0.0035**	**-0.0074**
		(0.0055)	(0.0051)	(0.0061)

Standard errors in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
Fuel-intensity: low in up to and median quantile of relative fuel use; high - from .6th upwards.

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