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Does knowledge spill to leaders or laggards? Exploring industry heterogeneity in learning by exporting

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Abstract

In recent years the international trade literature has focused on the effects of exporting and its benefits in an open economy. Scholars note that engaging in trade enhances knowledge spillovers, and results in income growth and income convergence among trading partners. Although the macro-literature has long addressed economic convergence, there has been relatively little research examining the effect of exporting on *ex post* firm performance. Likewise, there has been little research that examines the differential learning-by-exporting effects across industries. In this paper we build upon the convergence literature to argue that engaging in exporting provides firms, especially firms in technologically lagging industries, the opportunity to benefit disproportionately from knowledge spillovers. Using a sample of Spanish manufacturing firms from 1990 to 1997, we investigate empirically how exporting differentially influences the innovative outcomes of firms in technologically leading *vs* lagging industries. We find evidence that firms in technologically lagging industries (in which Spain lags the global technology frontier) learn more from exporting than those firms in technologically leading industries (in which Spain is at, or near, the global technology frontier). The results enrich the traditional convergence argument by suggesting that industry heterogeneity matters to knowledge transfer, and stands to play a substantial role in reducing knowledge gaps.

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INTRODUCTION

Theoretical work in the international trade literature proposes that open economies benefit nations through enhanced growth. Corroborating, empirical results suggest that trade openness leads to income growth and fosters income convergence among trading partners. The purported mechanism that acts as an engine to such convergence is the learning that occurs as a result of engaging in trade. That is, the exchange of tangible goods facilitates the bidirectional exchange of intangible knowledge across borders, and the learning that results helps decrease technological and income heterogeneity across nations (for a review see Grossman & Helpman, 1991a, b).

Although the macro-literature suggests that countries can benefit from an open economy, what remains less clear is whether, and how, exporting improves firm performance. Little research has been directed at the potential for firm-level learning from exporting. Moreover, to the extent that such firm-level learning exists, we understand little about the conditions that moderate these effects. The purpose of this study therefore is to examine learning from exporting arguments at the micro level by exploring whether industry heterogeneity moderates the relationship between exporting and innovation. In particular, as the macro-level development literature suggests, do firms from technologically lagging industries learn more from exporting than firms from technologically leading industries?

In order to test this argument, we examine the export behavior and *ex post* innovative outcomes of a sample of Spanish manufacturing firms from 17 distinct industries over the period 1990–1997. In order to explore the moderating effects of industry characteristics, we distinguish technologically leading industries from technologically lagging industries. We define the latter as those industries in which Spain lags the global technological frontier – that is, is at a comparative disadvantage *vis-à-vis* the rest of the world. We define the former as industries in which Spain is at, or near, the global technological frontier – that is, is at a comparative advantage *vis-à-vis* the rest of the world. We regress firm-level patent application counts (our dependent variable) on exporting across both sets of industries. We find that exporting is associated with the *ex post* increase in innovative productivity for firms in both technologically leading and technologically lagging industries; moreover, the results provide support for the convergence claim. Notably, firms from technologically lagging industries apply for more patents subsequent to exporting than firms in technologically leading industries. We interpret this finding as evidence that firms from technologically lagging industries learn from exporting at a faster rate than firms from technologically leading industries.

In the next section, we briefly review the convergence and learning-by-exporting literatures. Based on this review, we propose that firms in technologically lagging industries stand to learn more from exporting than those in technologically leading industries. We subsequently describe our method and the data we use to test such effects. The following section presents results. The final section concludes.

THEORY

Research in international trade has long emphasized the potential gains from trade. Recently, authors in this stream have highlighted the role that trade, and open economies, can play in the exchange of knowledge across borders. Grossman and Helpman (1991b) propose a formal model in which intangible ideas spill over through the exchange of tangible commodities. The assumption is that each country possesses a different stock of knowledge, and interaction through trade encourages this knowledge to spread among trading partners. The logic runs as follows. Trade opens a country to a distinct body of knowledge possessed by its trading partners. As that knowledge filters back to the domestic country and is incorporated into the domestic production function through technology transfer, the home country experiences higher growth. This phenomenon has been referred to as "learning by exporting" (for a review see Grossman & Helpman, 1991a).

Researchers assert that open economies foster the speed of knowledge transfer, and therefore should lead technological and income gaps between trading partners to shrink (Grossman & Helpman, 1994). However, there has been some debate in the literature as to whether developing or developed nations benefit more from trade. Feeney (1999) argues that both developed and developing economies stand to benefit equally from trade. Likewise, Ben-David and Loewy (1998) assert that free trade can reduce the income gap between developing and developed countries as well as among developed countries. By contrast, Grossman and Helpman (1991a) argue that trade openness allows developing countries access to the advanced technological knowledge that they lack, and hence to grow more rapidly. The greater the disparities between developing and developed countries, the more developing countries stand to benefit.

Following these fundamental insights, scholars have attempted to verify such phenomena empirically, and the focus has been predominantly at the macroeconomy level. The research question of interest has centered on whether countries can benefit from free trade (e.g., Edwards, 1993; Frankel & Romer, 1999). Although the results have been contentious, there seems to be some evidence that trade leads to income growth and convergence, and that developing countries stand to benefit from trade openness (for a review see Edwards, 1993; Slaughter, 1997). Research highlights the benefits of export-led growth policies for developing nations such as South Korea and Chile, which learned advanced knowledge from developed countries (Edwards, 1993; Guillén, 2001).

Although scholars have highlighted the potential for learning from exporting at the macroeconomy level, the empirical literature has just begun to examine these relationships at the firm level (e.g., MacGarvie, 2006; Salomon & Shaver, 2005a). Researchers have long recognized the importance of studying export behavior at the firm level; however, this stream has not received nearly the attention devoted to macro-level issues for two reasons. First, many research questions are concerned predominantly with macroeconomic factors – especially questions motivated by economic and legislative policymakers. Second, the data necessary to examine micro-level trade phenomena have been difficult to obtain.

In order to examine such effects at the firm level, scholars generally look to see whether total factor productivity increases after firms become exporters. Although some authors fail to find support for such productivity increases (e.g., Bernard & Jensen, 1999; Clerides, Lach, & Tybout, 1998; Delgado, Fariñas, & Ruano, 2002), others do find evidence consistent with learning (e.g., Aw, Chung, & Roberts, 2000; Blalock & Gertler, 2004; Ozler & Yilmaz, 2001). More recently, Salomon and Shaver (2005a) suggest that the mixed empirical findings might be a function of using productivity as the dependent variable. Those authors argue that in order to evaluate whether firms have learned, a better measure would directly assess that learning outcome. Because a variety of factors stand to influence the net effect of exporting on productivity, productivity effects can be difficult to tease out. Therefore firms' innovation productivity, rather than total factor productivity, may better capture the learning-by-exporting phenomenon. Using innovative productivity as the dependent variable, Salomon and Shaver (2005a) find a consistent increase in innovation for firms after they become exporters. Specifically, exporters tend to introduce more new product innovations very quickly after market entry, and file for significantly more patents several years after entry into export markets.

Although the empirical literature has begun to weigh in on learning-by-exporting issues at the firm level, we understand less about the heterogeneity that may exist in these learning benefits across industries. Industries, like countries, are not homogeneous in terms of their stock of knowledge (Ben-David & Loewy, 2000; Grossman & Helpman, 1991b). Because of historical endowments and factors of production, firms within countries specialize in various industrial activities, and over time relatively stable comparative advantages emerge (Porter, 1990). Consistent with such ideas, Aw and Hwang (1995) find the relationship between exporting and firm productivity in Taiwan to be highly dependent on product-specific environments. Aw et al. (2000) similarly find that productivity improved for Taiwanese firms in the textile and apparel industries after commencing exporting, but did not improve for firms in plastics, electronics, or transportation equipment industries.

If such industry heterogeneity exists, we would expect to find variance in learning outcomes across industries within the same country as in Aw et al. (2000). However, we believe that the heterogeneity in learning is likely to follow a more systematic pattern than unearthed in the aforementioned paper. Specifically, just as developing nations may stand to gain more from trading with developed nations, firms from technologically lagging industries (in which the home country industry lags the global technology frontier) may have more to gain from exporting than firms from technologically leading industries (in which the industry in the home country is already above, or near, the global technology frontier).

Prevailing logic suggests that, for firms in which the home country industry is at a relative disadvantage *vis-à-vis* the global technological frontier, interaction with export intermediaries, customers, and other agents provides exporting firms with an opportunity to benefit from advanced, industry-specific knowledge that does not exist in the home country. Firms that operate in industries in which their home country is a technological laggard are therefore exposed to technological knowledge in the destination country, from which they can gain technological insights that help them achieve innovation. By contrast, firms from home country industries that already are at, or near, the global technological frontier stand to learn less since they are exposed to the "state of the art" in their home environment. We therefore hypothesize that the greater the technological disparity between the home country industry and its potential export markets, the more a firm stands to learn from exporting. That is, we expect innovation rates to be greater for exporters from industries in which the home country is a technological laggard *vis-à-vis* the rest of the world compared with those in which the home country is a technological leader *vis-à-vis* the rest of the world. The next section describes our data and the empirical approach to test such effects.

DATA AND METHODS

Sample

The data we use in this study are from a yearly survey conducted by the Fundación Empresa Pública with the 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. Although the Fundación first administered the survey in 1990, and continues to do so, we were able to get access to the data from 1990 through 1997. The data cover the entire population of Spanish manufacturing 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. The initial sample included information on 2188 firms from 18 industries; however, in order to remain consistent with the additional data that we collected, we removed all firms from the sample that were classified into the "Miscellaneous Manufacturing" industry. We are therefore left with an initial set of 2137 firms from 17 distinct industries. We present the industry breakdown for the initial sample year in Table 1.

Although our initial sample comprised 2137 firms, when a firm drops from the sample in any given year, another of similar size, from the same industry, replaces it. This results in a base sample of 2957 firms. From the resultant 2957 firms we removed all 11 that reported engaging in foreign direct investment. For this set of firms there exist other, more direct, mechanisms to facilitate information exchange from outside the domestic market, and we do not want to spuriously attribute results from learning from foreign direct investment.[1] In addition, 3828 observations were missing data. Moreover, given an empirical approach in which we incorporate dynamics (we describe the method in detail below), we sacrifice an additional 7017 observations. Given this restriction, our usable sample reduces to 6543 firm–year observations from 1755 unique firms.

In order to complement the Fundación data, and to identify industries in which Spain is a technological laggard (leader) *vis-à-vis* the rest of the world, we collect R&D data from the OECD and GDP data from Global Insight. The OECD publishes yearly R&D figures from 27 of its member nations from 1987 to 1999. The GDP data are from 1980 to 1999. We describe our measures in the section that follows.

Dependent Variable

Since we attempt to measure the existence and the extent of learning by exporting, our dependent variable is innovative productivity. We proxy for innovative productivity using a count of patent applications. The survey administered by the Fundación Empresa Pública collects information on the number of patents applied for by the focal firm in a given year. Those seeking patent protec-

Table 1 Industry breakdown of the sample

Industry	*Number of firms*	*Percentage of total (%)*	*RDI average*	*Patent average*
1. Ferrous and non-ferrous metals	45	2.11	−0.23	0.17
2. Non-metallic products	161	7.53	−0.04	0.06
3. Chemical products	149	6.97	−0.99	0.44
4. Metallurgy and metallic products	223	10.44	−0.06	0.23
5. Agricultural machinery	125	5.85	−0.46	0.16
6. Office products and data processing	22	1.03	−0.15	0.30
7. Electrical accessories and materials	201	9.41	−1.44	0.39
8. Automobiles and motors	81	3.79	−0.61	0.16
9. Transport material	54	2.53	−0.22	0.09
10. Meat products	59	2.76	−0.16	0.04
11. Food and tobacco	229	10.72	−0.16	0.18
12. Beverages	53	2.48	−0.16	0.15
13. Textiles and clothing	249	11.65	−0.10	0.11
14. Leather and footwear	76	3.56	−0.01	0.06
15. Wood and wood products	146	6.83	−0.03	0.21
16. Paper and publishing	163	7.63	−0.07	0.22
17. Rubber and plastic products	101	4.73	−0.10	0.22
Total	2137	100.00		

tion 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 the EPC and aligned its national patent laws with prevailing European law on 20 March 1986 (Ulloa & 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 & Salas, 1993). While it costs more to file with the EPO, and the grant process takes longer (an average of 18 months for the EPO *vs* 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 PATENT APPLICATIONS captures the number of patent applications filed for protection in Spain, whether via the Spanish Industrial Property Registry or the via EPO.[2]

Patent data and patent counts have been used extensively in industrial economics research on technology and innovation as a measure of innovative productivity (e.g., Basberg, 1982, 1987; Comanor & Scherer, 1969; Henderson & Cockburn, 1994, 1996; Scherer, 1965). Authors have argued that patents accurately capture the intellectual property of the focal firm, and therefore serve as a direct and observable outcome of the innovation process (e.g., Archibugi & Pianta, 1996). Moreover, researchers have demonstrated how patent counts empirically capture an underlying, latent "innovation" construct. For example, Acs and Audretsch (1989), using both patent and product innovation counts as dependent variables, find a significant correspondence between results across many industries. Likewise, Hagedoorn and Cloodt (2003) demonstrate congruence among various measures of innovative performance such as patent counts, patent citations, and new product introductions. Taken together, these results indicate that patent counts can serve as a valid proxy for innovative productivity. Further, this manifestation of innovative productivity is consistent with measures of learning employed in the broader international business and innovation literatures (e.g., Cohen & Levin, 1989; Salomon & Shaver, 2005a).

Although patent counts have been shown to be valid indicators of innovative output, they are not without drawbacks. In particular, the propensity to patent is not constant across industries (Cohen & Levin, 1989; Griliches, 1990). It could therefore be argued that, because patents do not mean the same thing in each industry, they cannot be meaningfully compared across industries. However, as Griliches (1990) points out, with the proper controls, patents can still be used effectively in cross-industry studies. Because our data include a panel of firm-year observations from the Spanish economy at large, we incorporate lagged values of the dependent variable to control for industry, and firm, heterogeneity in patent behavior. We can therefore be more confident that our results capture the differential learning benefits across industries – and not simply patenting heterogeneity across firms or industries.

Independent Variables

Grossman and Helpman (1991b: 518) argue that exporting "tangible commodities facilitates the exchange of intangible ideas." Hence a measure of whether a firm has access to those ideas lies in whether or not it participates in export markets. 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, and zero otherwise. Because knowledge takes time to filter back to the focal firm, 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 one, two, and three years (Bernard & Jensen, 1999; Clerides et al., 1998; Salomon & Shaver, 2005a).

Research suggests that relative R&D expenditures can proxy for an industry's position in technological space (Buckley & Casson, 1976; Caves, 1996; Chung & Alcácer, 2002). R&D expenditures are a correlate of knowledge stock, and the technological position of industries in the home country *vis-à-vis* the rest of the world can be assessed by comparing them on the basis of their R&D investments (Porter, 1990). Therefore, in order to identify the industries in which Spain is a technological laggard (leader), we rely on industry-level R&D data published by the OECD in the ANBERD Database on Research and Development Expenditures. ANBERD contains data on 27 countries – the 30 OECD member countries excluding Austria, Luxembourg, and Switzerland – from 1987 to 1999. The R&D expenditures are reported at the four-digit industry level. Expenditures are expressed in millions of purchasing power parity equivalent US dollars. Because the Fundación data are at the three-digit ISIC level, we recoded the original OECD data, in accordance with the ISIC revision 3 (OECD, 2001), to match the 17 three-digit ISIC industries as reported in our data.

We then develop an index comparing the R&D expenditures in each of the 17 Spanish industries with those industries in other OECD countries. We calculate the index as follows. We begin by scaling the R&D expenditure in industry j from country k at time t by the GDP of country k at time t in order to eliminate size effects; we then average this R&D/GDP variable across all countries (other than Spain) at time t; we subsequently subtract the average R&D expenditure (scaled by GDP) of the OECD nations from the equivalent measure for Spain in industry j at time t.[3] We are left with a time-varying, industry-specific index comparing industries in Spain with those in the rest of the OECD on the basis of R&D expenditure.[4] Increasing values of the index indicate that Spain is a relative technological leader in a particular industry, whereas decreasing values indicate that Spain is a technological laggard in a given industry. This measure is consistent with prior empirical research in international business (e.g., Benvignati, 1990; Chung & Alcácer, 2002; Kravis & Lipsey, 1992). The following equation expresses this measure formally

$$RDI_{jt} = \frac{R_{jt}^{\mathrm{Spain}}}{GDP_t^{\mathrm{Spain}}} - \left[\sum_{k=1}^{n}\left(\frac{R_{kjt}}{GDP_{kt}}\right)\right] \times \frac{1}{n} \qquad (1)$$

where RDI_{jt} is the R&D index for the jth industry in year t; R_{jt}^{Spain} is the R&D expenditure of Spain in the jth industry in year t; R_{kjt} is the R&D expenditure for country k in industry j in year t; GDP_t^{Spain} is the GDP of Spain in year t; GDP_{kt} is the GDP of country k in year t; and n is the total number of OECD countries (excluding Spain).

In this paper we are interested in the moderating effects of RDI on the relationship between exporting and innovation. There are two general means to assess such moderation: either using multiplicative interaction terms, or creating subsample splits based on the median or mean of the variable of interest (for a review see Jaccard, Turrisi, & Wan, 1990). In this study we employ the latter technique. We do so because interpreting interaction terms in nonlinear regression formats is complicated by the underlying distribution of the dependent variable (in this case Poisson). We therefore split the sample into two groups using the median of RDI. We consider the industries above the median relative to be technological leaders, and those below the median relative technological laggards. We assess moderating effects by comparing the marginal effects of the coefficients across the two groups.[5]

Control Variables

Researchers have long considered the influence of firm size on innovative productivity (e.g., Schumpeter, 1942). Because exporters are generally larger than non-exporters, a reported effect of exports on innovation may spuriously capture the influence of size on innovation. We therefore control for firm size in order to diminish the potential for a size effect in these data. We define the variable SIZE as the natural log of total employees within the focal firm in a given year.

Scholars have similarly explored the influence of R&D inputs on innovative productivity (for a review see Cohen & Levin, 1989). We control for the effect of such R&D investments by including an R&D intensity measure. R&D INTENSITY is defined as R&D expenditures divided by total sales, expressed as a percentage.

Theories of firm-specific advantage suggest a link between a firm's intangible capabilities and its international business activity such as exporting (Caves, 1996; Salomon & Shaver, 2005b). Researchers typically proxy for such firm-level advantages using R&D and advertising intensities (e.g., Caves, 1996; Morck & Yeung, 1991, 1992). We therefore include ADVERTISING INTENSITY, in addition to R&D intensity, as a measure of a firm's marketing capabilities. The intuition is that firms that dedicate a greater proportion of their sales to advertising are likely to have a greater consumer orientation, and therefore an incentive to innovate more. We define ADVERTISING INTENSITY as advertising expenditures divided by sales expressed as a percentage.

Finally, research in international management points out that FDI parents make decisions with a greater global network in mind (e.g., Kogut, 1983; Prahalad & Doz, 1987; Rangan, 1998; Salomon & Shaver, 2005b). Parents may allow subsidiaries to operate as freestanding units in order to respond to local market conditions; alternatively, they can integrate the MNC under one roof for operating efficiency. For instance, an MNC may choose to conduct all R&D activities at the corporate headquarters and diffuse knowledge from one central point. In that case, we would expect headquarters to realize all innovative output. By contrast, a subsidiary might learn from its multinational network (either the parent or its affiliated subsidiaries). In such a case, the focal subsidiary could experience positive innovative benefits, and we would therefore capture learning from foreign ownership, yet erroneously attribute it to learning from exporting. In order to control for the way in which foreign ownership of the focal firm affects innovative productivity, we incorporate a measure of foreign capital participation (INWARD FDI). The variable is defined as the percentage of ownership held in the focal firm by foreign companies in a given year.[6]

Statistical Method

When selecting the appropriate multivariate method, we must take into account the nature of the dependent variable. Our dependent variable is a count measure that can take only non-negative integer values. Moreover, many of the observations are bunched close to zero. Authors suggest a Poisson regression model to deal with dependent count variables of this sort (Greene, 2003; Kennedy, 1998; Maddala, 1993). Myriad studies of innovation rely on this nonlinear estimation technique (e.g., Graves & Langowitz, 1993; Hausman, Hall, & Griliches, 1984). We therefore begin with a Poisson framework. Eq. (2) presents the probability density function of the Poisson distribution with parameter λ_i:

$$f(y_i|\mathbf{x}_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, \ldots \qquad (2)$$

This equation represents the probability that y_i will occur given a set of explanatory variables, where y_i is a scalar of the number of occurrences of a certain event, $\mathbf{x}_i$ is a vector of explanatory variables, and λ_i is a parameter of the function. Exogenous variables can be incorporated into the model by making λ a function of the covariates. This is expressed formally in the following equation:

$$\lambda_{it} = \exp(\beta_1 x_{i,t-p} + \beta_2 \mathbf{W}_{it}), \quad p = 1, 2, 3 \qquad (3)$$

where λ_{it} represents the expected number of innovations for firm i at time t, $x_{i,t-p}$ represents the exporting variable of interest for firm i at time $t-p$, and $\mathbf{W}_{it}$ is a vector of control variables. The βs are parameter estimates.

The Poisson regression is quite sensitive to its distributional assumptions. For instance, both the mean and the variance are assumed to be equal to λ. Should the mean and variance for the observed sample not equal λ, the likelihood function would be misspecified, leading to underestimation of standard errors and erroneous results.[7] The negative binomial regression allows for relaxation of the Poisson assumption that the mean and variance equal λ by introducing an individual unobserved disturbance to the model (e.g., Hausman et al., 1984; Henderson & Cockburn, 1996). Introducing the unobserved disturbance term to the Poisson model, Eq. (3) becomes

$$\lambda_{it} = \exp(\beta_1 x_{i,t-p} + \beta_2 \mathbf{W}_{it} + \varepsilon_{it}), \quad p = 1, 2, 3 \qquad (4)$$

where ε_{it} is the unobserved error term. In this model, ε_{it} is assumed to have a standard gamma distribution.

Given the panel data structure of our data, with several observations per firm, the possibility arises that ε_{it} will not be independent across time within firms. Otherwise stated, a systematic component may be embedded in the error, leading to serial correlation of residuals across observations within firms, and spurious regression results. Hausman et al. (1984) introduce a negative binomial model to control for firm-fixed effects of this sort; however, there has been considerable debate over whether this method effectively controls for individual effects (Allison & Waterman, 2002).

We therefore turn to a dynamic longitudinal model to deal with the potential for such serial correlation. We incorporate an INAR autoregressive process that includes lagged values of the dependent variable as regressors (Alzaid & Al-Osh, 1990).[8] Including firm dynamics provides three general benefits: first, it effectively reduces the potential for serial correlation of the errors; second, it allows for a dynamic component in the firm-specific effect rather than the static nature of most fixed effects; and third, to the extent that previous values of the dependent variable are associated with a firm's propensity to export, it controls for the possible endogeneity of exporting (Cameron & Trivedi, 1998; Greene, 2003). Because we use three-year lags of the independent variable of interest (exporting), we incorporate three lags of the dependent variable into every specification. We estimate the following model:

$$\lambda_{it} = \exp(\rho_1 y_{i,t-1} + \rho_2 y_{i,t-2} + \rho_3 y_{i,t-3} + \beta_1 x_{i,t-p} + \beta_2 \mathbf{W}_{it} + u_{it}), \quad p = 1, 2, 3 \tag{5}$$

where λ_{it} is the expected number of innovations for firm i at time t; y_{it-1}, y_{it-2} and y_{it-3} are the lags of the dependent variable for firm i at time t; $x_{i,t-p}$ represents the export status variable for firm i at time t; $\mathbf{W}_{it}$ is a vector of other explanatory variables; and u_{it} is an error term that we can now more confidently assume is free of serial correlation. The ρs and βs represent coefficient estimates.

RESULTS

Descriptive Statistics and Correlations

Table 2 presents descriptive statistics and a correlation matrix. Consistent with learning by exporting, we find positive correlations between each of the EXPORT lags and the dependent variable. Not surprisingly, R&D INTENSITY and ADVERTISING INTENSITY are also positively correlated with innovative outcomes. In addition, each of the EXPORT lags is positively correlated with R&D INTENSITY, ADVERTISING INTENSITY, and SIZE. This suggests that exporting firms spend more on R&D and advertising, and are generally larger than purely domestic firms.

The mean of the RDI variable is −0.32. This implies that, on average, Spanish industries tend to invest less in R&D in manufacturing industries than their OECD counterparts. Moreover, from Table 1, the average of RDI is negative across all industries. In fact, Spain is an ''absolute'' technological leader (RDI > 0) in only one industry (leather and footwear), and only for the years 1996 and 1997. Spain is an ''absolute'' technological laggard (RDI < 0) in all other industries during the sample period. Interestingly, RDI is negatively related to all manifestations of the dependent variable, and to firm-level R&D intensity. Although this is counterintuitive at first glance, it suggests that Spanish firms generally spend more on R&D, and innovate more, in those industries in which they are at a comparative disadvantage. Otherwise stated, Spain is a technological laggard in industries amenable to greater amounts of R&D expenditures and innovations.[9]

Surprisingly, RDI is negatively related to exporting. This suggests that, on average, Spanish firms from lagging industries are more likely to be exporters than Spanish firms from leading industries. At first glance, this result seems to contradict standard theories of international trade that suggest that countries export from a position of relative strength and comparative advantage (for reviews see Gandolfo, 1987; Helpman & Krugman, 1985). However, this negative correlation does not necessarily contradict such theories, as in these data RDI is negatively correlated with the overall worldwide trade intensity of the industries presented in Table 1. That is, those industries in which Spain is weaker (RDI is lower) are also those in which a greater proportion of worldwide trade occurs.[10]

Table 2 Descriptive statistics and correlations

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1. Patent applications$_{(t)}$	1.00											
2. Patent applications$_{(t-1)}$	0.36	1.00										
3. Patent applications$_{(t-2)}$	0.25	0.32	1.00									
4. Patent applications$_{(t-3)}$	0.29	0.22	0.32	1.00								
5. Export$_{(t-1)}$	0.07	0.08	0.08	0.09	1.00							
6. Export$_{(t-2)}$	0.07	0.07	0.09	0.09	0.86	1.00						
7. Export$_{(t-3)}$	0.10	0.07	0.07	0.09	0.80	0.86	1.00					
8. RDI$_{(t)}$	−0.05	−0.06	−0.05	−0.05	−0.13	−0.13	−0.13	1.00				
9. R&D intensity$_{(t)}$	0.10	0.12	0.11	0.10	0.18	0.19	0.19	−0.23	1.00			
10. Advertising intensity$_{(t)}$	0.07	0.07	0.06	0.05	0.19	0.20	0.20	−0.07	0.11	1.00		
11. Size$_{(t)}$	0.10	0.10	0.09	0.08	0.55	0.56	0.56	−0.20	0.21	0.22	1.00	
12. Inward FDI$_{(t)}$	0.04	0.03	0.03	0.03	0.35	0.35	0.35	−0.25	0.08	0.13	0.47	1.00
Mean	0.20	0.22	0.24	0.24	0.53	0.52	0.52	−0.32	0.64	1.36	4.17	16.74
s.d.	1.54	1.70	1.85	1.87	0.50	0.50	0.50	0.44	2.04	3.06	1.57	35.26
Min	0	0	0	0	0	0	0	−1.81	0	0	0	0
Max	92	92	92	92	1	1	1	0.01	63.70	48.00	10.14	100

Regression Results

The negative binomial regression results for the patent application dependent variable appear in Table 3. Again, we use median splits in order to explore the moderating effects of technological leadership on the exporting–innovation relationship (Jaccard et al., 1990). We label the industries in which Spain is below the RDI median (median=−0.119) as the ''relative'' technological laggard condition and the industries with values above the median as the ''relative'' technological leader condition.[11] The assumption inherent in considering these industries as ''relative'' leaders/laggards is that such a split meaningfully captures the proximity to the global technological frontier. That is, Spanish firms in industries that we characterize as ''relative'' technological leaders are closer to the global technological frontier than those that we consider as ''relative'' technological laggards. Therefore we should observe greater learning from exporting for the latter set of firms.

As we mentioned earlier, we control for unobserved firm heterogeneity by including an INAR(3) dynamic process into the model – for example, incorporating three lags of the dependent variable.

Table 3 Negative binomial regressions (median split) (Dependent variable=patent applications)

	Relative technological leaders				*Relative technological laggards*			
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
$Export_{(t-1)}$		0.834***				0.790***		
		(3.09)				(3.56)		
		[0.03]				[0.05]		
		{0.01}				{0.01}		
t-test of marginal effects from model 2 to model 6						1.05		
$Export_{(t-2)}$			0.743***				0.757***	
			(2.77)				(3.50)	
			[0.03]				[0.05]	
			{0.01}				{0.01}	
t-test of marginal effects from model 3 to model 7							1.12	
$Export_{(t-3)}$				0.670***				0.825***
				(2.54)				(3.85)
				[0.03]				[0.05]
				{0.01}				{0.01}
t-test of marginal effects from model 4 to model 8								1.51*
Patent $application_{(t-1)}$	0.549***	0.504***	0.508***	0.508***	0.625***	0.606***	0.600***	0.595***
	(4.00)	(3.78)	(3.75)	(3.74)	(7.28)	(7.31)	(7.20)	(7.21)
	[0.02]	[0.02]	[0.02]	[0.02]	[0.05]	[0.04]	[0.04]	[0.04]
Patent $application_{(t-2)}$	0.122	0.143	0.149	0.146	0.295***	0.290***	0.286***	0.289***
	(0.99)	(1.17)	(1.20)	(1.18)	(3.93)	(3.96)	(3.91)	(4.00)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]
Patent $application_{(t-3)}$	0.085	0.062	0.072	0.071	0.188***	0.156**	0.154**	0.145**
	(1.01)	(0.78)	(0.87)	(0.85)	(2.67)	(2.27)	(2.24)	(2.14)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
R&D $intensity_{(t)}$	0.186**	0.130	0.129	0.130	0.049*	0.040*	0.041*	0.039*
	(1.65)	(1.16)	(1.15)	(1.17)	(1.53)	(1.34)	(1.36)	(1.31)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
Advertising $intensity_{(t)}$	0.078	0.059	0.055	0.061	0.013	0.002	0.003	0.003
	(1.19)	(0.90)	(0.84)	(0.95)	(0.61)	(0.08)	(0.16)	(0.12)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Table 3 *Continued*

	Relative technological leaders				*Relative technological laggards*			
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
$Size_{(t)}$	0.381***	0.303***	0.303***	0.306***	0.275***	0.205***	0.210***	0.203***
	(4.40)	(3.39)	(3.36)	(3.38)	(4.88)	(3.47)	(3.58)	(3.46)
	[0.02]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]
Inward $FDI_{(t)}$	−0.005	−0.007**	−0.007*	−0.006*	−0.002	−0.003*	−0.003*	−0.003**
	(−1.18)	(−1.65)	(−1.64)	(−1.46)	(−1.15)	(−1.59)	(−1.60)	(−1.67)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Constant	−4.889***	−5.041***	−4.948***	−4.899***	−4.591***	−4.750***	−4.706***	−4.696***
	(−11.86)	(−12.03)	(−11.95)	(−11.90)	(−13.79)	(−13.94)	(−13.92)	(−13.94)
Year effects	Included	Included	Included	Included	Included	Included	Included	Included
N	3359	3359	3359	3359	3174	3174	3174	3174
Log-likelihood	−687.023	−682.208	−683.185	−683.774	−1069.019	−1062.666	−1062.870	−1061.624
$-2\Delta L$		9.630***	7.676***	6.498**		12.706***	12.298***	14.790***

*p<0.10; **p<0.05; ***p<9.01 (one-tailed tests).
t-statistics appear in parentheses ( ); marginal effects in brackets [ ]; variance of marginal effects in curly brackets { }.
Each specification includes year dummies as control variables.

Although not reported, we also include year dummies to control for time effects.

Columns 1 and 5 in Table 3 present base models with control variables only. For both sets of firms the one-year lag of patent applications has a positive and significant effect on current patent applications. This suggests that firms that applied for patents in the prior year apply for significantly more patents in the current year. Moreover, as we would expect, these effects tend to diminish over time: that is, the influence of current patent applications on future patent applications is strongest in the near term. SIZE is positive and significantly related to patent applications for both subsets of firms. Larger firms tend to apply for more patents. The results for R&D INTENSITY are mixed, though positive in directionality. The results for ADVERTISING INTENSITY are positive, but not significant. INWARD FDI is negatively related to patent applications.

In order to test our hypothesis, we introduce one-, two- and three-year lags of the exporting variable in columns 2, 3, 4, 6, 7 and 8. To determine whether or not there are statistically significant differences between the base models and the models including the lagged export variable, we employ the likelihood ratio test (Cameron & Trivedi, 1998). The likelihood ratio statistics comparing each export lag specification to the appropriate base case are reported at the bottom of the table. The differences in the log-likelihoods between the base models and all other models are statistically significant in every case ($p < 0.05$ in model 4 and $p < 0.01$ in all others).[12] This suggests that each of the models including a lagged value of exporting performs better in explaining a firm's innovative output than the base models alone. The change in likelihood ratio is greatest for the one-year export lag (column 2) in the technological leader condition, and for the three-year export lag (column 8) in the technological laggard condition. The specifications in columns 2 and 8 therefore fit the data best.

In all specifications in columns 2, 3, 4, 6, 7 and 8 we find a positive and significant relationship between previous exporting and current innovation. These results are consistent with a main effect of exporting on innovation, and suggest that exporting provides some learning benefits for all firms. This is consistent with recent literature suggesting that firms stand to gain from exporting (e.g., Salomon & Shaver, 2005a).

With regard to the moderating effects, our results imply some learning differences across the technological leader and technological laggard conditions. Specifically, for the technological leaders the one-year lag of the export status variable has the strongest statistical effect on patent applications, and this effect diminishes in statistical magnitude over time. By contrast, for firms in the technological laggard group, the three-year lag has the strongest statistical effect on current patent applications. In order to compare results across treatments, the standard approach is to use a comparison of coefficients (*t*-tests). However, using a simple comparison of coefficients (*t*-tests) in a nonlinear maximum likelihood framework can cloud interpretation owing to the inherent nonlinearity of the underlying p.d.f. function, and the specific location on the curve at which the coefficients are estimated. Therefore we calculate marginal effects across conditions and compare them by conducting a *t*-test of the calculated effects across the technological leader and laggard groups.[13] Although we find that the marginal effects of exporting on patent applications for the technological laggard group are consistently higher than those in the technological leader group, the *t*-test is significant only for the three-year lag. Specifically, for the three-year lag ($EXPORT_{t-1}$), we expect firms in the technological laggard group to gain an additional 0.02 of a patent (0.05–0.03) from exporting. This result implies a moderating effect of RDI on the exporting–patent application relationship, and also implies that firms in technologically lagging industries learn more from exporting.

The substantial correlations (see Table 2) among the one-, two- and three- year export lags indicate that there is within-firm persistence in export behavior over time. This begs the question of which lag is most explanatory as a determinant of innovative output across the technological leader and laggard conditions. We therefore ran models (not reported) including all three lags of export status in one specification. Despite high collinearity, we found positive and significant effects of the one-year lag for the technological leader condition and a positive and significant effect of the three-year lag for the technological laggard condition. Because technological knowledge takes time for firms to acquire, assimilate, and apply, the significant effect of the three-year lag in the technological laggard condition is more consistent with a learning story than the effect found in the technological leader condition. Because of the more contemporaneous impact of the effect, the latter is more subject to alternative interpretations. This provides additional support for our hypothesis that firms from technologically lagging industries learn more from exporting than those from technologically leading industries.

Additional Analyses

In addition to the results described above, we perform additional tests to examine differential learning effects across industries. In Table 4 we re-estimate the results presented in Table 3 using first and fourth quartile splits instead of median splits. This provides another assessment of whether interaction with foreign agents leads to greater knowledge spillovers and enhanced learning for firms in industries in which Spain lags the global technological frontier. If our hypothesis regarding how and why firms from technologically lagging industries stand to benefit accurately captures the phenomenon we examine, we should expect results that are stronger in economic significance for those firms in the technologically lagging condition, and results that are weaker in economic magnitude for those firms in the technologically leading condition. Comparing marginal effects across Tables 3 and 4, this is exactly what we find. Specifically, the evidence from columns 5–7 in Table 4 suggests that firms from industries in which Spain lags the global technological frontier by the greatest amount benefit the most from exporting. By contrast, the results in columns 2–4 suggest that firms from industries in which Spain is closest to the global technological frontier do not benefit from exporting. Moreover, for the one-, two- and three-year lags ($EXPORT_{t-1\sim3}$), the *t*-tests of marginal effects across conditions are highly significant. Taken together, these results provide further support for our hypothesis, and the underlying theoretical mechanism purported to drive that effect.[14]

We also analyze econometric specifications similar to those presented in Table 3 across the leather and footwear and electrical accessories and materials industries. The former is the industry closest to the global technological frontier (average RDI= -0.01) in the sample, and the latter is the furthest from the global technological frontier (average RDI=-1.44).[15] By conducting these additional tests, we can illustrate the effects that we describe in Table 3 in further detail, and gain a better understanding of how learning by exporting varies across specific industries. Further, these analyses help assess the robustness of our results to ensure that they are not an artifact of a given sample split.

Table 5 presents results across the two industries. In columns 2, 3, 4, 6, 7 and 8 we add lags of the export status variable. The coefficients for the lags of export status in columns 2, 3 and 4 (the technological leader condition) are positive but statistically insignificant. In contrast to the findings for the leather and footwear industry, the one- two- and three-year lag of export status in columns 6, 7 and 8 are positive and statistically significant for the technological laggard condition (the electrical accessories and materials industry). Comparing

Table 4 Negative binomial regressions (first *vs* fourth quartile split) (Dependent variable=patent applications)

Variable	*Relative technological leaders*				*Relative technological laggards*			
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Export$_{(t-1)}$		−0.193				0.995***		
		(−0.50)				(3.24)		
		[−0.01]				[0.07]		
		{0.01}				{0.02}		
t-test of marginal effects from model 2 to model 6						3.59***		
Export$_{(t-2)}$			−0.143				0.951***	
			(−0.37)				(3.19)	
			[0.00]				[0.07]	
			{0.01}				{0.02}	
t-test of marginal effects from model 3 to model 7							3.40***	
Export$_{(t-3)}$				−0.028				1.011***
				(−0.07)				(3.40)
				[0.00]				[0.08]
				{0.01}				{0.02}
t-test of marginal effects from model 4 to model 8								3.38***
Patent application$_{(t-1)}$	0.818***	0.826***	0.825***	0.820***	0.520***	0.529***	0.514***	0.519***
	(5.02)	(5.01)	(5.00)	(4.98)	(5.17)	(5.49)	(5.34)	(5.39)
	[0.02]	[0.02]	[0.02]	[0.02]	[0.05]	[0.05]	[0.04]	[0.04]
Patent application$_{(t-2)}$	−0.018	−0.019	−0.019	−0.018	0.298***	0.300***	0.298***	0.299***
	(−0.21)	(−0.21)	(−0.21)	(−0.21)	(3.85)	(3.97)	(3.96)	(4.00)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.03]	[0.03]	[0.03]	[0.03]
Patent application$_{(t-3)}$	0.123*	0.127*	0.125*	0.123*	0.120**	0.091*	0.091*	0.089*
	(1.29)	(1.32)	(1.31)	(1.29)	(1.81)	(1.44)	(1.45)	(1.42)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
R&D intensity$_{(t)}$	0.279**	0.297**	0.294**	0.282**	0.041	0.041*	0.041*	0.041*
	(2.00)	(2.06)	(2.02)	(1.93)	(1.24)	(1.30)	(1.33)	(1.32)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
Advertising intensity$_{(t)}$	−0.062	−0.051	−0.054	−0.061	−0.031	−0.035	−0.033	−0.035
	(−0.56)	(−0.45)	(−0.48)	(−0.54)	(−0.90)	(−1.02)	(−0.98)	(−1.02)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Size$_{(t)}$	0.468***	0.482***	0.478***	0.470***	0.358***	0.277***	0.274***	0.261***
	(3.88)	(3.88)	(3.85)	(3.78)	(4.62)	(3.44)	(3.40)	(3.21)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.03]	[0.02]	[0.02]	[0.02]
Inward FDI$_{(t)}$	−0.013**	−0.012*	−0.012*	−0.013**	−0.004**	−0.005**	−0.005**	−0.005**
	(−1.69)	(−1.61)	(−1.62)	(−1.67)	(−1.77)	(−2.13)	(−2.09)	(−2.03)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Constant	−5.966***	−5.948***	−5.962***	−5.966***	−4.394***	−4.769***	−4.683***	−4.671***
	(−8.15)	(−8.11)	(−8.14)	(−8.15)	(−10.65)	(−10.60)	(−10.65)	(−10.67)
Year effects	Included	Included	Included	Included	Included	Included	Included	Included
N	1798	1798	1798	1798	1682	1682	1682	1682
Log-likelihood	−311.045	−310.920	−310.976	−311.042	−686.556	−681.089	−681.314	−680.594
$-2\Delta L$		0.250	0.138	0.006		10.934***	10.484***	11.924***

*p<0.10; **p<0.05; ***p<0.01 (one-tailed tests).
t-statistics appear in parentheses ( ); marginal effects in brackets [ ]; variance of marginal effects in curly brackets { }.
Each specification includes year dummies as control variables.

marginal effects across the leather and footwear and electrical accessories and materials industries, we find that firms in the latter consistently benefit more from exporting. Although the results of the t-tests of marginal effects are not significant (probably because of the relatively small number of observations), the absolute size of the differences in marginal effects is greater than in Table 3 (0.07 greater for the one-year lag, 0.07 greater for the two-year lag, and 0.10 greater for the three-year lag).[16]

Taken together, the above results corroborate the findings from Table 3. We find that firms in technologically lagging industries consistently benefit more from exporting than firms in technologically leading industries.

Sensitivity and Robustness

In order to assess the robustness and sensitivity of the results, we tested several other variants of the models presented herein. First, because there is substantial heterogeneity in patent behavior across industries (see Table 1), the results may be biased to the extent that we are not adequately controlling for such heterogeneity. In this paper we attempt to control for industry heterogeneity in patent activity through the disaggregated, firm-level INAR(3) dynamic effect. We favored this approach over an industry-level INAR(3) patent variable because, aggregated to the industry level, firm variance on prior patent behavior subsumes industry variance. For example, if we aggregate all past patent applications in a given year of all firms in the

Table 5 Negative binomial regressions (Dependent variable=patent applications)

Variable	*Leather and footwear industry (leader)*				*Electrical accessories and materials industry (laggard)*			
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
$Export_{(t-1)}$		1.363				1.223**		
		(1.15)				(2.13)		
		[0.00]				[0.07]		
		{0.24}				{0.03}		
t-test of marginal effects from model 2 to model 6						0.26		
$Export_{(t-2)}$			0.286				1.156**	
			(0.31)				(2.05)	
			[0.00]				[0.07]	
			{3.86}				{0.03}	
t-test of marginal effects from model 3 to model 7							0.02	
$Export_{(t-3)}$				0.792				2.025***
				(0.85)				(2.91)
				[0.00]				[0.10]
				{1.30}				{0.04}
t-test of marginal effects from model 4 to model 8								0.08
Patent $application_{(t-1)}$	2.303***	2.103***	2.269***	2.340***	0.326***	0.327***	0.304***	0.319***
	(3.09)	(2.98)	(3.08)	(3.06)	(2.47)	(2.46)	(2.36)	(2.42)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.02]	[0.02]	[0.02]	[0.02]
Patent $application_{(t-2)}$	4.439***	4.509***	4.349***	4.492***	0.196*	0.191*	0.180*	0.175*
	(2.94)	(2.99)	(2.87)	(2.86)	(1.53)	(1.50)	(1.47)	(1.46)
	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Patent $application_{(t-3)}$	−25.165	−25.362	−33.703	−30.174	0.264***	0.185**	0.189**	0.153*
	(−0.01)	(−0.01)	(0.00)	(0.00)	(2.42)	(1.74)	(1.79)	(1.56)
	[−0.03]	[−0.03]	[−0.03]	[−0.02]	[0.02]	[0.01]	[0.01]	[0.01]
R&D $intensity_{(t)}$	−2.806*	−2.626*	−2.732*	−2.940*	−0.055	−0.070	−0.067	−0.086
	(−1.47)	(−1.37)	(−1.42)	(−1.47)	(−0.79)	(−1.02)	(−0.99)	(−1.26)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Advertising $intensity_{(t)}$	−0.698	−0.936	−0.735	−0.731	−0.068	−0.104	−0.077	−0.120
	(−0.80)	(−0.98)	(−0.80)	(−0.80)	(−0.58)	(−0.89)	(−0.69)	(−1.06)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[−0.01]	[0.00]	[−0.01]

Table 5 *Continued*

Variable	*Leather and footwear industry (leader)*				*Electrical accessories and materials industry (laggard)*			
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
$Size_{(t)}$	0.595	0.478	0.564	0.482	0.917***	0.829***	0.790***	0.683***
	(1.07)	(0.87)	(1.02)	(0.88)	(4.93)	(4.40)	(4.16)	(3.62)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.06]	[0.05]	[0.05]	[0.03]
Inward $FDI_{(t)}$	0.108**	0.110**	0.107**	0.114**	−0.004	−0.005	−0.005	−0.003
	(2.21)	(2.18)	(2.19)	(2.18)	(−0.87)	(−1.19)	(−1.09)	(−0.85)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Constant	−5.176***	−5.725***	−5.216***	−5.258***	−6.738***	−7.094***	−6.814***	−6.955***
	(−2.42)	(−2.57)	(−2.44)	(−2.49)	(−6.91)	(−6.78)	(−6.91)	(−6.83)
Year effects	Included	Included	Included	Included	Included	Included	Included	Included
N	207	207	207	207	571	571	571	571
Log-likelihood	−27.231	−26.447	−27.183	−26.849	−246.352	−244.000	−244.167	−241.198
$-2\Delta L$		1.568	0.096	0.764		4.704**	4.370**	10.308***

*p < 0.10; **p < 0.05; ***p < 0.01 (one-tailed tests).
t-statistics appear in parentheses ( ); marginal effects in brackets [ ]; variance of marginal effects in curly brackets { }.
Each specification includes year dummies as control variables.

leather and footwear industry, this captures the industry-level effect. An alternative to the firm- or industry-level dynamic effect would be to use an industry fixed effect. However, owing to extreme collinearity, we could not include industry fixed effects in addition to firm-level INAR(3) effects. Nevertheless, to ensure that our results were robust to the inclusion of industry, instead of firm, effects, we ran results with industry dummies in lieu of the firm-level INAR(3) dynamic effects. The results were consistent with, and statistically stronger than, those presented: therefore our inferences do not change.

Second, firms engaging in international activity, whether through exporting, importing, foreign direct investment, or licensing, stand to benefit from interacting with agents in foreign markets. To the extent that firms that export simultaneously engage in other forms of international activity that we cannot measure, we may spuriously attribute results to learning from exporting rather than learning from other forms of international activity. With respect to FDI, as described above, we eliminated all firms from the data that reported any outward foreign investment activity, and explicitly controlled for inward foreign investment in order to minimize the potential for these forms of bias. However, we did not explicitly address either importing or licensing. The Fundación collects data on the import behavior of firms. We therefore ran models including importing as a control, with various lag structures. The results were similar to those presented in the paper. However, we elected not to include this variable in the specifications presented herein because we wanted to focus specifically on exporting, and learning from exporting has received the bulk of the theoretical attention in the literature. Exploring learning from importing is outside the scope of the current study, but certainly a fruitful area for future research. Unfortunately, we do not have any data on the international licensing activity of firms. We therefore acknowledge that our model may not adequately control for such dynamics; and although we have done our best, given data limitations, our results may still suffer from omitted variable bias.

Third, our results might be biased to the extent that firms from industries in which Spain lags the global technological frontier are systematically exporting to non-OECD (developing) countries whereas those from industries in which Spain is at, or near, the global technological frontier are systematically exporting to OECD (developed) countries, or vice versa. In order to explore this possibility, we examined the variance in destination markets among the firms in this data. The Fundación Empresa Pública collects information on the breakdown of exports to OECD and non-OECD countries. We found that Spanish firms export predominantly to OECD countries, regardless of industry affiliation. OECD markets make up more than 80% of the export volume for the average firm in the sample. Further, the numbers are similar across lagging and leading industries. We specifically examined the impact of exporting to particular destination markets by splitting the sample into four separate conditions: OECD/Hi RDI; OECD/Low RDI; non-OECD/Hi RDI; and non-OECD/Low RDI. We found that firms from industries in which Spain lags the global technological frontier that export predominantly to OECD countries learn more from exporting than firms from industries in which Spain is at, or near, the global technological frontier that export predominantly to OECD countries. Likewise, firms from industries in which Spain lags the global technological frontier that export predominantly to non-OECD countries learn more from exporting than firms from industries in which Spain is at, or near, the global technological frontier that export predominantly to non-OECD countries. These results are consistent with those presented: therefore any bias due destination market selection is likely to be small.

Finally, following the prevailing literature on comparative advantage, we defined industries in which Spain lags (or lies near) the global technological frontier by using a comparative measure of RDI stock. That is, we look at the R&D intensity of an industry in Spain and compare that with a composite of R&D intensities from of other countries in the same industry. However, it could be that a better measure of technological advantage lies in RDI growth (the change in RDI over time) or its momentum (the comparative rate of change in the growth of RDI over time). In order to explore these alternatives, we examined the sensitivity of our results to various manifestations of RDI. In all cases, whether using RDI stock, RDI growth, or RDI momentum, firms from industries in which Spain lagged the global technological frontier learned more from exporting than those from industries in which Spain is at, or near, the global technological frontier. This lends additional credence to our findings, and allows much more confidence in the veracity of the findings.[17]

DISCUSSION AND CONCLUSION

Although extant research has highlighted the potential for learning from exporting at the macroeconomy level, the empirical literature has just begun to examine these relationships at the micro level. Research identifies opportunities for firms to learn from exporting, but we understand less about how micro- and macro-level influences combine to affect such learning. In this paper we have attempted to address this gap by examining the industry conditions that influence learning from exporting. We borrow from the economic convergence literature to argue that heterogeneity exists across industries in learning-by-exporting outcomes, and that firms in poorly endowed industries stand to gain more from exporting than firms in relatively well-endowed industries.

Consistent with our hypothesis, we find that the relative technological standing of industries significantly influences the amount of knowledge that flows from the host environment to the focal firm. Results suggest that exporting provides the opportunity for firms in technologically lagging industries to gain exposure to more advanced knowledge in their destination markets, and for firms in those industries to increase their patent activity disproportionately relative to firms in technologically advanced industries.

The outcomes of this study hold several important implications for both research and practice. First, in both technologically leading and lagging industries, we find that exporters increase their patent applications subsequent to exporting. This main effect of exporting on innovation is consistent with recent findings in the learning-by-exporting literature (Aw et al., 2000; Blalock & Gertler, 2004; Ozler & Yilmaz, 2001; Salomon & Shaver, 2005a). This study therefore corroborates existing evidence that suggests that exporting provides firms with more than just an outlet for their products, but that firms also benefit from learning that accrues from trade.

Second, this paper contributes to the extant strategy literature by measuring, and exploring, the moderating effects of an industry's comparative advantages on the exporting–learning relationship. Our findings suggest that the characteristics of industries in which firms participate explain, in part, the pattern of knowledge spillovers from exporting. This sheds light on economic convergence processes at the micro level. Our results indicate that firms from relatively weak industries stand to learn more by engaging in trade. Exporting exposes firms in technologically lagging industries to "state-of-the-art" technologies and the potential to improve their skills and capabilities. Over time, this may not only help enhance the position of the firm in its domestic environment, but – if knowledge spills over to its domestic competitors as

Branstetter (2001) and Keller (2002) suggest – may also improve the competitive position of the entire industry.

This latter point holds some insight for economic policymakers. If engaging in trade allows firms from technologically lagging industries to learn more than firms in technologically leading industries, then trade barriers meant to protect technologically weak industries may not provide the desired growth and development outcomes. Rather, eliminating trade barriers and enacting export-led growth policies for the weakest industries may represent a more efficient and more constructive way to encourage growth. However, rather than concluding that governments should enact export-led growth policies for all weak industries, we want to stress that combining our results with the existing literature suggests that the effect is likely to be contingent on the government's stance toward a particular industry. That is, consistent with traditional theories of trade and comparative advantage, it may be optimal in some cases for policymakers to encourage specialization in strong industries while allowing some industries in which the country is at a decided disadvantage to die. Moreover, the knowledge gap between some home country industries and their counterparts in the destination country may be too large to close. Therefore the strategy of enacting export-led growth policies in order to enhance innovation and growth will probably not be optimal for all technologically lagging industries. Our results raise the possibility, however, that if the government wants to encourage economic growth in certain 'strategic' sectors for whatever reason, export-led growth policies may be preferable to protectionist strategies as a tool for achieving such growth.

Our findings suggest several avenues for future research. The most obvious extension of this work would be to extend it to the firm level. Although we account for firm-level heterogeneity by introducing dynamics and by controlling for firm-level R&D investments, it remains an open question whether firm capabilities moderate the exporting–innovation relationship. That is, do technologically leading firms learn more than technologically lagging firms, or vice versa? An interesting theoretical debate arises when considering convergence and firm capability arguments side by side. Convergence arguments would suggest that technologically lagging firms stand to benefit most from exporting. By contrast, the firm capability literature maintains that technologically superior firms, those replete with absorptive capacity, stand to benefit most since they are better equipped to translate the knowledge inputs derived from foreign markets into innovative outcomes.

Another valuable extension of this work could examine other forms of industry heterogeneity in learning-by-exporting outcomes. Scholars have pointed out that learning is a function not just of information access, but also of the characteristics of the knowledge to be absorbed and transferred (e.g., Kogut & Zander, 1992, 1993; Martin & Salomon, 2003; Szulanski, 1996). For example, it might be that the knowledge required to achieve innovation is more tacit in high-tech industries than in low-tech industries. Under this condition, more involved methods of interaction than exporting might be required to source knowledge from the local environment (Kogut & Chang, 1991; Almeida, 1996). We might therefore expect exporting to result in fewer innovations for firms in high-tech industries than in low-tech industries.

Finally, it would be interesting to see how convergence arguments might apply to other modes of entry, such as licensing, joint ventures, and foreign direct investments. Although research suggests that firms invest in foreign markets with the intention of sourcing knowledge that resides abroad (Chung & Alcácer, 2002; Chung & Kalnins, 2001; Kogut & Chang, 1991; Martin & Salomon, 2003; Shaver & Flyer, 2000), few studies address whether firms in technologically lagging industries stand to benefit more from such investments.[18] In this regard, convergence logic can meaningfully inform how industry-level comparative advantages are likely to moderate the organizational learning outcomes associated with foreign investments, or other foreign entry modes.

While the outcomes from this research show some promise for continued study, and have implications for both scholars and practitioners, we draw one caveat: our study focuses solely on outcomes for firms in Spain, a relatively developed economy. For this reason we are cautious to generalize our results. Further corroboratory research is needed before we can draw stronger conclusions. But, these limitations notwithstanding, the results stand to make contributions to the fields of strategy, economics, and international business.

NOTES

[1]Although Spanish firms in some sectors invested abroad aggressively in the 1990s, most of this investment was in the service sector (Guillén, 2001,

2005). Spanish firms in the banking (notably BBV and Banco Santander), travel (e.g., Grupo Sol Melia), and telecommunications (Telefonica) industries were rather aggressive in investing abroad, especially in Latin America. However, Spanish firms are not nearly as strong globally in the manufacturing sector as in the service sector (Guillén, 2001, 2005). Because these data focus solely on manufacturing firms, much of this investment is not captured in our data. For that reason, and because these data come from reliable government sources, we believe the level of FDI represented in these data is accurate, although seemingly low; and when we include firms with foreign ownership in the analysis, we find results that are consistent with those presented.

[2]Because there is no extraterritoriality in patenting (e.g., the US does not recognize European patents, and vice versa), firms often have the incentive to file for patent protection simultaneously in several countries if they believe that they may, at any point, conduct business using those patents in those countries. Therefore a firm filing in Europe may also simultaneously file in the United States. For patents that are filed in one only jurisdiction (e.g., Spain), firms have one year from the file date (as per the Patent Cooperation Treaty of 1970) to file in other jurisdictions. If Spanish firms systematically apply for patents in other countries before they file in Spain, there may be some bias inherent in our results. Although we believe that this practice is neither likely nor prevalent in our data, the data from this source do not allow us insight into patterns of application activity.

[3]We also scaled the R&D expenditures by population. Using population instead of GDP as the scaling factor yielded equivalent results.

[4]Although the RDI measure varies over time, it was relatively stable throughout the time period of this study. There is little change in relative rank, and none of the industries switched from the technological laggard to the technological leader condition, or vice versa.

[5]Similar results were maintained when we conducted the subsample splits using the mean instead of the median.

[6]Again, because there are only 11 Spanish firms with any foreign direct investment, we do not define a similar (OUTWARD FDI) variable for Spanish-owned companies with foreign subsidiaries.

[7]When we tested for overdispersion using Cameron and Trivedi's (1986) diagnostic, we found evidence of such. Therefore we prefer the negative binomial model.

[8]For continuous dependent variables, the autoregressive model that includes exogenous regressors and lagged dependent variables has been proposed as a method of controlling for firm-specific effects (Greene, 2003). Al-Osh and Alzaid (1987) and Brännäs and Hellström (2001) argue that the traditional AR(1) model can be extended to the integer-valued autoregressive (INAR(1)) model applied to count data. Moreover, Alzaid and Al-Osh (1990) refine an integer-valued pth-order autoregressive structure (INAR(p)) process and address differences between the INAR(p) and AR(p) processes. We apply the INAR(p) process to our negative binomial model.

[9]For example, in the leather and footwear industry, where RDI is the highest, the average firm R&D intensity is 0.40%. By contrast, in the electrical accessories and materials industry, where RDI is the lowest, the average firm R&D intensity is 1.46%.

[10]We confirmed that the industries in which Spain is weaker are globally more trade-intensive by comparing the RDI data with industry trade figures from the OECD (2001) STAN: Database on Bilateral Trade. We thank an anonymous reviewer for motivating this consideration.

[11]We prefer median splits rather than splitting the data at the level of zero, because few industries in Spain lie above the zero point, and this allowed insufficient variance when estimating equations in the technological leader condition. The assumption in using median splits is that firms in industries above the median are more likely to come into contact with competitors that have "state-of-the art" technology (near the technological frontier) than firms in industries that are below the median RDI. Firms in industries below the median RDI are, on average, more likely to encounter "state-of-the-art" technologies in exterior markets. Nonetheless, we explored different cutoffs for creating the splits; and, regardless of whether the splits were conducted at the mean, at the median, or at the quartiles, results do not change.

[12]For example, in the case of column 1 and column 2, the log likelihood test statistic is $9.630 \rightarrow -2[(-687.023)-(-682.208)]$. The p-value of this statistic (distributed chi-square) is less than 0.01.

[13]The marginal effects represent the partial derivatives with respect to the mean of the variable in question.

[14]We thank an anonymous reviewer for motivating this analysis.

[15]Although the average RDI for the leather and footwear industry is negative, it is positive in some years, and it is the highest average RDI in the sample.

[16]We acknowledge that firms in the electrical accessories and materials industry apply for more patents, on average, than firms in the leather and footwear industry. However, as mentioned previously, by incorporating three-year lags of the dependent variable we can control for industry heterogeneity in patent behavior, and reasonably compare patents across industries (Griliches, 1990).

[17]All results discussed in this section are available from the authors upon request.

[18]See Penner-Hahn and Shaver (2005) and Berry (2006) for exceptions.

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