CONVERGENCE OR CAPABILITIES?
EXPLAINING FIRM HETEROGENEITY IN LEARNING BY EXPORTING

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Abstract

An interesting theoretical debate arises with respect to learning-by-exporting when considering macro-economic convergence and firm capability arguments side-by-side. Convergence theory intimates that technologically lagging firms stand to benefit most from exporting because exposure to the advanced technological knowledge in foreign markets allows them to make up for the disparity in capabilities and close the gap with their technologically endowed counterparts. By contrast, the capabilities literature posits that technologically superior firms stand to benefit most from trade since they are better equipped to translate knowledge inputs derived from foreign markets into innovative outcomes. In this paper, we focus on the effect of exporting on innovation and empirically explore whether technologically leading or lagging firms benefit disproportionately. Using a sample of Spanish manufacturing firms from 1990-1997, we empirically investigate how exporting differentially influences the patent output of technologically leading and lagging firms. We find that exporting is associated with the *ex post* increase in innovative productivity for both technologically leading and lagging firms. Moreover, the results provide support for the firm capability claim. Notably, technologically leading firms apply for more patents subsequent to exporting than technologically lagging firms.

Keywords: learning by exporting; knowledge transfer; technological innovation; convergence; capabilities; absorptive capacity

INTRODUCTION

Theoretical work in international business and international trade proposes that open economies benefit nations through enhanced growth. Empirical results corroborate that conjecture, suggesting that trade openness leads to income growth. One mechanism that acts as an engine to such outcomes is the learning that occurs as a result of engaging in trade. That is, the exchange of tangible goods facilitates the exchange of intangible knowledge across borders, and the learning that results helps increase productivity and fosters income growth.

Although the macro-economic literature suggests that countries can benefit from an open economy, what remains less clear is whether, and how, trade 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. For example, the macro-economic convergence literature, on the one hand, suggests that we might plausibly expect technologically lagging firms benefit most from international trade. On the other hand, firm capability arguments suggest that technologically superior firms, replete with some form of technological capabilities, stand to benefit most from exporting. An interesting debate arises when we consider these two perspectives side-by-side.

The purpose of this study therefore is to examine learning from exporting arguments at the micro- level by exploring whether, and how, firm heterogeneity moderates the relationship between exporting and innovation. In particular, we explore whether technologically lagging firms learn more from exporting (as convergence arguments would suggest) or whether technologically leading firms learn more from exporting (as firm capability arguments suggest). Our research question of interest then becomes: Do technologically leading or lagging firms learn more from exporting?

In order to test these arguments, we examine the export behavior and *ex post* innovative outcomes of a sample of 2137 Spanish manufacturing firms from 17 distinct industries over the 1990 to 1997 period. In order to explore the moderating effects of firm heterogeneity in technological capabilities, we discriminate technologically leading firms from technological lagging firms based upon relative expenditures in R&D. We define the latter as firms that lag the technological frontier. We define the former as firms that are at, or near, the technological frontier. We regress firm-level patent application counts (our dependent variable) on exporting across both sets of firms. We find that exporting is associated with the *ex post* increases in innovative productivity for firms in both the technological leader and technological laggard conditions; however, technological leaders apply for more patents subsequent to exporting than technological laggards. We interpret this finding as evidence that technologically leading firms learn from exporting at a faster rate than technologically lagging firms. The results therefore support for the firm capability claim.

In the next section, we briefly review the convergence and firm capability literatures in the context of learning-by-exporting. Based on this review, we generate two competing hypotheses. 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 macro economics has long emphasized the potential gains from trade. 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 spillover 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 and Helpman, 1991a; 1991b).

Researchers assert that open economies foster the speed of knowledge transfer and as such, should lead technological and income gaps between trading partners to shrink (Grossman and 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 as such, 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 macro-economy level. The research question of interest has centered on whether countries can benefit from free trade (e.g., Edwards, 1993; Frankel and 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 benefited from advanced knowledge in developed countries (see Edwards, 1993; Guillén, 2001).

At the more micro level, some scholars highlight inter-sectoral heterogeneity in learning-by-exporting outcomes. For example, Salomon and Jin (2006) find that industry heterogeneity moderates the relationship between exporting and a firm's innovative outcomes. They find variance in learning-by-exporting outcomes across industries in Spain. Aw and Hwang (1995) likewise find the relationship between exporting and firm productivity in Taiwan to be highly dependent on product-specific environments. In a follow-up study, Aw, Chung, and Roberts (2000) 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.

Although scholars have highlighted the potential for learning from exporting at the nation and industry levels, the empirical literature has just begun to examine these relationships at the firm level (e.g., MacGarvie, 2006; Salomon and 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 predominantly concerned with macro-economic factors – especially questions motivated by economic and legislative policy makers. Second, more practically, 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 if total factor productivity increases after firms become exporters. Although some authors fail to find support for such productivity increases (e.g., Bernard and Jensen, 1999; Clerides, Lach, and Tybout, 1998; Delgado, Fariñas, and Ruano, 2002), others do find evidence consistent with learning (e.g., Aw *et al*., 2000; Ozler and Yilmaz, 2001; Blalock and Gertler, 2004). More recently, research suggests that the mixed empirical findings might be due to using productivity as the dependent variable (e.g., MacGarvie 2006; Salomon and Shaver, 2005a). They 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. Likewise, MacGarvie (2006) demonstrates that exporting firms are more likely to cite foreign patents than their domestic counterparts after commencing exporting.

Hypotheses

As with the firm-level studies mentioned above, the perspective that we adopt in this study is that firms, not nations, engage in trade. Although goods flow between nations, it is generally firms that make export decisions, and firm outcomes that are impacted by those decisions. It is therefore important to consider learning-by-exporting outcomes at the firm level. Moreover, building upon the Salomon and Shaver (2005a) findings, we focus on the impact of exporting on firm innovation in order to accurately gauge learning outcomes.

Although the empirical literature has begun to weigh in on learning-by-exporting issues at the firm level, we understand less than we should about the heterogeneity that exists in these learning benefits across firms. Firms, like countries or industries, are not homogeneous in terms of their technological capabilities (Barney, 1991; Cohen and Levinthal, 1990; Henderson and Cockburn, 1996; Peteraf, 1993; Wernerfelt, 1984; 1995). We therefore expect to find variance in learning outcomes across firms based on their extant capabilities. However, the literature does not clearly suggest whether we should expect technologically inferior, or technologically superior, firms to benefit more from exporting. In fact, there is literature to support both contradictory positions.

Prevailing logic suggests 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. Competing in a foreign market allows exporting firms to amass market and technological information. For instance, exporters benefit from the technological expertise of their buyers (Clerides *et al*., 1998). Moreover, exporters receive valuable information about consumer product preferences and competing products (Vernon, 1966; 1979). In addition to the information gathered from customers, exporters confront competitors in the host country that might otherwise escape their purview, and firms may benefit from competitive spillovers. All these suggest that as information collected in the foreign market (whatever the source) filters back to the parent firm, it should incorporate the knowledge into its production function. This is likely to manifest as increased innovation (Salomon and Shaver, 2005a).

With respect to the differential benefits that accrue to exporters, the macro-economic convergence literature suggests that exporting stands to benefit the disadvantaged. Results from various macro- level studies indicate that trade openness disproportionately benefits developing countries (for a review see Edwards, 1993; Slaughter, 1997; Salomon and Jin, 2006). This is because interaction with export intermediaries, customers, and other agents provides firms from developing economies a greater opportunity to benefit from the advanced knowledge that they lack, and that does not exist in the home country. Moreover, the greater the disparity between a country and its trading partner, the more that country stands to gain (Grossman and Helpman, 1991a).

The corollary at the firm level would imply that technologically disadvantaged firms benefit more from exporting. Because exporting provides technologically lagging firms exposure to advanced technological knowledge in their destination markets, these firms gain a window into state-of-the-art technologies, and exporting affords them the opportunity to benefit from technological insights that thereby help them innovate. By contrast, since technological leaders are already at the technological frontier, they should benefit less from exporting because they will have little to learn. Based on convergence arguments then, the expectation is that the more a firm lags the technological frontier, the more it stands to benefit from exporting to improve its capabilities. That is, *ex post* innovation rates should be greater for technologically lagging exporters vis-à-vis their technologically leading counterparts. Stated formally,

Hypothesis 1a: All else equal, technologically lagging firms will learn more from exporting than technologically leading firms.

An interesting theoretical debate arises however when considering convergence and capabilities arguments side-by-side. Although convergence arguments would suggest that technologically lagging firms stand to benefit most from international trade, the capabilities perspective derives an alternative conclusion.

Strategy scholars have long recognized that firm-specific capabilities are critical to a firm's success (Barney, 1991; Peteraf, 1993; Wernerfelt, 1984; 1995). Consistent with this underlying conviction, empirical research has shown that distinctive technological, marketing, and managerial capabilities can be value creating for firms (see Mahoney and Pandian, 1992 for a review). Moreover, when it comes to innovative performance, technological capabilities play a central role. For example, in an empirical examination of the pharmaceutical industry, Henderson and Cockburn (1996) attributed a large proportion of the variance in innovative productivity to firm fixed effects. They surmised that innovative productivity was driven by firm heterogeneity in technological capabilities.

Cohen and Levinthal (1990) argue for a firm-specific technological capability they describe as "absorptive capacity". This construct captures "the ability of a firm to recognize the value of new external information, assimilate it, and apply it to commercial ends" (Cohen and Levinthal, 1990: 128). Absorptive capacity therefore confers upon a firm the ability to recognize the usefulness of external knowledge and use that knowledge to innovative ends. Moreover, according to Cohen and Levinthal (1990), absorptive capacity is a by-product of firm investments in R&D. Similarly, Henderson and Cockburn (1994) propose a construct referred to as “architectural competence” which refers to a firm’s ability to assimilate knowledge from outside firm boundaries. They find that architectural competence increases innovative productivity.

So while exporting increases the breadth, and potentially the flow, of knowledge inputs not available to firms in the domestic market, the capabilities literature would suggest that firms with existing technological capabilities are best suited to use those knowledge inputs to innovative ends. This is because technologically leading firms are better able to acquire and use information present in the external environment. Without such capabilities, a firm may lack the ability to assimilate complex external knowledge and use it to achieve innovation. Although the access to knowledge inputs through exporting may not differ from technologically leading firms, firms lacking technological capabilities may not be able to effectively use the information available from sources in the host environment. Thus, without technological capabilities, the requisite knowledge to achieve innovation may not spillover effectively to the focal firm. In fact, Penner-Hahn and Shaver (2005) find that firms that invested abroad innovate more in the years following those investments in the presence of, versus in the absence of, absorptive capacity.

The firm capabilities and macro-economic convergence literatures would therefore diverge with respect to which firms stand to benefit most from exporting. While convergence arguments suggest that we might plausibly expect technologically lagging firms to benefit more from exporting, the firm capabilities literature draws the converse conclusion. Because firm-level technological capabilities affect the amount of external information that firms are able to assimilate, technological capabilities will positively moderate the relationship between exporting and innovation. Based on capabilities arguments then, the expectation is that the closer a firm is to the technological frontier, the greater its technological capabilities, and the more it stands to benefit from exporting. That is, *ex post* innovation rates should be greater for technologically leading exporters vis-à-vis their technologically lagging counterparts. Stated formally,

Hypothesis 1b: All else equal, technologically leading firms will learn more from exporting than technologically lagging firms.

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 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.

*** Insert Table 1 about here ***

Although our initial sample was comprised of 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 6544 firm-year observations from 1755 unique firms.

In order to complement the Fundación data, and to identify whether a firm is a technological laggard (leader), we collected R&D expenditure and gross production data from the OECD. The OECD publishes yearly R&D figures in the ANBERD database. ANBERD contains information on industry level R&D expenditures from 27 countries – the 30 OECD member countries, excluding Austria, Luxembourg, and Switzerland – from 1987-1999. The OECD also publishes industry-level gross production data. Gross production represents the market value of finished goods aggregated up to the industry-level. The data are available for 22 countries (excluding Czech Republic, Hungary, Ireland, Luxembourg, Poland, Slovak Republic, Switzerland, and Turkey) from 1990-1997. We

[1] Although Spanish firms in some sectors aggressively invested abroad in the 1990's, most of this investment was in the service sector (see 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 solely focus 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 are accurate – although seemingly low; and when we include firms with foreign ownership in the analysis, we find results that are consistent with those presented.

describe how we use these data to generate 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 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 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). While 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 PATENT APPLICATIONS 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 as a measure of innovative productivity (e.g., Basberg, 1982, 1987; Comanor and Scherer, 1969; Henderson and 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 and 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 and Levin, 1989; Salomon and 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 firms or industries (Cohen and Levin, 1989; Griliches, 1990). It could therefore be argued that because patents do not mean the same thing for each firm, they cannot be meaningfully compared across firms. However, as Griliches (1990) points out, with the proper controls, patents can still be used effectively in cross-firm, 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 firm heterogeneity in patent behavior. We can therefore be more confident that our results capture the differential learning benefits across firms – 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." As such, 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, 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 and Jensen, 1999; Clerides *et al.*, 1998; Salomon and Shaver, 2005a).

Research suggests that relative R&D expenditures can proxy for a firm's technological capabilities, and its position in technological space (Caves, 1996; Chung and Alcácer, 2002; Cohen and Levinthal, 1990). R&D expenditures are a correlate of knowledge stock; and the technological capabilities of individual firms in Spain vis-à-vis the technological frontier can therefore be assessed by comparing them to some external metric on the basis of their R&D investments (Chung and Alcácer, 2002; Porter, 1990). In order to identify whether a firm is a technological laggard (leader), we compare firms in these data to comparable others (from the same industry) in the OECD on the basis of their R&D expenditures.

In order to make these comparisons, we rely on industry-level R&D expenditure and production data published by the OECD. The R&D expenditure data comes from the ANBERD Database on Research and Development Expenditures. Expenditures are expressed in millions of purchasing power parity equivalent U.S. dollars. We complement the ANBERD data with OECD data on gross production by industry.[2] Gross production data were expressed in the local country's national currency; however, we were able to transform them into purchasing power parity U.S. dollars using OECD published purchasing power parity exchange rates. Both R&D expenditure and industry production data are reported at the four-digit ISIC industry level. 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 in our data.

We then develop two indices to discriminate technological leaders from technological laggards. The first measures the focal firm's relative R&D intensity compared to the average industry R&D expenditures in 21 OECD countries (other than Spain). This gauges the firm's relative technological standing with respect to the average of other firms within the same industry from developed (OECD) countries. As such, it captures the firm's proximity to the global technological frontier and can be used to identify firms as either technological leaders or laggards (Salomon and Jin, 2006).

We calculate this Research and Development Index (RDI) as follows: We begin by

[2] Because gross production captures the market value of finished goods within a given industry, it can be compared to sales at the firm level. It can be viewed as the aggregated, macro-equivalent of firm sales.

scaling the R&D expenditures of firm *i* in industry *j* at time *t* by its sales at time *t* in order to eliminate size effects. We similarly scale the R&D expenditure in industry *j* from country *k* at time *t* by its gross production (GP) in industry *j* at time *t*. We average this R&D/GP variable across all countries for which we have data (other than Spain) at time *t*. We subsequently subtract the average R&D expenditure (scaled by GP) in industry *j* from the R&D expenditures of firm *i* from industry *j* at time *t*.[3] This produces a time-varying, firm-specific index comparing the firms in these data to the average R&D expenditures from its corresponding industry in developed countries. Increasing values of the index indicate that a firm is a relative technological leader whereas decreasing values indicate that a firm is a relative technological laggard. This measure is consistent with prior empirical research in international business (e.g., Benvignati, 1990; Chung and Alcácer, 2002; Kravis and Lipsey 1992; Salomon and Jin, 2006). Equation 1 expresses this measure formally:

$$RDI_{ijt}^{OECD} = RD_{ijt} / Sales_{ijt} - \left[\sum_{k=1}^{n} (RD_{jkt} / GP_{jkt}) \right] \times \frac{1}{n} \qquad (1),$$

where,

RDI_{ijt}^{OECD} : R&D Index for firm *i* from industry *j* in year *t*
RD_{ijt} : R&D expenditures of firm *i* from industry *j* in year *t*
$Sales_{ijt}$: Total sales of firm *i* from industry *j* in year *t*
RD_{jkt} : R&D expenditures in industry *j* from country *k* in year *t*
GP_{jkt} : Gross production in industry *j* from country *k* in year *t*
n : Total number of OECD countries (21 nations, not including Spain).

Although the RDI^{OECD} measure proxies for the technological capabilities of the focal firm vis-à-vis the global technological frontier (i.e., versus comparable firms in developed,

[3] We alternatively scaled the R&D expenditures by GDP and population. Using GDP or population instead of gross production as the scaling factor yielded equivalent results.

OECD economies), it may inhere some bias to the extent that Spain is comparatively advantaged in given industries. We therefore complement our first RDI measure with a second that compares firms in these data to their industry average (as reported in ANBERD) within Spain. This captures the firm's technological standing within Spain.

We calculate the second index similar to the first; however, instead of subtracting the OECD average R&D expenditure from industry *j* at time *t*, we now subtract Spain's average R&D expenditure (scaled by GP) from industry *j* at time *t* from the R&D expenditure of firm *i* from industry *j* at time *t*. Again, increasing values of the index indicate that a firm is a relative technological leader vis-à-vis its industry whereas decreasing values indicate that a firm is a technological laggard. Equation 2 expresses this measure formally:

$$RDI_{ijt}^{Spain} = RD_{ijt} / Sales_{ijt} - RD_{jt}^{Spain} / GP_{jt}^{Spain} \qquad (2).$$

Calculating two distinct RDI measures provides several benefits for our purposes. Assessing both 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 technological capabilities and technological leadership, we can use this variation in expected outcome to help inform our interpretation of the results. Although we expect the results to be consistent across measures, corroborating results add validity to our findings.

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: using multiplicative interaction terms; or creating sub-sample splits based on the median or mean of the variable of interest (for a review see Jaccard, Turrisi, and 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 industry-specific median of RDI. We consider firms above its industry-specific median relative technological leaders, and those below its industry-specific median relative technological laggards. We assess moderating effects by comparing the marginal effects of the coefficients across the two groups.[4]

Insert Table 2 about here

Table 2 presents the medians and means of RDI across all industries in this study. The medians and means of RDI^{Spain} are relatively smaller than those of RDI^{OECD}. Taken together, this indicates that the firms in Fundación data are marginally technologically superior, on average, to those in Spain, but technologically inferior to comparable firms in other OECD countries. That is, the firms in these data are technologically well-endowed domestic firms, but not at the absolute global technological frontier.

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.

[4] Similar results maintained when we conducted the sub-sample splits at the mean, at the quartiles, and at zero.

Scholars have similarly explored the influence of R&D inputs on innovative productivity (for a review see Cohen and 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 (see Caves, 1996; Salomon and Shaver, 2005b). Researchers typically proxy for such firm level advantages using R&D and advertising intensities (see e.g., Caves, 1996; Morck and 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 likely have a greater consumer orientation, and as such, a greater incentive to innovate. We define ADVERTISING INTENSITY as advertising expenditures divided by sales expressed as a percentage.

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 only take 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 non-linear estimation technique (e.g., Graves and Langowitz, 1993; Hausman, Hall, and Griliches, 1984). We therefore begin with a Poisson framework. Equation (2) presents the probability density function of the Poisson distribution with parameter λ_i:

$$f(y_i \mid x_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!}, \quad y_i = 0,1,2,\ldots \qquad (2).$$

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, 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 lambda a function of the covariates. This is expressed formally in the following equation:

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

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 W_{it} is a vector of control variables. The betas are parameter estimates.

The Poisson regression is quite sensitive to its distributional assumptions. For instance, both the mean and variance are assumed to be equal to lambda. Should the mean and variance for the observed sample not equal lambda, the likelihood function would be misspecified leading standard errors to be underestimated and to erroneous results.[5] The negative binomial regression allows for relaxation of the Poisson assumption that the mean and variance equal lambda by introducing an individual unobserved disturbance to the model (e.g., Hausman *et al*., 1984; Henderson and Cockburn, 1996). Introducing the unobserved disturbance term to the Poisson model, equation (3) becomes:

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

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

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

Given the panel 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 with fixed effects to control for serial correlation of this sort; however, there has been considerable debate regarding whether this method effectively controls for individual effects (Allison and 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 (see Alzaid and Al-Osh, 1990).[6] 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 and 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:

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

where λ_{it} is the expected number of innovations for firm i at time t, $y_{i,t-1\sim3}$ are the lags of the

[6] 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 (1994) 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 *p*th-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.

dependent variable for firm i at time t, $x_{i,t-p}$ represents the export status variable for firm i at time t, W_{it} is a vector of other explanatory variables, and u_{it} is an unobserved disturbance term that we can now more confidently assume is free of serial correlation. The rhos and betas represent coefficient estimates.

RESULTS

Descriptive Statistics and Correlations

Table 3 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 INTENSTITY, and SIZE. This suggests that exporting firms spend more on R&D and advertising, and are generally larger than purely domestic firms.

The means of RDI^{Spain} and RDI^{OECD} variables are 0.01 and -0.00 respectively. This implies that the firms in these data invest more in R&D than their industry counterparts in Spain, but less than comparable firms in other OECD countries. Not surprisingly, the RDI^{Spain}, RDI^{OECD}, and R&D Intensity measures are highly correlated. Because the RDI measures have an embedded firm specific component, they necessarily increase in a firm's R&D intensity because the industry specific component does not vary across firms within a given industry. Moreover, the similarity across the two RDI measures implies a remarkable concatenation between Spain and the rest of the developed world in R&D expenditures – that is, industries in Spain tend to be similarly R&D intensive in their OECD counterparts, and the variances in R&D expenditures in both Spain and the OECD follow a similar pattern across industries over time.

*** Insert Table 3 about here ***

We compare the innovative activity of non-exporting firms to exporting firms in both the low-RDI and high-RDI conditions in Figures 1 and 2. Exporters (regardless of whether technologically leading or lagging) consistently have greater average patent application counts than their non-exporting counterparts. Moreover, the results illustrate a slightly greater propensity to patent among technologically capable exporters (in the high-RDI condition). This relationship becomes pronounced toward the latter years of the panel. While consistent with the firm capabilities argument, this effect should be interpreted with caution for several reasons. First, based on the patterns across the low- and high- RDI conditions, it is unclear whether the differences are statistically and/or economically meaningful. Second, this effect is solely illustrated contemporaneously. It does not assess if the direction of causality runs from innovation to exporting, vice versa, or both. Finally, it does not control for many other firm effects that we include in the multivariate analyses. Therefore, to better understand the nature of this relationship, we turn to the multivariate regression analyses.

Insert Figures 1 and 2 about here

Regression Results

Negative binomial regression results for the patent application dependent variable appear in Table 3. We present the results using median splits of RDI^{OECD} in order to explore the moderating effects of technological leadership on the exporting-innovation relationship (Jaccard *et al*., 1990). We label the firms below the RDI^{OECD} median as “relative” technological laggards and the firms with values above the median as “relative” technological leaders. The assumption inherent in considering these firms as “relative” leaders/laggards is that such a split meaningfully captures the proximity to the global technological frontier. That is, Spanish firms that we characterize as “relative” technological leaders possess greater technological capabilities, and are closer to the global technological frontier, than those that we consider as “relative” technological laggards. As such, we can plausibly expect to observe systematic variance in learning from exporting outcomes, in one direction or the other, in firms across conditions.[7]

As we mentioned earlier, we control for unobserved firm heterogeneity by including an INAR(3) dynamic process into the model – e.g., incorporating three lags of the dependent variable. Although not reported, we also include year dummies to control for systematic time effects.

*** Insert Table 4 about here ***

Columns 1 and 5 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

[7] We prefer median splits rather than splitting the data at the level of zero in order to make the sample balanced across the technological leader and laggard conditions. A balanced sample aids with inference. Nonetheless, we explored different cutoffs for creating the splits; and regardless of whether the splits were conducted at the mean, at the median, at zero, or at the quartiles, results do not change.

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 the set of technological leaders, but not significant for the set of technological laggards except in column 5. The results on R&D INTENSITY and ADVERTISING INTENSITY are positive but not significant for both sets of firms.[8]

In order to test our hypotheses, 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 and 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 ($p<.01$ for models 2, 3, and 4; $p<.05$ for model 6 and 7; and $p<.10$ for models 8).[9] 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 model alone. The change in likelihood ratio is greatest for the three-year export lag (column 4) in the technological leader condition, and for the one-year export lag (column 6) in the technological laggard condition. The specifications in columns 4 and 6 therefore fit the data best.

[8] The correlations between the RDI variables on the one hand and the R&D Intensity variable on the other lead to some question as to whether R&D Intensity should be included as a control variable in the regression analysis. We opted to include R&D Intensity in the analyses because there was significant variation among firms within groups (i.e., across the relative leader and laggard conditions). When we eliminated R&D Intensity from the specification, results did not change.

[9] For example, in the case of column 1 and column 2, the log likelihood test statistic is 11.389 → -2 ((-1220.222)-(-1214.527)). The p-value of this statistic (distributed Chi-square) is less than .01.

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 and Shaver, 2005a).

With regard to the moderating effects, our results imply some learning differences across the technological leader and technological laggard conditions. Specifically, for technologically lagging firms, 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 with greater technological capabilities (the technologically leading condition), 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 due to the inherent non-linearity of the underlying p.d.f. function, and the specific location on the curve at which the coefficients are estimated. Therefore, we calculate, and compare, the marginal effects across conditions.[10] We find that the marginal effects of exporting on patent applications for firms with technological capabilities (the technological leader group) are consistently higher than for those firms lacking such capabilities (technological laggard group). For example, for the one-year lag ($EXPORT_{t-1}$), we would expect firms in the technological leader group to gain an additional 0.07 of a patent (0.09 – 0.02) from exporting. This result provides support for hypothesis 1b. That is, the results imply a

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

moderating effect of technological capabilities on the exporting-innovation relationship such that technological leaders learn more from exporting.

Insert Table 5 about here

In Table 5, we re-estimate the results from Table 4 using the median split of the RDI^{Spain} variable. This provides another assessment of whether interaction with foreign agents leads to greater knowledge spillovers and enhanced learning for technologically leading or lagging firms. The evidence across columns 2-4 and 5-7 corroborate our previous findings. The results confirm that firms with technological capabilities benefit more (learn at a faster rate) from exporting than those that lack such capabilities. Taken together then, the results from Tables 4 and 5 reject hypothesis 1a in favor of hypothesis 1b.

DISCUSSION AND CONCLUSION

Although extant research has highlighted the potential for learning from exporting at the macro-economy 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 the micro- level determinants of learning from exporting. In this paper, we focus on a particular theoretical debate that arises when considering macro-economic convergence and firm capabilities explanations for firm heterogeneity in learning-by-exporting. We attempt to reconcile this debate.

Convergence arguments suggest that technologically lagging firms stand to gain more from exporting, and as a result, subsequently catch up with (converge to) their technologically leading counterparts. By contrast, the firm capabilities literature suggests that technologically leading firms stand to gain more from exporting because they are better suited to use the knowledge available in export markets to commercial ends. Although we find that exporting provides the opportunity for all firms to benefit from exposure to the knowledge available in their destination markets, the results indicate that heterogeneity exists across firms in learning-by-exporting outcomes. Specifically, we find evidence that firms with superior technological capabilities learn at a faster rate than those that lack those capabilities, supporting the firm capabilities claim.

The outcomes of this study hold several important implications for both research and practice. First, in both technologically leading and lagging conditions, 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 and Gertler, 2004; Ozler and Yilmaz, 2001; Salomon and Shaver, 2005a). This study therefore corroborates existing evidence that suggests that exporting provides firms more than just an outlet for their products, but that firms also benefit from the learning that accrues from trade.

Second, this paper contributes to the extant strategy and international business literatures by measuring, and exploring, the moderating effects of technological capabilities on the exporting-learning relationship. Our findings suggest that substantial heterogeneity exists across firms in learning-by-exporting outcomes. The results indicate that technologically capable firms stand to benefit most from exporting; and although technologically lagging firms did benefit from exporting, exporting did not allow them to close the gap with their technologically leading counterparts.

Third, these findings hold implications for the literatures on international expansion and firm performance. One of the basic premises of research on international expansion is that in order to succeed abroad, firms must possess some advantageous, intangible knowledge-based assets (Buckley & Casson, 1976; Hymer, 1976). Moreover, this research shows that international expansion is value creating for firms with distinctive technological capabilities (for reviews see Caves, 1996; Dunning, 1993; Morck and Yeung, 1991, 1992; Salomon and Shaver, 2005b). The results from this study are consistent with those from the broader international strategy literature, with one exception. Not only do these results imply that technologically endowed firms are better suited to expand abroad, but that such an expansion allows those firms to build upon, and reinforce, that existing advantage.

Finally, our findings provide some practical implications for managers. Regardless of the motivation for entering foreign markets, not all firms will benefit equally. In order to maximize the learning benefits of exporting, managers should be aware of the impact of their existing technological capabilities, with the understanding that those with existing technological capabilities are best positioned to benefit from knowledge spillovers. For technologically capable firms therefore, exporting can be considered a strategic action through which firms can enhance their competitive position. Moreover, the learning that accrues as a result of exporting provides value to firms beyond simply providing a sales outlet for existing products, and those benefits should be valued accordingly.

While the outcomes from this research show some promise for continued study and have implications for both scholars and practitioners, it is important to acknowledge one caveat. Although these findings provide support for the firm capabilities story at the micro-level, this does not necessarily invalidate the arguments proffered by convergence theory, especially at the macro-economy level. For example, it could be that firms from developing countries benefit more from exporting than firms from developed countries, with technologically capable firms from developing countries benefiting the most. Said results would certainly reconcile the predictions of the disparate literatures. Although our findings do not support such a view, we cannot meaningfully test such a conjecture given the single country context of this study. In addition, given Arrow's (1951) impossibility theorem demonstrating the difficulty of aggregating individual actions to the macro- level, it would be both premature, and unwise, to summarily dismiss the convergence view. For these reasons, we are cautious to generalize our results. Further corroboratory research is needed before we can draw stronger conclusions. But its limitations notwithstanding, these results stand to make contributions to the fields of strategy, economics, and international business; and we hope to have presented a first pass at what is surely a much more complicated phenomenon. We hope others will refine and improve upon our contribution by looking at improved data sets with more fine-grained measures.

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Table 1. Industry breakdown of the sample

Industry	Number of Firms	Percentage of Total
1. Ferrous and non-ferrous metals	45	2.11%
2. Non-metallic products	161	7.53%
3. Chemical products	149	6.97%
4. Metallurgy and metallic products	223	10.44%
5. Agricultural machinery	125	5.85%
6. Office products and data processing	22	1.03%
7. Electrical accessories and materials	201	9.41%
8. Automobiles and motors	81	3.79%
9. Transport material	54	2.53%
10. Meat products	59	2.76%
11. Food and tobacco	229	10.72%
12. Beverages	53	2.48%
13. Textiles and clothing	249	11.65%
14. Leather and footwear	76	3.56%
15. Wood and wood products	146	6.83%
16. Paper and publishing	163	7.63%
17. Rubber and plastic products	101	4.73%
Total	2137	100.00%

Table 2. Medians and means of RDI by industry

Industry	RDI^{Spain} Mean	RDI^{Spain} Median	RDI^{OECD} Mean	RDI^{OECD} Median
1. Ferrous and non-ferrous metals	0.004	0.001	-0.001	-0.004
2. Non-metallic products	0.003	-0.000	-0.001	-0.004
3. Chemical products	0.021	0.007	0.006	-0.008
4. Metallurgy and metallic products	0.004	-0.000	0.003	-0.001
5. Agricultural machinery	0.014	-0.000	-0.000	-0.012
6. Office products and data processing	0.017	0.009	-0.026	-0.034
7. Electrical accessories and materials	0.014	0.001	-0.029	-0.041
8. Automobiles and motors	0.011	0.004	-0.007	-0.014
9. Transport material	0.014	-0.000	-0.017	-0.031
10. Meat products	0.001	-0.000	-0.001	-0.002
11. Food and tobacco	0.002	-0.000	-0.000	-0.002
12. Beverages	0.002	-0.000	-0.000	-0.002
13. Textiles and clothing	0.004	-0.000	0.002	-0.002
14. Leather and footwear	0.004	-0.000	0.003	-0.001
15. Wood and wood products	0.001	-0.000	-0.001	-0.002
16. Paper and publishing	0.003	-0.000	0.001	-0.001
17. Rubber and plastic products	0.004	-0.000	-0.001	-0.005

Table 3. 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. $RDI^{Spain}_{(t)}$	0.10	0.12	0.11	0.10	0.18	0.19	0.19	1.00				
9. $RDI^{OECD}_{(t)}$	0.07	0.08	0.08	0.08	0.08	0.09	0.09	0.82	1.00			
10. R&D intensity$_{(t)}$	0.10	0.12	0.11	0.10	0.18	0.19	0.19	1.00	0.82	1.00		
11. Advertising intensity$_{(t)}$	0.07	0.07	0.06	0.05	0.19	0.20	0.20	0.11	0.11	0.11	1.00	
12. Size$_{(t)}$	0.10	0.10	0.09	0.08	0.55	0.56	0.56	0.21	0.08	0.21	0.22	1.00
Mean	0.20	0.22	0.24	0.24	0.53	0.52	0.52	0.01	-0.00	0.64	1.36	4.17
S.D.	1.54	1.70	1.85	1.87	0.50	0.50	0.50	0.02	0.02	2.04	3.06	1.57
Min	0	0	0	0	0	0	0	-0.00	-0.05	0	0	0
Max	92	92	92	92	1	1	1	0.64	0.62	63.70	48.00	10.14

Figure 1. Patents by exporting status (RDI^{OECD})

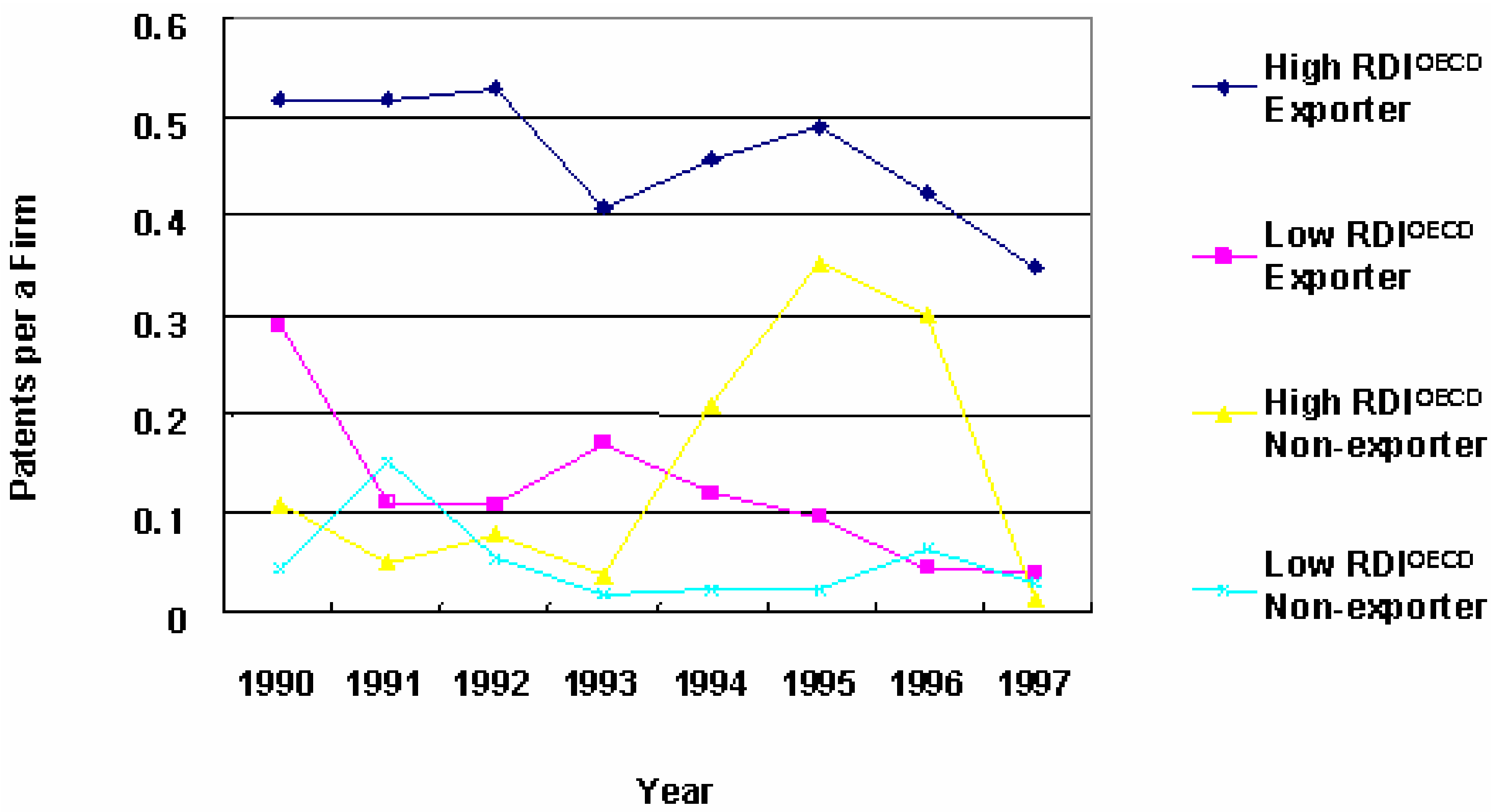

Figure 2. Patents by exporting status (RDI^{Spain})

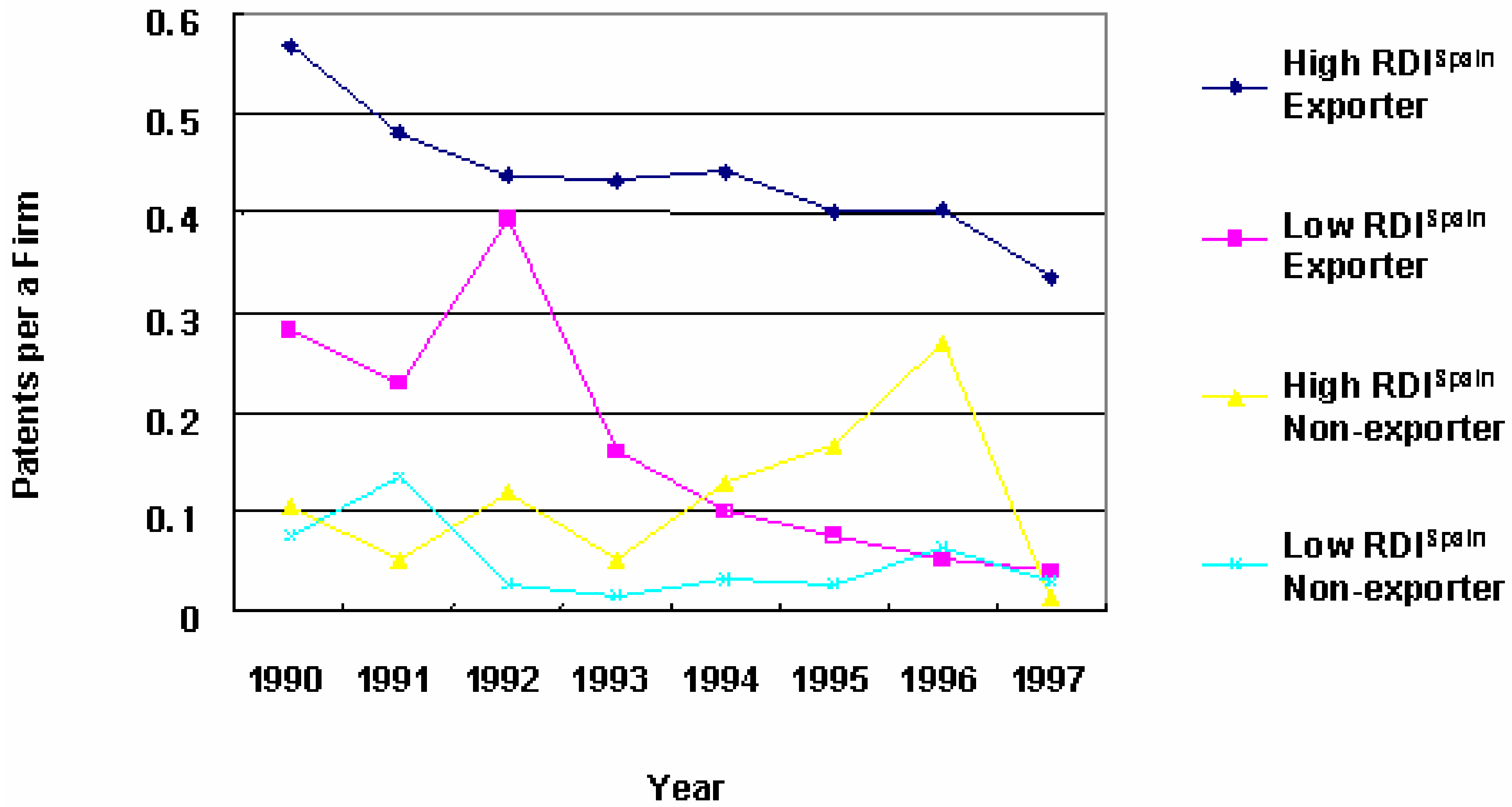

Table 4. Negative binomial regressions (Median split by RDI^{OECD})
(Dependent variable = Patent application)

Variable	Relative Technological Leaders				Relative Technological Laggards			
	1	2	3	4	5	6	7	8
$\text{Export}_{(t-1)}$		0.776*** (3.36) [0.09]				0.600** (2.26) [0.02]		
$\text{Export}_{(t-2)}$			0.745*** (3.30) [0.09]				0.539** (2.01) [0.02]	
$\text{Export}_{(t-3)}$				0.831*** (3.71) [0.09]				0.469** (1.77) [0.01]
$\text{Patent application}_{(t-1)}$	0.462*** (6.89) [0.06]	0.456*** (6.94) [0.06]	0.448*** (6.82) [0.06]	0.445*** (6.84) [0.06]	0.779*** (3.45) [0.02]	0.779*** (3.57) [0.02]	0.780*** (3.55) [0.02]	0.776*** (3.51) [0.02]
$\text{Patent application}_{(t-2)}$	0.202*** (3.19) [0.03]	0.212*** (3.32) [0.03]	0.212*** (3.34) [0.03]	0.217*** (3.49) [0.03]	0.347** (1.69) [0.01]	0.325* (1.59) [0.01]	0.316* (1.58) [0.01]	0.321* (1.58) [0.01]
$\text{Patent application}_{(t-3)}$	0.171*** (2.83) [0.02]	0.146*** (2.45) [0.02]	0.147*** (2.47) [0.02]	0.139*** (2.37) [0.02]	-0.036 (-0.24) [0.00]	-0.058 (-0.36) [0.00]	-0.045 (-0.30) [0.00]	-0.044 (-0.29) [0.00]
$\text{R\&D intensity}_{(t)}$	0.010 (0.34) [0.00]	0.011 (0.40) [0.00]	0.011 (0.41) [0.00]	0.011 (0.41) [0.00]	0.974 (0.61) [0.03]	0.636 (0.40) [0.02]	0.680 (0.43) [0.02]	0.771 (0.48) [0.02]
$\text{Advertising intensity}_{(t)}$	0.021 (0.96) [0.00]	0.012 (0.54) [0.00]	0.013 (0.60) [0.00]	0.013 (0.59) [0.00]	0.025 (0.44) [0.00]	0.012 (0.22) [0.00]	0.015 (0.26) [0.00]	0.017 (0.31) [0.00]
$\text{Size}_{(t)}$	0.252*** (4.76) [0.04]	0.194*** (3.47) [0.03]	0.197*** (3.54) [0.03]	0.190*** (3.41) [0.02]	0.123* (1.35) [0.00]	0.051 (0.53) [0.00]	0.053 (0.55) [0.00]	0.064 (0.66) [0.00]
Constant	-4.050*** (-12.58)	-4.336*** (-12.66)	-4.297*** (-12.72)	-4.298*** (-12.78)	-4.308*** (-9.27)	-4.348*** (-9.33)	-4.274*** (-9.19)	-4.287*** (-9.21)
Year Effects	Included	Included	Included	Included	Included	Included	Included	Included
N	2531	2531	2531	2531	4013	4013	4013	4013
Log likelihood	-1220.222	-1214.527	-1214.730	-1213.282	-534.870	-532.327	-532.850	-533.288
$-2\Delta L$		11.389***	10.984***	13.879***		5.085**	4.039**	3.164*

*: $p<.10$; **: $p<.05$; ***: $p<.01$ (One-tailed tests)
t-statistics appear in (parentheses); marginal effects in [brackets]

Table 5. Negative binomial regressions (Median split of RDI^{Spain})
(Dependent variable = Patent applications)

Variable	Relative Technological Leaders				Relative Technological Laggards			
	1	2	3	4	5	6	7	8
Export$_{(t-1)}$		1.037*** (4.57) [0.10]				0.412* (1.46) [0.01]		
Export$_{(t-2)}$			0.896*** (4.09) [0.09]				0.465* (1.63) [0.01]	
Export$_{(t-3)}$				0.885*** (4.12) [0.09]				0.533** (1.87) [0.02]
Patent application$_{(t-1)}$	0.476*** (7.18) [0.06]	0.468*** (7.29) [0.05]	0.457*** (7.10) [0.05]	0.454*** (7.11) [0.05]	0.791*** (3.15) [0.02]	0.791*** (3.22) [0.02]	0.798*** (3.24) [0.02]	0.798*** (3.26) [0.02]
Patent application$_{(t-2)}$	0.199*** (3.34) [0.02]	0.209*** (3.47) [0.02]	0.207*** (3.46) [0.02]	0.210*** (3.59) [0.02]	0.451* (1.31) [0.01]	0.448* (1.30) [0.01]	0.445* (1.28) [0.01]	0.452* (1.30) [0.01]
Patent application$_{(t-3)}$	0.179*** (2.95) [0.02]	0.145*** (2.48) [0.02]	0.152*** (2.57) [0.02]	0.147*** (2.51) [0.02]	-0.141 (-0.51) [0.00]	-0.165 (-0.59) [0.00]	-0.170 (-0.61) [0.00]	-0.177 (-0.63) [0.00]
R&D intensity$_{(t)}$	0.022 (0.76) [0.00]	0.023 (0.85) [0.00]	0.022 (0.81) [0.00]	0.021 (0.77) [0.00]	0.691 (0.38) [0.02]	0.436 (0.24) [0.01]	0.418 (0.23) [0.01]	0.338 (0.18) [0.01]
Advertising intensity$_{(t)}$	0.025 (1.15) [0.00]	0.013 (0.59) [0.00]	0.015 (0.73) [0.00]	0.016 (0.73) [0.00]	0.025 (0.40) [0.00]	0.014 (0.23) [0.00]	0.013 (0.22) [0.00]	0.016 (0.27) [0.00]
Size$_{(t)}$	0.297*** (5.76) [0.04]	0.218*** (4.02) [0.02]	0.226*** (4.16) [0.03]	0.225*** (4.17) [0.03]	0.107 (1.07) [0.00]	0.058 (0.56) [0.00]	0.049 (0.46) [0.00]	0.040 (0.38) [0.00]
Constant	-4.207*** (-12.96)	-4.617*** (-13.20)	-4.503*** (-13.24)	-4.462*** (-13.25)	-4.375*** (-8.97)	-4.400*** (-9.01)	-4.349*** (-8.92)	-4.346*** (-8.91)
Year Effects	Included	Included	Included	Included	Included	Included	Included	Included
N	2825	2825	2825	2825	3719	3719	3719	3719
Log likelihood	-1276.845	-1266.148	-1268.318	-1268.253	-481.678	-480.612	-480.346	-479.909
-2ΔL		21.394***	17.055***	17.186***		2.133	2.663	3.539*

*: p<.10; **: p<.05; ***: p<.01 (One-tailed tests)
t-statistics appear in (parentheses); marginal effects in [brackets]