Learning by Exporting: New Insights from Examining Firm Innovation

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Empirical findings across many nations show that exporters have superior productivity compared to nonexporters and that this relationship is driven by productive firms becoming exporters. The conclusion drawn from these studies is that there is little learning from exporting. We, however, assess if there are ex post *benefits that accrue to exporting firms by examining innovation outcomes. We argue that exporters can often access diverse knowledge inputs not available in the domestic market, that this knowledge can spill back to the focal firm, and that such learning can foster increased innovation. We examine product innovation and patent application counts of a representative sample of Spanish manufacturing firms from 1990 to 1997. To conduct the analysis, we use a nonlinear GMM estimator for exponential models with panel data that allows for predetermined regressors and linear feedback. We find that exporting is associated with innovation. Moreover, the panel data allow us to explore the temporal relationship between exporting and innovation. In contrast to existing findings, we find evidence of learning by exporting—albeit in dimensions not previously examined in the literature.*

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1. Introduction

Exporting is the most prevalent form of international expansion. For example, according to Balance of Payments data, US firms exported \$1.07 trillion of goods and services in 2000 and increased foreign direct investment (FDI) by \$152 billion (US BEA, 2001). Likewise, in data that we describe in detail shortly, almost half of the firms in the Spanish manufacturing sector export, while less than 1% have FDIs.

Yet, despite the preponderance of exporting, we know relatively little about this international expansion strategy from a firm-level perspective. Much of the research regarding international expansion strategies focuses on activities such as direct investment or joint ventures (e.g., Caves, 1996). Moreover, although an abundant literature in international trade exists (for reviews see Helpman and Krugman, 1985; Gandolfo, 1987), the empirical focus has largely been at the industry or country level of analysis. For the most part, however, firms engage in trade—not industries or nations. Therefore, the inferences from the more macro level might be misleading in guiding firm strategies.

Although firm-level studies of exporting have received comparatively little attention, a literature is beginning to emerge.[1] In this literature, one relationship that has been noted across several nations is that exporters, compared to nonexporters, tend to be more productive (e.g., Aw and Huang, 1995; Clerides et al., 1998; Bernard and Jensen, 1999; Delgado et al., 2002). Finding the temporal sequencing that drives this relationship is vital in order to draw conclusions with respect to firm strategy. Namely, is the relationship driven by productive firms becoming exporters or exporting enhancing firms' productivity or both? To date, the evidence suggests that productive firms become exporters and that exporting does not increase productivity. Hence, the conclusion has been that there is little learning by exporting.

Learning by exporting is purportedly driven by information exchange from the foreign market, often through export intermediaries or directly from customers. Scholars have tested for this effect by examining labor efficiency, average variable cost, and total factor productivity. We depart from the existing literature and focus our investigation on innovative outcomes rather than productivity measures, arguing that they can more directly measure the outcome of interest—learning by exporting.

Empirically, we examine exporting behavior and *ex post* innovative outcomes using a representative sample of the Spanish manufacturing sector between 1990 and 1997. We employ two measures of innovation:

1. The relative paucity of research is largely a reflection of the unavailability of firm-level exporting data.

product innovation counts and patent applications. We document that exporting is associated with the *ex post* increase in both of these measures, however, with slightly different lag structures. Notably, product innovations tend to increase soon after exporting with the greatest impact 2 years after exporting. Patent applications increase with a greater lag in time. The existence of learning by exporting suggests that exporting can influence firm outcomes beyond providing a sales outlet for existing products. Therefore, it can be a strategic tool to facilitate firm innovation.

In the next section, we briefly review the extant research on learning by exporting and discuss how these arguments would be reflected in firm innovation. We then describe the data and provide some descriptive results. We subsequently detail the method we employ to test our arguments, present empirical results, and discuss the robustness of our findings. The final section concludes.

2. Learning by Exporting

Firm-level data from a growing set of countries show that exporting firms or plants have superior productivity compared to nonexporters. These countries include the United States (Bernard and Jensen, 1999); Columbia, Mexico, and Morocco (Clerides et al., 1998); Spain (Delgado et al., 2002); and Taiwan and Korea (Aw and Huang, 1995). Discerning the cause of this relationship is important in order to guide firm strategies. It is expected that exporters will have some productivity advantages before they enter export markets because they must offset costs of transportation and adaptation to host country market conditions. Should this be the driver of the relationship, the implication for firm internationalization strategies is that firms should expand from a position of strength in order to cope with the difficulties of selling in a foreign market.

Of potentially greater strategic interest is if the reverse relationship exists. Here, engaging in exporting would allow a firm to enhance its productivity and overall competitive position. This possibility has been dubbed "learning by exporting" in the literature. Under this condition, a strategic consideration for making an investment is forward looking, and values the increased productivity that would stem from exporting.

The mechanism through which learning by exporting is argued to occur is by exporting firms accessing information to which they would otherwise not be privy. Grossman and Helpman (1991, 1993) argue that trade facilitates a bidirectional exchange of knowledge across borders. The conjecture is that exporting firms, through interaction with foreign agents, are exposed to knowledge inputs not available to firms whose operations are confined to the domestic market.[2] Therefore, competing in a foreign market allows exporting firms to amass market and technological information. For instance, exporters might benefit from the technological expertise of their buyers (Clerides et al., 1998). Moreover, exporters might receive valuable information about consumer product preferences and competing products. They might also confront competitors in the host country that would have otherwise escaped their purview. As the information collected from these sources filters back to the parent firm, it should incorporate the knowledge into its production function.

Anecdotally, there is support for these arguments.

> "A good deal of the information needed to augment basic capabilities has come from the buyers of exports who freely provided product designs and offered technical assistance to improve process technology in the context of their sourcing activities." (Evenson and Westphal, 1995)

> "Participating in export markets brings firms into contact with international best practices and fosters learning." (World Bank, 1997)[3]

> "The first thing I do when I meet with exporting firms is take them to see the competition: their products, and sometimes their manufacturing process. That way they may be able to see where they stand vis-à-vis the market." Author's interview—translated—with Eva Blasco, Valencia Institute for Exports, November 2001.

Although the potential for learning by exporting has been highlighted and there are anecdotal accounts of its existence, the econometric evidence to date provides almost no support for this claim. In all of the aforementioned studies, the overall evidence suggests that productive firms become exporters and exporting does not enhance firm productivity.

One explanation for these results is that although exporting facilitates information flow from the host market, it does not provide sufficient information flow to result in the predicted effects. Under

2. This is because knowledge is spatially bound and unavailable to those who do not participate within that boundary (e.g., Kogut, 1991; Nelson, 1993; Almeida and Kogut, 1999).

3. Clerides et al. (1998) highlight these first two quotes.

this condition, more involved methods of international expansion are required to source knowledge from the local environment. These arguments are at the center of the asset-seeking FDI literature, which argues that firms must acquire or locate proximally to host nation firms in order to benefit from the knowledge that resides in the host location. Otherwise stated, this literature presumes that firms must establish a physical presence in the host environment in order to benefit from Marshallian location externalities (e.g., Marshall, 1920; Kogut and Chang, 1991; Cantwell, 1993; Almeida, 1996; Siotis, 1999).

A related alternative for the paucity of evidence stems from the nature of information exchange from exporting. Perhaps the mechanisms that have been described to foster learning by exporting will more likely transfer information about the product versus the process. In this case, exporters would learn more about competing products and customer preferences from export intermediaries, customer feedback, and other foreign agents than they would learn about process technologies. Because consumers from different nations do not share identical tastes, the end products desired by consumers in the destination country may vary from those offered in the home country. Market information passed from the foreign customer to the focal firm might help firms tailor products to meet the specific needs of foreign customers (Vernon, 1966, 1979) but have a negligible impact on productivity.

A final explanation for the lack of empirical substantiation of the learning by exporting hypothesis could be because of temporal issues in using productivity as a measure of learning. Through repeated interactions with various agents in the foreign environment, the focal firm may become privy to technological discoveries made in the foreign location. However, if domestic, "intranational" spillovers are pervasive, as Branstetter (2001) and Keller (2002) suggest, then firms may not be able to appropriate returns from their technological gains. Domestic competitors might compete away innovation benefit before a firm is able to realize it. As such, learning might never materialize as increased productivity.[4] And even if firms can appropriate those returns, it may take some time for the technological information that the firm incorporates into its production function to result in productivity gains. Although this effect should eventually filter into the firm's production function and result in increased productivity, we believe that there may be more direct ways to measure the learning outcome.

If export intermediaries, customers, or other agents in the foreign environment provide feedback regarding demands that go unmet, new products that can be launched, or technologies that exist in the host

4. We thank an anonymous reviewer for suggesting this consideration.

location, then directly assessing these outcomes might avoid complications that arise in assessing productivity. For example, firms might have to adopt different production processes or incur launch costs for new products. Moreover, these actions might result in changes to the production mix at existing plants or the launch of new plants that raise production costs, and lower productivity, in the near term. Similarly, if productivity spillovers among exporters (e.g., Aitken et al., 1997) or "intranational" spillovers exist, the net effect of exporting on productivity can be difficult to tease out. To the extent that information from the foreign market facilitates innovations, this can be more directly assessed in firms' efforts to launch new products or patent and protect their innovations. For this reason, we depart from the current literature and assess product innovations and patent applications rather than productivity. These measures of innovation provide an alternative and arguably, a more direct way to assess information exchange from the foreign market to the exporter. We describe our data and approach in the following sections.

3. Data

The data that we employ are from a yearly survey initiated in 1990 by the Fundación Empresa Pública with the financial support of the Spanish Ministry of Industry. The Fundación surveys a sample of Spanish manufacturing firms to get a representative picture of the country's manufacturing sector. The data cover the entire population of Spanish firms with 200 or more employees and include a random sample of 5% of the population of firms with at least 10 but fewer than 200 employees. Our data focus on the years 1990–1997. The initial survey collected information on 2,188 firms from 18 distinct industries. We present the industry breakdown for the initial sample year in Table I.

When a firm drops from the sample in any given year, another with similar characteristics replaces it. The resulting base sample then is an unbalanced panel of 3,060 firms and 14,282 firm–year observations. From this sample we removed all observations that reported any foreign ownership. For these firms there exist other, more direct, mechanisms to facilitate information exchange from outside the domestic market due to foreign ownership. Therefore, we focus only on Spanish firms without foreign ownership.[5] The empirical approach, which we describe below in detail, requires no gaps on the within-firm time series. In addition, lagged values of the independent variables serve as instruments. Given

5. We find results that are consistent with those that we report when we include firms with foreign ownership.

TABLE I.
INDUSTRY BREAKDOWN

Industry	Number of Firms	Percentage of Total
1. Ferrous and nonferrous metals	45	2.06%
2. Nonmetallic mineral products	161	7.36%
3. Chemical products	149	6.81%
4. Metallurgy and metallic products	223	10.19%
5. Agricultural machinery	125	5.71%
6. Office products and data processing	22	1.01%
7. Electrical accessories and materials	201	9.19%
8. Automobiles and motors	81	3.70%
9. Transport material	54	2.47%
10. Meat products	59	2.69%
11. Food and tobacco	229	10.47%
12. Beverages	53	2.42%
13. Textiles and clothing	249	11.38%
14. Leather and footwear	76	3.47%
15. Wood and wood products	146	6.67%
16. Paper and publishing	163	7.45%
17. Rubber and plastic products	101	4.62%
18. Miscellaneous manufacturing industries	51	2.33%
TOTAL	2,188	100%

these restrictions, our usable sample is 1,567 firms and 6,359 firm–year observations when we examine the 1-year lag of exporting, 1,321 firms and 4,792 firm–year observations when we examine the 2-year lag, and 1,113 firms and 3,471 firm–year observations when we examine the 3-year lag.

These data offer a particularly good setting in which to study the phenomenon of interest. First, the survey collects data on the innovative outcomes and exporting status of a sample of firms from a single economy over time. Second, approximately half of all sample firms engage in exporting. For example, 1,017 of the 2,188 firms reported that they exported in 1990 (46%). This provides rich variance among firms' exporting strategies. Moreover, there is very little direct investment in these data. Only 7 of the 2,188 firms in 1990 reported that they had controlled assets in foreign countries (i.e., had FDIs).[6] Therefore, we do not expect our results to spuriously capture learning from FDI.

6. The FDI measure captures whether or not a firm has foreign operations in a given year. As such, it represents a dichotomous measure of the stock of FDI at any given point in time.

4. Dependent Variables

As previously described, we focus on two dependent variables—product innovation counts and patent application counts. Assessing both measures of innovation mitigates some of the deficiencies inherent in selecting one measure to the exclusion of the other. Moreover, because each variable might pick up different aspects of innovation, we can use this variation in expected outcome to help inform our interpretation of the data. For instance, Afuah (1998) suggests that market knowledge about consumer preferences generally leads to product innovation while technological knowledge lends itself to invention (i.e., patents).

4.1 Product Innovation Counts

The most direct way to assess product innovation is to directly measure it. The instrument used by the Fundación Empresa Pública asks firms to report the number of new and modified products realized in a given year. We label this variable PRODUCT INNOVATIONS.

Scholars have noted that innovation counts are subjective (Archibugi and Pianta, 1996). Moreover, our use of self-reported values could magnify this subjectivity. To assess this concern, we examined the raw data and it appeared to reflect some subjectivity. For example, the maximum value that PRODUCT INNOVATIONS takes is 950, yet the mean is 2.90. Although at first glance the maximum value may appear out of line with the rest of the data, this is not the case. The other values that this firm reports over time are very comparable to this value. To the extent that this reflects the means by which subjectivity enters the data, the panel data design can aid in controlling for such effects.[7]

4.2 Patent Application Counts

Another way in which we expect the flow of knowledge to be manifest is through patent applications. The survey collects information about the number of Spanish patents applied for by a firm in a given year. Those seeking patent protection must file an application with the appropriate agency that governs patenting in the country or region in which it seeks protection. The European Patent Office (EPO), established as a result of the European Patent Convention (EPC) of Munich in October 1973, currently oversees and governs patent applications and grants in 19 European countries (EPO, 2000). Spain formally became a member of

7. In sensitivity analyses we dropped those firms that reported extreme values (e.g., greater than two standard deviations away from the mean). Results remained qualitatively unchanged.

the EPC and aligned its national patent laws with prevailing European law on March 20, 1986 (Ulloa and Salas, 1993). However, it still maintains a national patent office. Thus, any firm choosing to patent its technology in Spain has two available options. The firm may submit its application to the EPO and designate Spain as one of the countries in which it seeks protection. Alternatively, it may apply directly to the Spanish Industrial Property Registry (SIPR). Both offices use identical criteria for granting patents and both methods offer the same protection to patent holders in Spain (Ulloa and Salas, 1993). Although it costs more to file with the EPO and the grant process takes longer (an average of 18 months for the EPO versus 12 with the SIPR), if applying for protection in more than one EPC country, applying through the EPO saves on paperwork and administrative costs (EPO, 2000). The variable that we label PATENTS captures the number of patent applications filed for protection in Spain, whether via the Spanish Industrial Property Registry or the EPO.

Patent data and patent counts have been used extensively in industrial economics research on technology and innovation (e.g., Scherer, 1965; Comanor and Scherer, 1969; Basberg, 1982, 1987; Henderson and Cockburn, 1994, 1996; Hall et al., 2001). Further, strengths and weaknesses of the measure have been well documented (Hall et al., 2001).

The variable that we employ departs somewhat from existing research in that we measure total patent applications (whether granted or not) rather than a count of patent applications that were later granted. As a result, these counts likely upwardly approximate the number of patents that a firm ultimately receives. For instance, the EPO (2000) notes that European patent submissions have a 67% success rate. Unfortunately, these data do not identify the firms or patents by name; therefore, we are unable to assess which patent applications were successful. A potential problem in assessing patent applications versus granted patents is that it may capture spurious applications filed by the focal firm. Nevertheless, because the patent application process is not costless, we expect that patent applications reflect a firm's belief that it has innovated. Therefore, a benefit of this measure is that it captures the number of innovations for which the firm believes it is worthwhile pursuing patent protection. That is, patent counts of applications filed and later granted may understate the number of innovations actually achieved by the firm.[8]

The mean value of this variable is 0.48, yet the maximum reaches the exorbitant value of 245. Although this value is much different than

8. Using a distributed lagged model the relationship between patent applications and R&D in these data follow a similar relationship between granted patents and R&D found by Hausman et al. (1984).

the average in the data, again, it is consistent with the other values reported by this company throughout the panel, and our interpretations are consistent when we exclude extreme values of this variable in sensitivity analyses.

5. Independent Variables

5.1 Export

Export status (EXPORT) was collected in the survey. This measure captures whether or not the focal firm sold to foreign markets in a given year. The variable EXPORT takes the value 1 if the firm exported in a given period, 0 otherwise. We complement this measure of status with one that captures the volume of trade. Grossman and Helpman (1991) suggest that the volume of trade is likely to covary with the intensity of interaction with destination markets. Therefore, we define EXPORT VOLUME as the natural log of total foreign sales (in thousands of Spanish pesetas plus one—to define this value for nonexporters).

Because knowledge takes time to filter back to the focal firm and be incorporated in its activities, the benefit of exporting may not be realized until future periods. For that reason, we lag the export status variable. Based on the length of our panel and prior research, we use lags of 1, 2, and 3 years (Bernard and Jensen, 1998, 1999; Clerides et al., 1998).

5.2 Control Variables

We control for firm size in event there is a relationship between innovation counts and size. Because exporters tend to be larger than nonexporters, by omitting this variable, a reported effect of exporting might capture a spurious effect based on size. Size is measured as the natural logarithm of total employees. We favor the use of employment for the size control given the expected reverse causality between product innovations and sales. For instance, we expect a company that launches many new products in a year to increase sales. Controlling for size with total employment is less likely to be as sensitive to this reverse relationship. For example, firms might have excess workforce capacity with which to produce new products.[9]

9. In sensitivity analyses, we included sales as the control for size. We found the pattern of results and values of the coefficient estimates consistent to what we find when using the employment control. The level of significance of exporting status was somewhat suppressed when product innovation was the dependent variable, but not when patent application was the dependent variable. This is consistent with our concern that sales are more sensitive than employment to a reverse causality interpretation where product innovation contemporaneously increases sales.

Similarly, scholars have long explored the association between R&D (as an innovative input) and innovative productivity (for a review see, e.g., Cohen and Levin, 1989). Therefore, we control for contemporaneous R&D spending by including R&D intensity as a control variable. The variable is defined as R&D expenditures divided by sales, expressed as a percentage. We favor including the intensity measure as a control because we control for size in the specification and R&D spending is highly correlated with size. Specifications that include both size and R&D in peseta amounts, report similar results with respect to the EXPORT variables. However, the coefficient estimates of size and R&D fluctuate across specifications, likely due to the collinearity of these variables. If we exclude the control for firm size and control for R&D in peseta amounts, we reach similar conclusions regarding our variables of interest.[10]

We expect consumer product-oriented firms to develop more new products. To control for this possibility we add advertising intensity (ADVERTISING) as a proxy for the firm's consumer orientation. Our expectation is that this variable captures the importance of firm product development, where advertising reflects greater focus on new products. This variable is defined as advertising expenditures divided by sales expressed as a percentage. Again, we favor the inclusion of the intensity measure due to the correlation between peseta values of advertising and sales. Because we measure this contemporaneously with the dependent variables, there is the possibility that a relationship between advertising and product innovation might be driven by a reverse causality. Namely, firms that have many product innovations in a given year increase their advertising activities.

6. Descriptive Results

We compare the innovative activity of exporting and nonexporting firms in Figures 1 and 2. Exporters consistently have greater average product innovation and patent application counts than their nonexporting counterparts. Although consistent with a learning-by-exporting argument, this effect should be interpreted with caution as it is solely illustrated contemporaneously. It does not assess if the direction of causality runs from innovation to exporting, vice versa, or both. Nor does it control for many other firm effects that we include in the multivariate analyses.

10. In specifications that we do not report, we assess the sensitivity of our results by including lagged values of R&D intensity as controls. The results do not change the interpretation of our variables of interest.

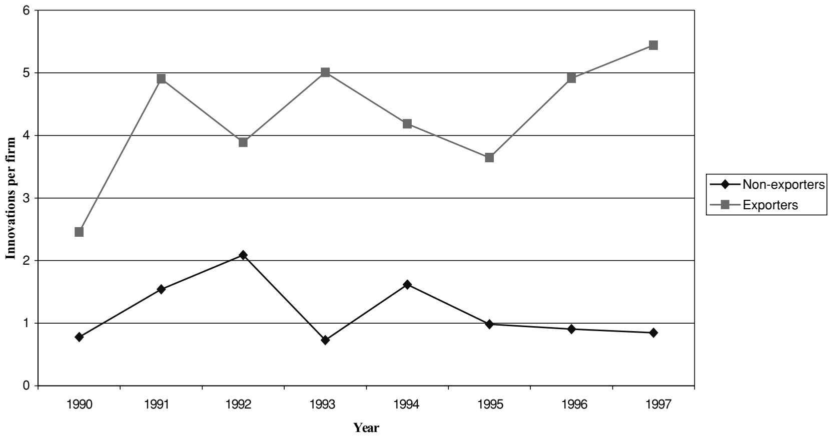

FIGURE 1. PRODUCT INNOVATION BY EXPORT STATUS

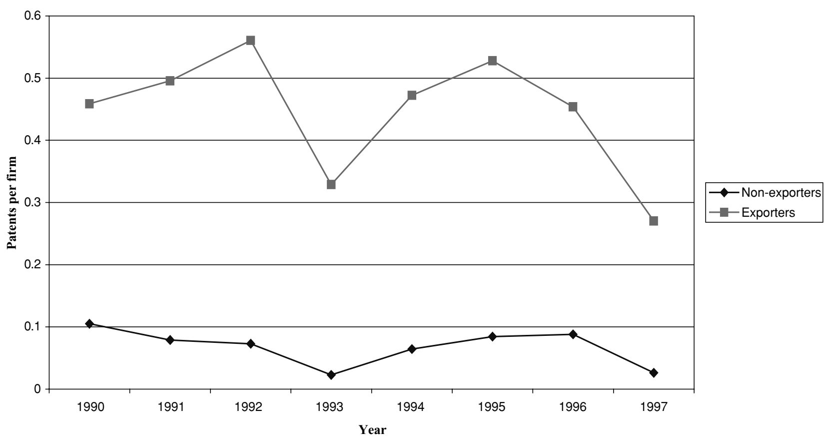

FIGURE 2. PATENTS BY EXPORT STATUS

Table II presents summary statistics and product moment correlations for the full sample. Although most correlations are as expected, a few merit some attention. First, we find positive correlations between lagged values of export status/volume and the dependent variables (Product Innovations and Patent Applications), which is consistent with our hypothesis of learning by exporting. However, the correlations also indicate that: (a) exporting firms are larger, (b) exporting firms have greater R&D and advertising intensities, (c) larger firms are more innovative, and (d) advertising and R&D intensity are positively related

TABLE II.
DESCRIPTIVE STATISTICS AND PRODUCT MOMENT CORRELATIONS

	1	2	3	4	5	6	7	8	9	10	11
1. Product Innovations$_{(t)}$	1										
2. Patent Applications$_{(t)}$	0.02	1									
3. Export Status$_{(t-1)}$	0.08	0.05	1								
4. Export Status$_{(t-2)}$	0.08	0.05	0.85	1							
5. Export Status$_{(t-3)}$	0.09	0.05	0.79	0.84	1						
6. Export Volume$_{(t-1)}$	0.08	0.07	0.96	0.86	0.82	1					
7. Export Volume$_{(t-2)}$	0.09	0.07	0.84	0.96	0.86	0.91	1				
8. Export Volume$_{(t-3)}$	0.09	0.07	0.78	0.84	0.96	0.87	0.91	1			
9. R&D Intensity$_{(t)}$	0.06	0.07	0.18	0.17	0.17	0.20	0.19	0.18	1		
10. Advertising Intensity$_{(t)}$	0.04	0.12	0.22	0.22	0.22	0.23	0.23	0.23	0.13	1	
11. Size$_{(t)}$	0.06	0.08	0.48	0.49	0.49	0.61	0.61	0.61	0.22	0.22	1
Mean	2.81	0.25	0.44	0.44	0.43	5.18	5.09	5.04	0.55	1.19	3.78
Standard error	23.36	3.94	0.50	0.50	0.50	6.05	6.04	6.02	1.92	2.68	1.41
Minimum	0	0	0	0	0	0	0	0	0	0	0
Maximum	950	245	1	1	1	18.44	18.16	18.79	41.90	44.90	9.57

to innovation. Therefore, to better understand the nature of these relationships, we turn to the multivariate analyses.

7. Statistical Approach

The approach that we take in assessing if there is learning by exporting is to regress our measures of innovation on lagged values of the export measures (i.e., EXPORT and EXPORT VOLUME). The dependent variables that we examine are count measures in that they can only take nonnegative integer values. Moreover, many of the observations are bunched close to 0, or equal to 0. We also expect that there exists substantial heterogeneity among firms in their innovation counts and patent applications, which is potentially a function of variables that we cannot measure.

In choosing the estimation procedure, we first considered Poisson or negative binomial models with random effects. However, these models assume that the unobserved effects are uncorrelated with the regressors. Given the nature of the question that we study, we did not want to impose such a restriction. Although a fixed effect estimator generally allows for the regressors and unobservables to correlate (e.g., Hausman et al., 1984; Cameron and Trivedi, 1986, 1998), fixed effect estimators for Poisson and negative binomial models assume that the regressors are strictly exogenous (e.g., Montalvo, 1997; Blundell et al., 2000). If the independent variables are predetermined (i.e., past shocks of the dependent variable influence the independent variables) or endogenously determined (i.e., current shocks affect the dependent and independent variables), then the results from this estimator will not be consistent.

Because we are concerned that positive shocks to innovation will be correlated with future exporting (e.g., existing research that shows that productivity precedes exporting), we expect that our focal independent variable is predetermined and not strictly exogenous. Therefore, to estimate the effect of exporting on innovation we employ the nonlinear GMM method discussed and implemented by Windmeijer (2002).

The underlying model of this estimation method takes the following form:

$$y_{it} = \exp(x_{it}\beta + \eta_i) + u_{it} = \mu_{it}\nu_i + u_{it}, \tag{1}$$

where $\mu_{it} = \exp(x_{it}\beta)$ and $\nu_i = \exp(\eta_i)$.

In this equation, y_{it} is the number of product innovations or patent applications achieved by firm i at time t; x_{it} is a matrix of explanatory variables (including the export variable of interest) for firm i at time t;

η_i is a firm fixed effect; and u_{it} is a disturbance term with expected value 0.

This model assumes that $\mathrm{E}(\eta_i u_{it}) = 0$; $\mathrm{E}(u_{it} u_{is}) = 0$, $s \neq t$; and x_{it} is predetermined (i.e., $\mathrm{E}(x_{it} u_{it+j}) = 0$, $j \geq 0$ and $\mathrm{E}(x_{it} u_{it-s}) \neq 0$, $s \geq 1$). Wooldridge (1997) proposed the following transformation (quasi-differencing) to eliminate the firm fixed effect:

$$q_{it} = \frac{y_{it}}{\mu_{it}} - \frac{y_{it-1}}{\mu_{it-1}}. \tag{2}$$

Under the assumption that x_{it} is predetermined (i.e., $\mathrm{E}(x_{it} u_{it+j}) = 0$, $j \geq 0$), the following moment conditions hold:

$$\mathrm{E}(q_{it} \mid x_{it-s}) = 0, \quad s \geq 1. \tag{3}$$

Windmeijer (2000) notes that the estimate of β goes to infinity if x_{it} contains only nonnegative values. He argues that this problem can be remedied by transforming x_{it} into deviations from its overall mean. Because the regressors in our model have this nonnegative property (e.g., export sales, R&D, advertising, employees), we use this approach. We employ the *ExpEnd* program to estimate this model (Windmeijer, 2002).

In addition to the export variable, we also treat R&D, advertising, and firm size as predetermined in our estimation because we expect past innovation shocks to influence all of these regressors. For example, past positive shocks in innovation likely increase the need for R&D—especially the development component (Montalvo, 1997); advertising—to promote the product; and employees—due to the likelihood of increased sales.

An advantage of this GMM estimator is that a slight modification to the moment conditions allows us to examine the sensitivity of the results to models that allow for linear feedback (i.e., a dynamic model). With the same variable definitions as above, the underlying specification of this model is

$$y_{it} = \gamma y_{it-1} + \mu_{it} \nu_i + u_{it}. \tag{4}$$

The Wooldridge quasi-differencing transformation for this dynamic process is

$$q_{it} = \frac{y_{it} - \gamma y_{it-1}}{\mu_{it}} - \frac{y_{it-1} - \gamma y_{it-2}}{\mu_{it-1}}. \tag{5}$$

Therefore, with predetermined explanatory variables (i.e., x's) the following moment conditions hold (Windmeijer, 2002):

$$\mathrm{E}(q_{it} \mid y_{it-s-1}, x_{it-s}) = 0, \quad s \geq 1. \tag{6}$$

8. Results

Table III reports the results from regressing product innovation counts on export status. In columns 3.1–3.3, we present results from models including firm fixed effects with predetermined regressors. In columns 3.4–3.6, we include the linear feedback effect as described above. All specifications include year dummy variables; however, we do not present them in order to focus on the variables of interest. To assess the overall performance of the models, we report p-values of the Sargan test, at the bottom of each column. The Sargan tests whether the moment conditions of the underlying model are valid, with the null hypothesis that they are valid. In order to test for residual serial correlation, we report p-values from first- and second-order autocorrelation tests as described by Windmeijer (2002). The presence of first-order serial correlation is inconsistent with the assumption underlying regressions with predetermined regressors; second-order serial correlation is inconsistent with the assumption underlying regressions with linear feedback.

In column 3.1, we present a model specification with the 1-year lagged export status variable.[11] The coefficient estimate of EXPORT in this specification is not statistically different from 0.[12] In column 3.2, we replace the 1-year lag of export with a 2-year lag. Due to the increased lag structure, the sample size reduces. The coefficient estimate remains positive in magnitude, and becomes statistically significant (albeit at the 10% level). Column 3.3 replaces the 2-year lag with a 3-year lag of export and suffers a further reduction in sample size due to the increase lag structure. The coefficient estimate of EXPORT in this column is again not statistically different than 0. In all cases, the Sargan test does not reject the null hypothesis that the moment conditions are valid ($p < 0.05$). However, columns 3.2 and 3.3 suggest that first-order serial correlation persists even after including firm effects ($p < 0.05$) and that the model might be misspecified. In both columns, the serial correlation is negative.

We assessed if the change in coefficient estimate and significance levels in column 3.2 was driven by the reduction in sample size compared to that in columns 3.1 and 3.3. We examined the 1-year lag of exporting with the reduced sample in column 3.2 and found comparable results to those presented in column 3.1. With the sample in column 3.3,

11. Because the moment conditions for this estimator are $\mathrm{E}(q_{it} \mid x_{it-s}) = 0,\ s \geq 1$, we use further lagged values of exporting as instruments for the lagged export variables that we present in the table.

12. The results reflect output from one-step GMM estimates. Although not as efficient as the two-step estimates, one-step estimates are more reliable for finite sample inference because the standard errors of the two-step procedure are generally downwardly biased (see Arellano and Bond, 1991; Windmeijer and Bond, 2002).

TABLE III.
PRODUCT INNOVATION RESULTS: GMM ESTIMATES

Dependent Variable = Product Innovations$_{(t)}$	3.1	3.2	3.3	3.4	3.5	3.6
Product Innovations$_{(t-1)}$				−0.765***	−0.633***	−0.202
				(−3.43)	(−3.16)	(−1.27)
Export$_{(t-1)}$	0.379			0.599**		
	(0.62)			(1.85)		
Export$_{(t-2)}$		0.919*			0.934**	
		(1.35)			(2.04)	
Export$_{(t-3)}$			0.362			0.415
			(0.61)			(0.73)
R&D Intensity$_{(t)}$	0.377*	0.324**	0.494	0.037	0.055*	0.425
	(1.54)	(1.77)	(1.22)	(1.01)	(1.28)	(1.12)
Advertising Intensity$_{(t)}$	0.133	0.092	0.124	−0.072**	−0.082**	0.070
	(0.95)	(0.60)	(0.61)	(−1.73)	(−2.17)	(0.34)
Size$_{(t)}$	−0.128	−0.348	−0.253	−0.012	−0.017	−0.214
	(−0.44)	(−1.19)	(−0.99)	(−0.05)	(−0.06)	(−0.88)
n	6,359	4,792	3,471	4,792	4,792	3,471
Sargan test (p-value)	0.06	0.10	0.11	0.26	0.13	0.28
First-order autocorrelation (p-value)	0.28	0.01	0.00	0.41	0.41	0.38
Second-order autocorrelation (p-value)	0.55	0.22	0.22	0.08	0.05	0.13

t-values in parenthesis below coefficient estimates.
***p-value < 0.01 (one-tailed test).
**p-value < 0.05.
*p-value < 0.10.
Year dummies included but not presented.

again we found that the 2-year lag of export status was positive with a comparable level of statistical significance. Finally, we included all three lags of export status in one specification. Despite high collinearity, we found a positive and significant effect of the 2-year lag.

In order to explore whether the residual serial correlation biases the results, we employ the dynamic model specification in columns 3.4–3.6. Specifically, we add a 1-year lag of the dependent variable into the specification and use the moment conditions described in equation (6). We find that the effect of the lagged dependent variable is negative and significant in all specifications, which is consistent with the negative serial correlation in columns 3.1–3.3.[13] Because of the nonlinear functional form, and with the dependent variable being bound at 0, our interpretation of a negative lagged dependent variable is that firms with positive innovation counts in 1 year often realize zero counts in the following year—once controlling for firm effects. Corroborating this interpretation, when we estimate models without firm effects and with linear feedback we find that the lagged dependent variable is positive and significant in all cases. Furthermore, the Sargan test and the tests of serial correlation in columns 3.4–3.6 suggest that the moment conditions are valid, and that the model is well specified.

We return now to our variables of interest. Column 3.4 includes the 1-year lagged export status variable in a dynamic specification. The coefficient estimate of EXPORT in this specification is positive and statistically different from 0. However, we should be careful in interpreting this result in comparison to column 3.2 because the sample size is reduced in column 3.4.[14] In column 3.5, we replace the 1-year lag of export with a 2-year lag. The coefficient estimate remains positive and increases in both magnitude and level of significance. Column 3.6 replaces the 2-year lag with a 3-year lag of export. The coefficient estimate of EXPORT in this column is not statistically significant.

The results in Table III along with the sensitivity analyses suggest that firms do realize increased product innovation after exporting and that this effect is most pronounced 2 years after the commencement of exporting. This finding is consistent with learning by exporting. An alternative explanation for the relationship centers on the definition of the product innovation dependent variable. The variable is defined

13. Blundell et al. (2000) similarly find a negative effect of a lagged dependent variable using a comparable linear feedback model.

14. Because the moment conditions for this estimator are $E(q_{it} \mid y_{it-s-1}, x_{it-s}) = 0, s \geq 1$, the sample size reduces in column 3.4 (to equal that in column 3.2) when we introduce the dynamic specification. This occurs because we use further lagged values as instruments. Samples from model specifications in columns 4.4, 5.4, and 6.4 in Tables IV, V, and VI, respectively, likewise reduce to equal those in columns 4.2, 5.2, and 6.2.

to include all product improvements and modifications. Because firms might modify products for export markets, the results might potentially capture this effect. However, using a lagged value of EXPORT somewhat mitigates this concern because firms will most likely record product modifications required to commence exporting in the year that they first export. Likewise, the fact that the magnitude of this effect strengthens in the 2-year lag versus the 1-year lag is not entirely consistent with such an interpretation.

In addition, the increase in product innovation soon after exporting is consistent with other results in the exporting literature. Bernard and Jensen (1999) find that exporting plants' sales grow very quickly immediately after exporting and subsequently grow at a slower rate. Our results, combined with their observations, suggest that part of this sales growth might stem from new product modifications and launches.

The results for our analysis of patent applications appear in Table IV. Again, year dummy variables were included in all specifications, but not presented in order to focus on the variables of interest. Column 4.1 presents the specification with the 1-year lagged variable of export status. We find a positive and significant relationship between this variable and patent applications. A 2-year lag replaces the 1-year lag of export status in the specification presented in column 4.2. In this specification, the export status variable becomes larger in both magnitude and statistical significance. As we noted previously, the sample size also reduces due to the increase in the lag structure. Finally, in column 4.3, the 3-year lag of export status replaces the 2-year lag in column 3. In this specification, the coefficient estimate increases in magnitude again and remains statistically significant. In all specifications, the Sargan test does not reject the null hypothesis that the moment conditions are valid ($p < 0.05$); however, the serial correlation tests in columns 4.1 and 4.3 indicate the presence of first-order serial correlation ($p < 0.05$). As in the previous table, the estimates of serial correlation are negative.

As before, we assessed if the results across columns were driven by the different sample sizes. We found no effect of such. When we regressed patent applications on the 1-year lag of export status using the samples in columns 4.2 and 4.3, we found an effect where the coefficient estimate and statistical significance were of similar magnitude to that in column 4.1. Further, when we regressed patent applications on the 2-year lag of export using the sample in column 4.3, we found a positive and statistically significant result. This is consistent with the result presented in column 4.2. Finally, we included all lagged variables of export in one specification. Although all the coefficient estimates were

Table IV. Patent Application Results: GMM Estimates

Dependent Variable = Patent Applications$_{(t)}$	4.1	4.2	4.3	4.4	4.5	4.6
Patent Applications$_{(t-1)}$				−0.217	−0.126	−0.120
				(−1.17)	(0.65)	(−0.51)
Export$_{(t-1)}$	1.065***			1.001**		
	(2.69)			(2.50)		
Export$_{(t-2)}$		1.190***			1.231***	
		(2.48)			(2.74)	
Export$_{(t-3)}$			1.496***			1.522***
			(2.75)			(2.72)
R&D Intensity$_{(t)}$	0.374*	0.520*	0.360**	0.620**	0.494*	0.382*
	(1.43)	(1.43)	(1.70)	(2.06)	(1.57)	(1.41)
Advertising Intensity$_{(t)}$	0.189*	0.150**	0.158	0.201*	0.156**	0.191*
	(1.56)	(1.70)	(1.23)	(1.57)	(1.84)	(1.58)
Size$_{(t)}$	0.452***	0.180	0.040	0.315**	0.116	0.004
	(2.56)	(0.92)	(0.15)	(1.81)	(0.66)	(0.02)
n	6,359	4,792	3,471	4,792	4,792	3,471
Sargan test (p-value)	0.41	0.47	0.64	0.31	0.36	0.54
First-order autocorrelation (p-value)	0.01	0.05	0.03	0.31	0.15	0.44
Second-order autocorrelation (p-value)	0.23	0.07	0.87	0.07	0.23	0.63

t-values in parenthesis below coefficient estimates.
***p-value < 0.01.
**p-value < 0.05.
*p-value < 0.10.
Year dummies included but not presented.

directionally consistent, we did not find statistical significance for any of the lags—likely due to collinearity.

We introduce linear feedback to the patent application specification in columns 4.4–4.6. Across those columns, the Sargan test does not reject the null hypothesis that the moment conditions are valid ($p < 0.05$). Likewise, the tests of serial correlation do not reject the null of no autocorrelation ($p < 0.05$). As in Table III, we find that the lagged dependent variable is negative; however, unlike product innovations, the effect is not statistically different than 0. With regard to the independent variables of interest, we find results similar to those presented in columns 4.1–4.3. Specifically, the effects of lag export status increase in magnitude from columns 4.4 through 4.6.

These results suggest that the information exporters gather from the foreign market facilitates innovation in the form of increased patent activity. Moreover, this result is consistent with the time delay that we would expect for such an effect. Namely, the magnitude of this effect increases as the lag increases to 3 years. This is in contrast to the results for product innovation, where the effect is most strongly manifest in the 2-year lag. The difference in lag structure is consistent with our expectation of how information flow from the foreign market would differently manifest itself in these two measures. Specifically, technological knowledge or knowledge that would foster patentable innovations takes longer to filter back and be beneficial to the exporting firm than product related knowledge that can foster product modifications relatively quickly.

Altogether, the results presented in Table IV provide further support for learning by exporting. Moreover, because the patent measure captures the number of applications filed for protection in Spain, the result implies that exporting makes the firm more innovative in ways that are valued in its home nation. Thus, information that passes from the host environment to the focal firm encourages the firm to innovate in ways that are useful in the domestic market. The lagged nature of the effect of exporting on patent applications might aid in reconciling the results that we present with existing studies which show that exporting is not associated with productivity improvements. Should the effects of exporting manifest in patent applications 2 or 3 years after exporting commences, the innovations that drive the patent applications might not be fully implemented to the production function within that time period. Therefore, any productivity increase might take longer than the 3-year window that has currently been examined in the extant research.

An alternative explanation that would reconcile the results stems from the fact that we measure patent applications rather than patents granted. It could be possible that exporters believe that they benefit from knowledge access by exporting and as a result file for patents. However, their assessment of the benefit of exporting is not realized and the patent applications are not granted. Under this condition, productivity might not improve because there is no unique innovation. The direct test of this explanation would be to assess if exporting firms are less likely to have their patent applications approved. Unfortunately, the data we have at our disposal are not suited to perform that test.

In Tables V and VI, we reestimated the results substituting the exporting dummy variable with export volume. This provides another assessment of whether interaction with foreign agents leads to greater knowledge spillovers and enhanced learning because we measure the level of the interaction with foreign markets by the EXPORT VOLUME variable. We find results that are largely consistent with those previously presented.

Table V presents the specification where PRODUCT INNOVATION serves as the dependent variable. In contrast with the previous results, we find that the 1-year lag of export volume is positive and statistically significant in column 5.1. In column 5.2, we find that the coefficient estimate of the 2-year lag of export volume is positive and significant, with a magnitude larger than in column 1. As in Table III, the effect of the 3-year lag remains nonsignificant. The results in columns 5.4–5.6 are analogous to those presented in Table III. However, we do find evidence that second-order serial correlation persists in columns 5.5 and 5.6 ($p < 0.05$). We surmise that the model is better specified with export status in lieu of export volume.

Table VI presents the results where PATENT APPLICATION serves as the dependent variable and EXPORT VOLUME as the focal independent variable. Consistent with the previous results, the 1-year lag is positive and significant across both specifications (i.e., columns 6.1 and 6.4). Likewise, the 2- and 3-year lagged values of export volume take positive and significant coefficient estimates. Once again, the magnitude of this coefficient estimate increases from the first to the third lag. Therefore, the results in this table confirm the previous results that show a stronger effect of exporting on patent applications with lags of 2 or 3 versus 1 year. Altogether, the consistency of the results across specifications provides some support for the learning by exporting hypothesis.[15]

15. For robustness, we checked all results presented herein against the Hausman et al. (1984) conditional negative binomial fixed effects model and negative binomial models without firm effects. Although the coefficient estimates and level of significance varied across some specifications, the results with respect to the variables of interest are consistent. As such, our inferences do not change.

TABLE V.
PRODUCT INNOVATION RESULTS: GMM ESTIMATES

Dependent Variable = Product Innovations$_{(t)}$	5.1	5.2	5.3	5.4	5.5	5.6
Product Innovations$_{(t-1)}$				−0.745***	−0.533***	−0.370**
				(−3.97)	(−4.32)	(−2.15)
Export Volume$_{(t-1)}$	0.066*			0.068***		
	(1.31)			(2.34)		
Export Volume$_{(t-2)}$		0.100**			0.101**	
		(1.90)			(2.13)	
Export Volume$_{(t-3)}$			0.033			0.047
			(0.59)			(0.91)
R&D Intensity$_{(t)}$	0.342**	0.266**	0.474	0.034	0.097**	0.112**
	(1.61)	(2.03)	(1.19)	(1.25)	(2.18)	(2.04)
Advertising Intensity$_{(t)}$	0.143	0.102	0.127	−0.075**	0.101	0.052
	(0.96)	(0.58)	(0.63)	(−2.14)	(0.41)	(0.21)
Size$_{(t)}$	−0.173	−0.421*	−0.248	0.047	−0.036	0.137
	(−0.70)	(−1.46)	(−0.92)	(0.17)	(−0.09)	(0.34)
n	6,359	4,792	3,471	4,792	4,792	3,471
Sargan test (p-value)	0.05	0.09	0.09	0.21	0.03	0.51
First-order autocorrelation (p-value)	0.31	0.01	0.00	0.43	0.48	0.88
Second-order autocorrelation (p-value)	0.57	0.20	0.20	0.05	0.01	0.03

t-values in parenthesis below coefficient estimates.
*** p-value < 0.01
** p-value < 0.05.
* p-value < 0.10.
Year dummies included but not presented.

Table VI.
Patent Application Results: GMM Estimates

Dependent Variable = Patent Applications$_{(t)}$	6.1	6.2	6.3	6.4	6.5	6.6
Patent Applications$_{(t-1)}$				−0.222	−0.117	−0.037
				(−1.26)	(−0.60)	(−0.20)
Export Volume$_{(t-1)}$	0.101***			0.092**		
	(2.82)			(2.57)		
Export Volume$_{(t-2)}$		0.114***			0.114***	
		(2.38)			(2.64)	
Export Volume$_{(t-3)}$			0.138***			0.136***
			(2.73)			(2.77)
R&D Intensity$_{(t)}$	0.430*	0.441	0.381*	0.659**	0.441*	0.390
	(1.49)	(1.11)	(1.35)	(1.93)	(1.30)	(1.26)
Advertising Intensity$_{(t)}$	0.180*	0.121*	0.122	0.188*	0.111**	0.140
	(1.35)	(1.42)	(1.04)	(1.41)	(1.45)	(1.27)
Size$_{(t)}$	0.514***	0.139	0.069	0.368**	0.097	0.063
	(3.05)	(0.65)	(0.27)	(2.13)	(0.51)	(0.25)
n	6,359	4,792	3,471	4,792	4,792	3,471
Sargan test (p-value)	0.42	0.50	0.67	0.32	0.43	0.64
First-order autocorrelation (p-value)	0.01	0.08	0.03	0.27	0.13	0.26
Second-order autocorrelation (p-value)	0.18	0.10	0.87	0.05	0.27	0.79

t-values in parenthesis below coefficient estimates.
***p-value $<$ 0.01.
**p-value $<$ 0.05.
*p-value $<$ 0.10.
Year dummies included but not presented.

9. Alternative Explanations and Robustness

Even though the results presented are consistent with the learning by exporting hypothesis, we consider alternative interpretations to evaluate the veracity and assess the robustness of these findings. Generally, the results might be misleading if some underlying latent variable drives the relationship between exporting and innovation. For instance, if an omitted variable such as market growth induces firms both to export and innovate, then we may find a spurious correlation between exporting and innovation. Likewise, if "intranational" spillovers are more prevalent than international spillovers for this set of firms, and "intranational" spillovers increase concurrently with export activity, then we may mistakenly interpret increased innovation as evidence of learning rather than a result of domestic spillovers. Although the existence of an underlying latent variable as an alternative explanation cannot be fully dismissed, we have taken steps to mitigate the potential for this type of spurious relation by controlling for unobserved firm heterogeneity, by considering the effect of different lagged values of the focal independent variable, and by employing an estimator that can accommodate predetermined regressors.

Of particular concern is the possibility that reverse causality running from innovation to exporting manifests in the lagged export variable. Spurious relationships of this sort arise because residual serial correlation in the error persists even after controlling for firm effects and predetermined regressors. This might occur because the dependent variables follow a dynamic process whereby current realizations of innovation depend upon past realizations rather than some stable firm effect. To more directly assess this alternative explanation, we estimated models that explicitly consider such dynamics. Although we do not find evidence of pervasive or persistent serial correlation across specifications, there were some models in which we did find residual autocorrelation. We therefore acknowledge that our model may not adequately control for such dynamics; and although we have done our best given the data limitations, our results may still suffer from omitted variable bias.

Finally, although the firm effects subsume industry variance provided that firms do not switch industries over time throughout the sample period, we explored industry variance and the structural stability of our parameters. We find results to be robust to the inclusion of industry fixed effects in lieu of the firm effects. Although variance across industries exists, the general pattern of results remains largely unchanged. Unfortunately, because of sample size reductions, we were unable to run models similar to those that we present on an industry-by-industry basis.

10. Discussion and Conclusion

Although extant research demonstrates that productive firms are likely to become exporters, there has been little evidence of the reverse relationship. This has led scholars to conclude that little learning accrues to firms that engage in exporting. We argue that using innovation as a measure of learning provides a more direct appraisal of the phenomenon, and that firms can strategically access foreign knowledge bases and increase innovation through exporting activities. Consistent with this argument, we find that exporting is related to *ex post* increases in two measures of firm innovation—product innovations and patent applications.

We find that exporters increase their patent applications subsequent to exporting. In addition, this effect is more pronounced with further lags. We also find evidence that exporters increase product innovations. This effect, in comparison, is most pronounced 2 years subsequent to exporting. These results speak to the time-bound nature of knowledge transfer. For instance, results for product innovations suggest that exporting firms gather and process consumer feedback fairly quickly, and that this subsequently results in the tailoring of products to meet the needs of heterogeneous foreign consumers. By contrast, the results suggest that technological information received from foreign sources takes longer to spill back for patents than for product innovations. It takes time for firms to incorporate the technological knowledge needed to realize patents.

Although these results are consistent with learning by exporting, we highlight two caveats. First, we discuss the learning benefits associated with export activity; however, learning is an inherently complex concept. Trying to gauge whether a firm learned can be a particularly daunting task. It could simply be that events missing from this empirical analysis, that take place concurrently with exporting, actually lead to the innovation. We have taken steps to mitigate the possibility that some underlying latent effect of this sort leads firms to both export and innovate. However, we cannot fully rule out the possibility that results are driven by omitted variables. Although we have found evidence consistent with learning, we cannot be sure that the results are, *de facto*, a result of learning.

Second, although our empirical design controls for stable industry factors influencing the dependent variables through the firm fixed effect, we do not explicitly investigate variance across industries. Industries are neither homogeneous in technology stock nor in export behavior. As such, learning by exporting is likely not uniform across industries. In some industries learning from exporting might be pronounced, while in others the learning benefits might be relatively muted. Future work could examine such heterogeneity in export patterns to determine the industries in which exporting matters most, and the economic convergence literature might help inform such work (e.g., Ben-David and Loewy, 1997; Guillen, 2001). At the macro level, this literature suggests that less developed nations stand to gain more from trade than their developed counterparts. At the industry level, that insight may manifest as export firms in technologically weak industries learning at a faster rate than export firms in technologically strong industries. We may therefore expect the magnitude of the coefficient to be greater in industries in which Spain is a technological laggard (e.g., electrical accessories and materials) than in those in which Spain is a technological leader (e.g., leather and footwear). Although exploring such industry heterogeneity certainly represents an important question, this is outside the scope of the current study, and our data are not well suited to examine such a hypothesis given the requirements of the econometric approach that we employ. Nevertheless, questions such as these present interesting avenues for future research.

Ultimately, further corroboratory research is needed before stronger conclusions can be drawn; but these limitations notwithstanding, our results suggest that exporting is more than just an activity to increase the scope of a company's product market. It is an activity that may generate information that the firm can use to innovate. Therefore, exporting can be considered a strategic action through which firms can enhance their competitive position. In fact, the results on patent applications in Spain suggest that firms may use the knowledge acquired abroad to increase their competitive position at home.

Rather than concluding that all firms should consider exporting in order to enhance their innovation, we want to stress that combining our results with the existing literature highlights that the effect is likely contingent. Learning by exporting is predicated on the firm receiving information from foreign customers and export intermediaries. This, in turn, tends only to occur if the firm is able to sell its products in the foreign market or gain access to export intermediaries. Firms will often need enhanced productivity in order to be competitive in the face of transportation and product adaptation costs. Should they lack this competitiveness, it is unlikely that they will be able to effectively compete in export markets and this in turn will limit the flow of knowledge. As a result, the strategy of engaging in exporting to enhance innovation will likely not be optimal for all companies.

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