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Aoife Hanley and Joaquín Monreal-Pérez

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Are Newly Exporting Firms more Innovative? Findings from Matched Spanish Innovators*

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Abstract:
The prevalence of Internet-based sales by exporters vs. non-exporters is highlighted in a recent World Bank Report (Ferro, 2011) suggesting the use of sophisticated processes when selling overseas. We investigate the count of new process/ product innovations for a group of newly exporting Spanish firms vs. a non-exporter control group. We use propensity score kernel matching and difference-in-differences to help deal with endogenous exporting, sunk exporting costs and common macroeconomic shocks. Our results confirm that selection into exporting is largely driven by productivity and industry technological differences, consistent with exporting sunk costs. We find some evidence of 'technology upgrading' through higher contemporaneous process innovation rates.

Keywords: exporting, innovation, Propensity Score Kernel Matching, Learning-by-exporting.

JEL classification: F14, F23, O3

Aoife Hanley[a]
Christian-Albrechts-University, Kiel &
Institute for the World Economy, Kiel

***Corresponding author**
Institute for the World Economy, Kiel
Hindenburgufer 66
D-24105, Kiel, Germany
E-Mail: Aoife.Hanley@ifw-kiel.de
Phone: +49 (0)431 85853
Fax: +49 (0)431 85853

Joaquín Monreal-Pérez[b]
Institute for the World Economy, Kiel &
University of Murcia

University of Murcia
Avda. Teniente Flomesta
nº 5 - 30003-Murcia, Spain
E-Mail: jomonreal@um.es

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1 Background

In a study of the hypothesized productivity dip for firms who quit their export markets, Girma et al. (2003) observe a surprising persistence in productivity growth rates for exporters quitting their foreign markets and conclude that [1]:

'.....the benefits from exporting are due to exposure to *best practice technology* (our italics), rather than scale economies or competition effects' (pp.186)

The reasoning is based on symmetry: exporters stand to make productivity gains vs. non-exporters mostly due to a greater ability to spread costs over a wider output base. Having quit their export markets, these efficiency gains should disappear unless caused by long-lasting technology improvements.

Is there direct evidence that firms improve their way of doing things (technology) as a result of exporting? While there is recent evidence on how firms upgrade their *products* prior to entering exporting by investing more in quality or R&D (Iacovone and Javorcik, 2010; Bustos, 2011), the literature is largely silent on *technology* upgrading (i.e. *process* innovations).[2]

Yet, the positive productivity growth of newly exporting firms (e.g. Delgado et al., 2002; Clerides et al., 1998) strongly hints at changes in the way in which firms produce and sell their products pre- and post the transition to exporting. Analogously, if firms adjust their products to foreign customer needs and reduce their operational costs, they stand to gain higher export shares in these new markets (Lachenmaier and Wößmann, 2006). What remains unanswered is whether product and process improvements help firms to select into export markets.

This is the gap in the literature that this current analysis sets out to fill: Do newly exporting firms upgrade products and technologies? And secondly, do changes to these products or processes arise before or at the time of the switch to exporting? One must consider that while firms may expect to offset sunk export costs through the introduction of process innovations (selection arguments), a firm's exporting experience can boost its innovative capacity (learning).

To address this question we uniquely apply a combination of propensity score matching with difference-in-differences to a cohort of newly exporting Spanish firms in 2006.[3] As in Girma et al., we augment propensity score matching with a difference-in-differences methodology. [4] This dual approach allows us to best tackle both endogenous exporting whereby R&D intensive firms select into exporting ('learning-to-export' /'product upgrading') whilst neutralizing the bias of common macroeconomic shocks (difference-in-differences). A further benefit of this methodology is that it

[1] Wagner (2002) and Girma et al., (2004) both show the positive productivity impacts for new exporters

[2] The exception being Caldera (2010) who uniquely estimates selection into exporting as a function of innovation in a framework which recognizes the potential endogeneity of innovation. However, she does not distinguish between product and process innovation in this instrumented analysis.

[3] Wagner (2002) and Girma et al. (2004) both apply matching methodologies to discern ex-post productivity changes for exporting firms

[4] See Blundell and Costa Dias (2000) for an excellent review of this approach.

sidesteps problems of sunk exporting costs as flagged up in other studies (Bustos, 2011; Caldera, 2010). Finally, this framework allows us to test product upgrading arguments (where ex ante R&D increases are associated with higher export propensities) while simultaneously considering innovation outcomes for newly exporting firms.

Consistent with the stylized facts, we find that the ex ante most productive and high-tech firms self-select into export markets. A firm's R&D, though positively related to export entry, is insignificant in the propensity score estimations.[5] Uniquely, we find in the kernel estimations that newly exporting firms are 11 percent more likely than non-exporters to report changes in their manufacturing processes in the year that they switch to exporting. One year later, these differences disappear.

Our paper is organized as follows. The next section summarizes the methodology. Then follows a short description of our data. This is followed by an analysis section followed by a concluding section.

2 Methodology

In attempting to look at the innovation/exporting nexus, we face the ubiquitous selection problem where:

'If today's export starters are 'better' than today's non-exporters (and have been so in the recent past), we would expect that they should, on average, perform better in the future even if they do not start to export today'. (Wagner, 2002, p288)

Here a lack of statistically relevant and intuitively compelling instruments for a firm's innovation makes it difficult to deal with self-selection unless we isolate from our sample the group of newly exporting and non-exporting firms. Following Heckman et al. (1997) we can calculate the average effect of exporting as:

$$E\{y^1_{t+s} - y^0_{t+s} | EXPORT_{it} = 1\} = E\{y^1_{t+s} | EXPORT_{it} = 1\} - E\{y^0_{t+s} | EXPORT_{it} = 1\}$$

where the last expression term is needed in order to infer the innovation propensity rates for the group of firms that did not switch to exporting. To get this term, we match each firm that switched to exporting with a derived counterfactual, constructed over the distribution of non-exporting firms. We apply the Stata propensity score routine, *psscore*, based on Rosenbaum and Rubin (1983). Specifically, the first-stage Probit captures the likelihood that firms become exporters based on observable pre-exporting attributes of the firm (firm size and age, R&D status, technology status and productivity). Both control (never-exporters) and treatment (newly exporting firms) firm groups are

[5] A simple Probit of lagged R&D on innovation, controlling for the switch to exporting status shows R&D is a significant driver of both product and process innovation.

then assigned to strata according to the propensity score and the balancing property checked for each stratum.[6]

In our model, productivity is measured alternatively as sales per worker and total factor productivity, size as number of employees, age as the number of years a firm has been in existence, R&D as a dummy variable for whether a firm conducts R&D and the industry fixed effect is a technology index where higher values denote a high-tech industry.[7] Finally, innovation is broadly defined binary variable denoting the introduction of products/ processes which are new to the firm.

In estimating innovation rates, we opt for the Stata *attk* procedure proposed by Heckman et al. (1998) which builds on traditional pairwise matching by using the full distribution of firms falling under common support in the pre-exporting Probit.[8] The nonparametric matching estimator constructs a match for each newly exporting firm using a kernel-weighted average over multiple non-exporting firms. Assuming that the common support conditions hold, we now have a consistent estimator of the propensity of exporter switchers to innovate, had they not decided to export: $E\{y^0_{t+s}|EXPORT_{it} = 1\}$

Finally, we apply a further correction is to difference out time varying external shocks (e.g. exchange rate movements) by applying Difference-in-Differences to the innovation outcomes.

3 Data

The data we use is for newly exporting firms in 2006 for which we have information on innovation outputs. The firms are extracted from the annual *Spanish Business Strategy Survey* (SBSS), a public database containing survey data for a representative panel of manufacturing firms with at least 10 employees. Pre-exporting data for 2005 contains key correlates for export market entry. Also available is data for 2007, the year following entry.

Important for propensity score matching is a valid control group for the 3 yearly cross-sections. There are just over 600 of such non-exporting firms (non-exporting in 2005, remaining non-exporting in 2006-2007). This means that for 2006 we record 38 newly exporting firms over a total of 646 non-exporters. This breakdown (circa 6 percent) is in line with Girma et al. (2004) who, using data for UK

[6] We assume that the assumption of conditional independence holds: i.e. that firms in the control and treatment group largely select into exporting based on these observable pre-exporting attributes. Specifically, their differing ability to bear sunk exporting costs. The implication being that both productivity and firm size play a key role in informing the decision (Wagner, 2002; Bernard and Jensen, 1999; Clerides, Lach and Tybout, 1998) and firm age (Barrios, Görg and Strobl, 2003). R&D capacity (Caldera, 2010) should also play a role in co-determining the export decision

[7] Total factor productivity was used as our preferred productivity measures in earlier estimations. Although showing a positive effect on selection into exporting (as expected), estimates were biased for having overrepresented large firms who reported values for capital stock

[8] We use the Stata default Gaussian kernel with bandwidth 0.06. Smith and Todd (2005) give an excellent summary of this and other matching techniques. An advantage of this matching technique is that it reduces the asymptotic mean squared error found in traditional pairwise matching.

firms, similarly report that only 6 percent of non-exporters became new exporters. This fact they attribute to sunk exporting costs.

Consistent with the evidence that exporting firms are 'better' than their non-exporting peers, Table 1 shows how the newly exporting cohort in the year before they commenced exporting. They are older, larger, are more likely to carry out R&D, belong to a high-technology sector and have higher labor productivity. Also clear is that newly exporting firms are more likely to report an innovation outcome in the period following the transition to exporting.

4 Analysis

The descriptive statistics reveal differences between the control and treatment groups. But are these differences significant? For this we conduct a simple Probit with a dummy variable denoting whether the firm transitioned to exporting in 2006. Consistent with Bustos (2011) there is a significant correlation between the switch to exporting and the appearance of newly introduced products / manufacturing processes contemporaneous with the switch. Uniquely, we also find that the positive effect carries through to the year following the transition, $t+1$.

Looking at the marginal effects for product and process innovations in period t+1, we see some similarities with the descriptive statistics reported earlier. The baseline probability is calculated at the average values of the continuous variables and setting all dummy variables to 1 (consistent also with the no-exporting control group). Accordingly, the baseline for the control group is 2.9 and 21.8 percent for new products and processes respectively. For firms transitioning to exporting, the predicted probability of producing an innovation rises to 7 percent (0.041 + 0.029) and 45.7 percent (23.9 + 21.8) percent for products and processes respectively.[9] Clearly, new processes are introduced with greater regularity than are new products.

Commenting on the other covariates: there is some evidence that the youngest firms are least likely to innovate, except surprisingly for newly introduced processes one year after entry. Here firms from the youngest age quartile are most likely to be active. Finally, firms that conduct R&D exhibit strong and significant returns to innovation.

Clearly, the simple Probit is not set up to deal with endogenous exporting. We therefore turn to the estimates from the propensity scored and matched kernels, reporting first the related balancing tests in Table 3.[10] Table 4 reports the results from the propensity scoring analysis. The selection arguments are well supported here, most notably in the case of productivity. Here, the most productive firms who can afford the sunk costs of exporting are also the most likely to switch to exporting. Similarly, firms

[9] We recall from the descriptive statistics (see Table 1) the values were 24 and 42 percent for newly exporting firms.
[10] The Stata balancing rule is at the 0.01 level of significance.

from the highest-tech sectors. R&D which played a positive and significant role in the earlier bivariate Probit, remains positive as expected but insignificant.

Once satisfied that the firms belong to homogeneous groups based on their pre-exporting attributes, the analysis procedes to the matching analysis. Overall, there is little evidence of returns to a firm's innovation from exporting. The exception being an 11 percent increase in the rate of process innovations for newly exporting firms in the year that they transition to exporting. It appears therefore, that when we decompose the innovation-exporting nexus into the selection effects (i.e. derivation of exporting propensity based on pre-export attributes) and contemporaneous/ex-post innovation, there is little residual variation between the exporting and non-exporting group.

5 Conclusions

Overall, when we apply a matching methodology with difference-in-differences to investigate comtemporaneous and ex-post changes to a newly exporting firm's technology and product, we find some support for technology (not product) upgrading. However, differences in innovation outcomes for export switchers and never-exporters are largely determined by ex ante productivity and industry-heterogeneity.

What are the policy implications of our findings? Most interesting is the doubling of innovative production processes in the lead up to, and in tandem with, the move to export markets. Iacovone and Javorcik (2010) have described how new 'export discoveries' is a small numbers game. We agree that innovation is a small numbers game: Discoveries of new products as a precursor to exporting increases to 4 percent from 3 percent, depending on the estimation. However, the impact of exporting on a firm's *manufacturing processes*, not captured in the Iacovone and Javorcik study, is more pronounced. Even having controlled for selection of the most productive and sectorally high-tech firms, there are residual differences in process innovation rates which are caused by the switch to exporting.

Why the differences in process innovation rates? Overseas exporters may have to align production to help meet the myriad needs of overseas markets and reduce costs. One example of this realignment: The introduction of Internet product-tracking helping new exporters to transact over a greater geographic and cultural distance. The predominance of such Internet-based operations for exporters was recently highlighted in a World Bank paper (Ferro, 2011). Clearly, exporting 'raises the bar' for firms who may be forced into more imaginative and cost-efficient ways of producing and selling product overseas.

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Table 1 Comparisons for export starters and non-exporters

	Non-exporters						
	t+1		*t-1*				
	product innovation	**process innovation**	**employees**	**age (years)**	**R&D carried out**	**high-tech sector**	**productivity**
mean	0.05	0.19	64	20	0.09	0.54	2.86
sd	0.22	0.39	234	16	0.29	0.46	0.55
median	0	0	22	16	0	0.41	2.82
N	646	646	474	467	473	642	474
	Newly exporting firms						
	t+1		*t-1*				
mean	0.24	0.42	108	27	0.18	0.71	3.13
sd	0.43	0.50	167	24	0.39	0.65	0.57
median	0	0	27	20	0	0.43	3.17
N	38	38	38	37	38	38	38

Table 2 Bivariate Probit with Marginal Effects

	(1)	(2)	(3)	(4)
	Product innovation		Process innovation	
period	*t*	*t+1*	*t*	*t+1*
newly exporting (*t*)	0.116	0.041	0.227	0.239
	(2.82)**	(1.35)	(3.23)**	(2.95)**
small firm	-0.003	0.017	0.012	-0.053
	(0.13)	(0.96)	(0.26)	(0.91)
Age:				
1st tercile	-0.006	-0.041	-0.011	0.176
	(0.26)	(2.05)*	(0.22)	(2.69)**
2nd tercile	-0.033	-0.022	-0.045	0.108
	(1.33)	(1.24)	(0.93)	(1.64)
RD carried out	0.209	0.279	0.276	0.335
	(4.72)**	(5.45)**	(4.20)**	(4.20)**
high-tech sector	0.031	0.020	-0.005	0.008
	(2.15)*	(1.73)	(0.14)	(0.21)
Productivity	0.019	0.014	0.061	0.045
	(1.01)	(0.80)	(1.78)	(1.07)
Observations	503	452	503	452
LR chi2	52.61	50.57	41.62	42.07
Prob > chi^2	0.0000	0.0000	0.0000	0.0000
Pseudo r^2	0.2071	0.2616	0.0881	0.0859
Pred. P at $\bar{x}$	.044	.0286171	.1626522	.2175961

Note: Absolute value of z-statistics in parentheses * significant at 5%; ** significant at 1% All covariates 1-year lags. Base categories for 'Age' is 'oldest'. All controls calculated for t-1

Table 3 Balancing tests: Propensity Scoring

	Balancing tests: 465 'never-exporters' and 38 new exporters (Stata '*psscore*')			
	Block 1	Block 2	Block 3	Block 4
Non-switching firms	366	77	22	0
Switching to exporting	18	12	7	1
P|T| > |t|	0.014	0.77	0.28	NA
Variables in block balanced	Yes	Yes	Yes	NA

Table 4 Selection into Exporting (Propensity Scoring)

1st stage Probit: Firm switches to exporting (Stata '*psscore*')		
	coefficient	SE
Small firm	0.16	(.247)
Age:		
1st tercile	-0.33	(245)
2nd tercile	-0.26	(.242)
R&D carried out	0.30	(.271)
Productivity:		
1st tercile	-0.50**	(.234)
2nd tercile	-0.56***	(.220)
High-tech sector:		
1st tercile	-0.42*	(.219)
2nd tercile	-0.66***	(.239)
constant	-0.67	
Observations		503
Pseudo R2		0.0849
Percentiles (Propensity score):		
P50		0.05
P25		0.03
P75		0.09
Final # blocks		4

Table 5 Exporting and innovation (Kernel Matching)

Second stage: Kernel Treatment with Difference-in-Differences (Stata command 'attk')		
	Average treatment effect of switch to exporting	SE
	Process innovation	
t	0.11*	0.068
t+1	0.065	0.119
	Product innovation	
t	0.02	0.05
t+1	-0.093	0.075

Notes: All estimations applying common support assumption Bootstrapped standard errors, common support assumption applied for all kernel estimates

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