Measuring the Effects of Internationalization on Technological Innovation Efficiency

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Abstract
It is argued that international firms are more innovative than non-international ones as they are able to scan and integrate knowledge and technology. In this paper we aim to observe whether this internationalization advantage also helps firms to improve the efficiency of the technological innovation process. Following a two-stage methodology, we first estimate the technological innovation efficiency by means of an intertemporal DEA and then explain it based on firm internationalization. Results of the first stage indicate that there is much room to improve the technological innovation efficiency of the firms under analysis and results from the second stage indicate that firm internationalization foster innovation efficiency.
Abstract

It is argued that international firms are more innovative than non-international ones as they are able to scan and integrate knowledge and technology. In this paper we aim to observe whether this internationalization advantage also helps firms to improve the efficiency of the technological innovation process. Following a two-stage methodology, we first estimate the technological innovation efficiency by means of an intertemporal DEA and then explain it based on firm internationalization. Results of the first stage indicate that there is much room to improve the technological innovation efficiency of the firms under analysis and results from the second stage indicate that firm internationalization foster innovation efficiency.

Keywords: Internationalization, innovation, efficiency

INTRODUCTION

It is widely agreed that technological innovation represents a source of competitive advantage that positively affects firms’ internationalization (Kyläheiko et al., 2011; Lachenmaier & Wössmann, 2006; Pla & Alegre, 2007; Vila & Kuster, 2007). Innovation leads to internationalization when firms are able to create a new product that generates demand not only in the home market but also in other foreign markets (Basile, 2001; Cassiman & Golovko, 2010). However, the relation between these two processes does not end here and firms, once they develop activities abroad, acquire knowledge about foreign markets and competitors and can become more competitive themselves (Golovko & Valentini, 2011). This need of competitiveness is associated with a higher commitment to innovation (Hitt et al., 1997), especially to product one and patents.
However, a question arises when we look at the efficiency of the technological innovation in international environments. Does internationalization make firms be more efficient in their technological innovation process? To answer this question we develop a two-stage paper. In the first-stage we propose a measurement of technological innovation process efficiency and in the second-stage we explain this efficiency based on firms’ internationalization. In the first-stage we do not use a simple measure of innovation input or innovation output since the result would be one-eyed. Tidd and Bessant (2009) stress that innovation is a complex process and that it should be evaluated as such, not as a single input or output activity. On one hand, solely considering the innovation inputs could lead to misleading results (Koellinger, 2008), e.g. R&D expenditures that are not transformed into innovations are sunk cost that could negatively alter the efficiency score. On the other hand, only considering the innovation outputs without taking into consideration the effort needed to achieve those outputs (innovation inputs) might overestimate the efficiency score.

The aim of this research is tow-fold. First, considering two innovation inputs (R&D capital stock and technological knowledge) and two outputs (number of product innovations and patents) we estimate the technological innovation efficiency in order to observe how efficient firms are when transforming the innovation inputs into innovation outputs. Second, we aim to evaluate how internationalization affects this technological innovation efficiency. To achieve our objective we analyze a panel data sample of 3456 observations corresponding to 536 Spanish manufacturing firms for the period 1992-2005.

Although few studies have sought to measure technological innovation efficiency, most of them have employed mixed innovation inputs or outputs beyond the innovation process (Guan et al., 2006; Zhong et al., 2011), others have disregarded the lag effect of R&D on innovation outputs (Guan et al., 2006; Lee et al., 2010) or have used macro-level data (Lee et al., 2010). Moreover, the linkage between firms’ internationalization and technological innovation efficiency is practically non-existent. Within this context, the contribution of this paper is threefold. First, we estimate a technological innovation efficiency measure considering exclusively innovation inputs and outputs in the analysis, which allows an objective evaluation of the technological innovation process. Second, this paper takes into consideration the lagged effects of innovation inputs in producing the desired outputs while
estimating efficiency. And thirdly, we link the efficiency of the technological innovation process with firms’ internationalization – all these at a micro-level.

This paper proceeds as follows. In the second section the theoretical framework is developed and the hypotheses are presented. The data and methods for developing the empirical analysis are described in the third section. The results from the first- and second-stage estimations are shown in the fourth section, while the fifth is reserved for discussion and conclusions.

THEORETICAL FRAMEWORK

The evolution of the international economy has revealed important changes regarding the structure of the relationships among economic agents and the variables determining the conditions of competitiveness (Fletcher, 2001). There are two main factors that stand out over many others: the first is the growing number of elements of economic organization affected by internationalization; the second refers to the increasing complexity of the innovative process (Molero, 1998; Rogers, 2004). Internationalization is an important issue for firms that often results in vital growth, useful learning outcomes and superior financial performance (Prashantham, 2005). The first important steps in firms’ internationalization process are generally assumed to be trade related, and although import activity is considered to play a role, it is export activity that is most often recognized as being the initial real step in the internationalization process (Jones, 2001). However, this is not an easy process because international markets face a greater competitive pressure than national markets (Prashantham, 2005). In order to survive in the competitive scene that companies have faced in recent years, which is characterized by a high level of dynamism (Díaz et al., 2008; López & García, 2005; Teece, 1998), the continual renewal of competitive advantage through innovation and the development of new capabilities have become necessary (Cho & Pucik, 2005; Grant, 1996). In this context, technology represents one of the most important factors in increasing the national and international competitiveness of the firms (Cassiman & Golovko, 2010), while successful technological innovation in new products and processes is increasingly more regarded as the central issue in economic development (Porter, 1998).
Although a lot of research is being focused on the internationalization of the firm and the technological innovation process (Cassiman & Golovko, 2010; Díaz et al., 2008; Filipescu et al. 2009; Golovko & Valentini, 2011; López & García, 2005; Monreal et al., 2012; Salomon & Shaver, 2005), up to the best of our knowledge there is no evidence regarding the effect that internationalization has upon the efficiency of the technological innovation process.

Learning by Doing Concept

Internationalization is generally argued to be a very beneficial strategy for a firm. Firms engaged in international activities provide gains for employees in the form of higher pay and better employment, show faster productivity growth, are more innovative and have higher survival chances compared to their home counterparts (Bernard & Jensen, 1999). Academic evidence emphasizes the so-called learning-by-exporting concept (MacGarvie, 2006; Salomon & Shaver, 2005; Zhang et al., 2010) according to which internationalization may also serve as a way to acquire new information, in particular new technological knowledge not available in the home markets that may increase firm innovation. Indeed, once a firm is involved in more international markets and/or more deeply in a given one, it is more likely to proactively acquire new knowledge about foreign competition, markets, products, which are unavailable in the home market (Damijan et al., 2010). This is useful for pursuing larger-scale R&D projects and developing other innovative activities through further investments in technology, since constant innovation is required to sustain competitiveness (Salomon & Shaver, 2005; Zhang et al., 2010).

Internationalization can also reduce costs associated with innovation and, consequently, achieve greater returns from continuous technological innovations; thus, firm internationalization is considered one of the main determinants of its innovation (Kotabe et al., 2002). In other words, increased international involvement induces a firm to subsequently develop more innovations and to achieve greater returns from innovation by operating in more markets (Harris & Li, 2009; Hitt et al., 1997). Therefore, firms could enhance their competency base by learning from their interactions with international markets and, thus develop their innovative capacities even further (Harris & Li, 2009; Zhang et al., 2010). Such learning derived from global markets can foster increased R&D and
product/process innovation within firms through gains in firm productivity. To sum up, a firm’s increased presence in international contexts boosts the returns to its sustained innovative efforts (Alvarez & Robertson, 2004), and may also lead to more rapid capitalization of R&D and innovation costs.

**Technological Innovation Efficiency Concept**

When evaluating the performance implications of innovation activities, some studies have focused on the short-term direct effect of innovation inputs on firm performance (George et al., 2002), while others seek the long-term indirect effect through the innovations achieved (Balkin et al., 2000). In addition, different types of innovation inputs have been used, such as R&D expenditures (O’Regan et al., 2006), R&D intensity (Hitt et al., 1997) and R&D manpower (Wang & Huang, 2007), and a variety of innovation outputs like product innovations (Li, 2000), process innovations (Akgün et al., 2009) and patents (Zahra & Nielsen, 2002). This use of a wide range of measurements and effects has led to results that are often inconclusive and ambiguous, highlighting the need for further examination of the innovation-performance relationship.

Technological innovations are achieved through a long and complex process, involving the phases of searching, selecting, implementing and capturing value (Tidd & Bessant, 2009) and a realistic evaluation of the how the technological innovation activities are effected should encompass the innovation process as a whole. The resource-based view (RBV) gives us support for considering innovation as a process and for evaluating it from an efficiency perspective; RBV supports the concept of the transformation of firm resources – R&D – into desirable outputs – innovations – through the use of the internal capabilities – efficiency. These capabilities are defined as the firm ability to use and transform the owned resources to a desired end. Furthermore, without these capabilities – efficiency – the mere possession of a large quantity of resources – R&D – does not guarantee the creation of a competitive advantage – innovations – or superior performance (Song et al., 2007). As previously commented, we define technological innovation efficiency as the relative capability of a firm to maximize innovation outputs given a certain quantity of innovation inputs.
Measuring efficiency of innovation activities from the technical efficiency perspective (Farrel, 1957) is not new in the literature but the relevant empirical evidence is limited. Divergences can be observed in these studies as some included inputs and outputs beyond the technological innovation process (e.g. Guan et al., 2006; Hashimoto & Haneda, 2008) and some did not take into consideration the time lag required before R&D projects are completed and innovation outputs are achieved (Guan et al., 2006; Revilla et al., 2003). Finally, those papers at a micro-level that exclusively considered inputs and outputs of the technological innovation process and controlled for the lagged effects (e.g. Guan & Chen, 2010; Wang & Huang, 2007) do not explain the efficiency based on the international firm activity. Following the above-mentioned, our hypothesis is posed:

Hypothesis: High rates of firm internationalization positively affect the efficiency of the technological innovation process.

METHODS

Data and Sample

In order to empirically test our hypothesis we used the Survey of Business Strategy (SBS), which is a firm-level panel dataset of Spanish innovating and non-innovating manufacturing firms covering the period from 1990 to 2005. The SBS is random and stratified according to industry sector - NACE-Rev.1 classification- and firm size (Fariñas & Jaumandreu, 2000). The aim of the SBS is to document the evolution of the characteristics of the strategies used by Spanish firms. It provides information on markets, customers, products, employment, outcome results, corporate strategy, human resources, and technological activities.

The sample consist of an unbalanced panel since not all the firms answered throughout the 16 years, that is, new firms are were added each year and others ceased to provide information. After deleting

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1 Firms with between 10 and 200 employees are selected trough a random stratified sample. Firms with more than 200 employees are surveyed on a census based.

2 In the first wave of the SBS, in 1990, 2188 firms were surveyed according the criteria above mentioned in footnote 3. By the year 2005, SBS had an unbalanced panel of 4050 firms surveyed. Aiming keeping the original firms during the complete panel motivated the consecutive waves of the SBS. Each year, the SBS intended to add to the sample all the new firms with more than 200 employees and a random and stratified sample which, approximately, represent the 5% of the new firms with between 10 and 200 employees. The annual response rate was around 90% (see http://www.funep.es/see/sp/sinfo_cobertura.asp for detail information of the SBS).
observations with missing values in the variables under analysis, we considered two main aspects to restrict the firms in our data. First, firms should have answered the SBS for at least six consecutive years. Second, since the one key component of the paper is to calculate the efficiency of the technological innovations, those firms that did not registered any R&D expenditures during any year of the panel were excluded from the sample. As explain latter, we calculated the inputs and outputs of the technological innovation efficiency as the mean of the current year plus the three previous years, leading to remain with a sample covering the period from 1994-2005. Due to the sensibility to extreme values of the program used to estimate the intertemporal DEA, those observations that registered cero outputs were removed from the sample. In order to avoid the creation of a spurious or mediocre frontier in the first-step, we kept as much information as possible. That is, whether a firm with six observations of positive inputs had the second and fourth observations with cero outputs, we removed from the sample uniquely the second and fourth observations and kept the rest for performing the DEA bootstrap. Nevertheless, due to a restriction of the method used in the second-stage (Tobit model with random effects) we had to remove all observations of this example, leading a difference in the sample size between the two stages.

Then, the final sample of the first-stage consists of 2472 observations of 415 firms. In the second-stage analysis the sample gathers 2315 observations of 362 firms from which 11.34 percent have observations for the complete panel.

**Measurement of Technological Innovation Efficiency**

The traditional cost-benefit analysis, following a parametric approach, in which the single optimized regression is assumed to apply to each firm under the analysis, has the major weakness that it requires the imposition of a specific function form and specific assumption about the error distribution. Additionally, for a standard parametric method is very problematic to jointly consider multiple inputs and multiple outputs, as the innovation activity usually embraces. Data envelopment analysis (DEA) overcomes these problems since it uses a mathematical programming model to estimate the best-practice frontier without a specific functional form assumption and, permits the evaluation of firms based on simultaneous dimensions given that it allows the use of multiple inputs and outputs. DEA
can be used to calculate the maximal performance measurement of each decision making unit (DMU) - firms in this case - given a certain number of inputs, relative to all DMUs in the sample.

Farrell (1957) introduced the first systematic measurement of technical efficiency. Latter, Charnes et al. (1978) established he CCR DEA model under the assumption of that production exhibited constant returns to scale (CRS). This model was extended, by Banker et al. (1984), for the case where there are variable returns to scale (VRS). The main difference between the CRS and the VRS is that the former assumes that the plant is operating at its optimal scale or minimum average cost, while the latter avoids this assumption. Following Alvarez and Crespi (2003) we use the VRS to estimate our model since we consider it more accurate in the sense that small firms, generally, operate with a production scale lower than the optimal. Furthermore, Frantz (1992) argues that usually plants do not operate at optimal scale due to market structure and the competitive market pressures the firm are subjugated to. Additionally, the VRS allows us to exclusively measure the inefficiency caused by the suboptimal level of outputs given a certain amount of inputs and not the inefficiency caused by the inadequate plant size. We use the VRS intertemporal DEA output-oriented since we consider that firms first establish the R&D budgets (inputs) and then seek innovation achievements, that is, output maximization.

We consider more convenient using the intertemporal estimation rather than a cross-sectional estimation because the latter assumes a yearly technical change while the intertemporal model assumes stability and comparability between firms over the years of analysis (Mittal et al., 2005). Shepard’s distances are employed in the model, where the efficiency score are less or equal than the unity. If a firm obtaining a score equal to the unit indicates that it is on the frontier and, thus, is efficient in the transformation of inputs to obtain the desires outputs. The efficiency score obtained were transformed into percentage, where the 100% indicates that firm is 100% efficient in transforming its innovation inputs into innovation outputs. The model estimation was carried out using FEAR software (Wilson, 2008).
Inputs and Outputs Selection

Recall that RBV considers that firms use their multiple resources (inputs) and transform them into multiple outputs through the use of their capabilities. Based on this productive perspective and on the existent literature we select the two technological innovation inputs to be transformed into two technological innovation outputs. R&D capital stock and high-skilled staff\(^3\) are the two inputs selected. The R&D capital stock has been used in previous studies analyzing the innovative firm efficiency following the DEA approach (e.g. Wang, 2007). It was estimated using the traditional way (Griliches, 1979), where the R&D capital stock (RDCS) depends on the R&D expenditure (RD) of firm \(i\) at time \(t\) plus the previous R&D expenditures done by the firm affected by a depreciation rate \((\gamma)\). The previous R&D expenditures goes up to four years before \(t\) \((w=1\ldots4)\) and the depreciation rate was set to 20%.

\[
RDCS_{it} = RD_{it} + \sum_{w=1}^{4} (1 - \gamma)^w RD_{i(t-w)}
\]

(1)

Since DEA methodology demands it, R&D expenditures were deflated at year 1995 before calculating RDCS. Due to the lack of a suitable deflator for R&D expenditures (Lichtenberg, 1984) we selected as a deflator the intermediate input price indices from the EU KLEMS (2008) database.

The high-skilled staff, representing the technical knowledge resources, is also considered in the literature as innovation inputs (Damanpour & Aravind, 2006). The basis of this argument is that the technical employees and employees with higher academic training, with diversified backgrounds and managerial skills, influence positively the transformation of technological investments into product and process innovation achievements through the generation of ideas (Ettlie et al., 1984; Koellinger, 2008). Thus, the second input used in this study is the mean of the current year plus three previous years of the number of high-skill staff.

As mentioned before, we selected two outputs of the innovation process that account for the number of product innovations (NPI) and the number of patents (NPAT). Some studies have considered new product rate or sales due to new product as the innovation output in their efficiency analysis (Guan et

\(^3\)Some authors (Guan & Chen, 2010) also considered the number of R&D employees as an input but in our case we do not include it since the R&D expenditures also includes the salaries of the R&D personnel.
al., 2006; Guan & Chen, 2010) but we consider the first measurement as a better one fitting to our objective since NIP only account for the technological innovation process and not for the firm capacity to profit from the innovations. As well, the rate of patents achieved is a common innovation output used in the literature to account for innovation outputs (e.g. Revilla et al., 2003; Hashimoto & Haneda, 2008). Both rate of new products and patents were calculated as the mean of the last four years.

The Model

In order to test our hypothesis, we take the technological innovation efficiency, estimated in the first state, as the dependent variable. The main explanatory variable in our analysis is the firm internationalization that is measured as the percentage of total sales due to international sales. The theoretical and empirical evidence offer guidance regarding what variables should also be included as explanatory variables. Firm age is included in our model since it represents the firm experience, learning capacity and knowledge base and entrepreneurial behavior of firms (Sorensen & Stuart, 2000; Galende & De la Fuente, 2003; Santamaría et al., 2009). Firm age embodies management and organizational excellence, enhancing absorption capacity, and enabling the integration of the external knowledge acquired in international markets (Bughin & Jacques, 1994; Dyerson & Mueller, 1999). To calculate firm age, we subtracted the year of the firm’s foundation year from the current year t.

The model also controls for the possible effect of industry competitiveness on the technological innovation efficiency. Firms competing in dynamic markets or in markets with high concentration rates might not have tolerance to be inefficient in order to compete successfully. We used market dynamism and the number of competitors in the main market. For both variables the firm must respond according to the values previously defined by the SBS. The former could take values of 0 = recessive, 0.5 = stable or 1 = expansive. The latter is measured as a four-level ordinal variable taking values of 1 = less than 10; 2 = from 11 to 25; 3 = more than 25; and 4 = atomized. Finally, the model

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6 Although, the process innovations might also derived from R&D activities, due to lack of data we could not include it in the analysis. The OECD (2005) also considers organization and marketing innovations as outcomes but they are not included in the analysis due to the fact that they might not depend on R&D activities.
also controls for the firm size that is measured as the number of employees. Table 1 contains the mean, standard deviation and correlation of the variables.

Since our dependent variable range from 0 to 100, and due to the panel structure of our sample, the most adequate model to estimate is the random effects tobit model, which is express as:

\[
\text{Technological Innovation Efficiency}_{i,t} = \alpha_0 + \beta_1\text{Internationalization}_{i,t} + \\
\beta_2\text{Internationalization}^2_{i,t} + \beta_3\text{Age}_{i,t} + \beta_4\text{Market dynamism}_{i,t} + \beta_5\text{Number of competitors}_{i,t} + \beta_6\text{Firm size}_{i,t} + \mu_i
\]

where \(i = 1, \ldots, N\) and \(t = 1, \ldots, T\) represent the cross-sectional units and the time periods, respectively. The common error term \(\mu_i\) splits into a time-invariant individual random effect \((\nu_i, \text{and a time-varying idiosyncratic random error})\) \((\epsilon_{it})\). As observed in equation (2), the squared value of internationalization is introduced in the model in order to control for a liner effect.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Tech. Innov. Eff.</td>
<td>31.333</td>
<td>34.469</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Internationalization</td>
<td>30.914</td>
<td>26.965</td>
<td>-0.0970*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Firm age</td>
<td>3.24</td>
<td>0.776</td>
<td>-0.0307</td>
<td>-0.0794*</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Market Dynamism</td>
<td>0.612</td>
<td>0.347</td>
<td>0.0903*</td>
<td>0.0506*</td>
<td>0.0309</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5. Number of Competitors</td>
<td>1.468</td>
<td>0.901</td>
<td>0.1383*</td>
<td>-0.0286</td>
<td>-0.0355</td>
<td>-0.0097</td>
<td>1</td>
</tr>
<tr>
<td>6. Firm size</td>
<td>473.676</td>
<td>967.517</td>
<td>-0.1041*</td>
<td>0.1810*</td>
<td>0.1310*</td>
<td>0.0285</td>
<td>-0.1004*</td>
</tr>
</tbody>
</table>

Note: * p-value <= 0.05

RESULTS

Stage I: Technological Innovation Efficiency

As mentioned before, an intertemporal DEA output-oriented model was used to estimate the efficiency scores of each DMU. As DEA methodology demands, we estimated a separately frontier – DEA model- for each of the 19 industries under analysis in our sample, assuming that each subsample fulfill the three necessary conditions of homogeneity (Haas & Murphy, 2003); a) the DMUs are engaged in the same process; b) all DMUs are evaluated under the same measures of efficiency and; c) all DMUs operates under the same conditions.
Recall that the efficiency scores range from 0 to 100. The interpretation of these values should be that the difference between the score obtained and 100 is the percentage of inefficiency. For example, a firm with a score of 84 would indicate that at the same level of inputs the firm is 16% inefficient, relative to its industry, due to the lack of capability to transform innovation inputs into innovation outputs. This score also indicates the firm is 84% efficient.

Due to a limitation of space, we cannot show the efficiency score for each firm under analysis, but in Table 2 we present the mean and median of the efficiency scores (EFF) and the percentage of efficient firms by industry. In this table there are also presented the number of firms analyzed as well as the mean of the inputs and outputs used for calculating the efficiency scores. What calls our attention is the observe heterogeneity between the different industries regarding the efficiency scores.

As observed in Table 2, six of the industries under analysis showed a mean of the efficiency scores lower than the 20%, showing a great room for improving the technological innovation efficiency of the Spanish manufacturing firms. Nevertheless, five industries show efficiency scores averages larger than the 40%. The highest mean of the technological innovation efficiency is the one of the timber industry (60.2%), followed by the other transport equipment industry with an efficiency average of 47.6%. Contrary, the lowest averages of the efficiency scores are those for the textile and clothing (10.6%), chemical (16.3%) and rubber and plastic products (16.3%). Based on these results, we cannot say that one industry is more efficient than other since no common frontier has been established due to the DEA methodology requirements (Brown, 2006). But what we can learn from these results is that the uncertainty or risk associate to successful innovations outcomes is higher in those sectors with lower efficiency scores. In other words, it is easier to obtain innovations in the timber industry where technology and products are not as complex as those in chemical industries where many attempts and tests have to be performed before launching the new –or improved- product.
<table>
<thead>
<tr>
<th>Industries</th>
<th>Tech. Int.</th>
<th>N</th>
<th>RDSCS</th>
<th>HSS</th>
<th>NPI</th>
<th>PATT</th>
<th>EFF (mean)</th>
<th>EFF (median)</th>
<th>EFF (Std. Dev)</th>
<th>% of EFF = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meat industry</td>
<td>LMTs</td>
<td>59</td>
<td>2099096</td>
<td>33.071</td>
<td>5.559</td>
<td>0.157</td>
<td>40.3</td>
<td>38.0</td>
<td>25.9</td>
<td>20.34</td>
</tr>
<tr>
<td>Foodstuffs and tobacco</td>
<td>LMTs</td>
<td>147</td>
<td>1059052</td>
<td>18.112</td>
<td>3.070</td>
<td>0.245</td>
<td>28.0</td>
<td>23.1</td>
<td>23.5</td>
<td>11.56</td>
</tr>
<tr>
<td>Beverages</td>
<td>LMTs</td>
<td>72</td>
<td>943752.1</td>
<td>32.130</td>
<td>1.747</td>
<td>0.719</td>
<td>27.4</td>
<td>15.6</td>
<td>23.2</td>
<td>22.22</td>
</tr>
<tr>
<td>Textiles and clothing</td>
<td>LMTs</td>
<td>220</td>
<td>567941.3</td>
<td>5.812</td>
<td>13.847</td>
<td>0.510</td>
<td>10.6</td>
<td>3.3</td>
<td>17.2</td>
<td>5.00</td>
</tr>
<tr>
<td>Leather and footwear</td>
<td>LMTs</td>
<td>45</td>
<td>202806.9</td>
<td>0.569</td>
<td>8.583</td>
<td>0.222</td>
<td>37.7</td>
<td>33.1</td>
<td>29.4</td>
<td>20.00</td>
</tr>
<tr>
<td>Timber industry</td>
<td>LMTs</td>
<td>71</td>
<td>810632.4</td>
<td>15.352</td>
<td>1.880</td>
<td>0.254</td>
<td>27.7</td>
<td>16.1</td>
<td>24.8</td>
<td>21.13</td>
</tr>
<tr>
<td>Paper industry</td>
<td>LMTs</td>
<td>14</td>
<td>977823.7</td>
<td>120.383</td>
<td>0.214</td>
<td>0.000</td>
<td>40.9</td>
<td>38.1</td>
<td>24.2</td>
<td>35.71</td>
</tr>
<tr>
<td>Publishing and printing</td>
<td>LMTs</td>
<td>324</td>
<td>4720492</td>
<td>40.197</td>
<td>2.848</td>
<td>1.024</td>
<td>16.3</td>
<td>7.4</td>
<td>18.5</td>
<td>4.32</td>
</tr>
<tr>
<td>Chemicals</td>
<td>HTs</td>
<td>117</td>
<td>747858</td>
<td>8.321</td>
<td>2.778</td>
<td>0.442</td>
<td>16.3</td>
<td>5.2</td>
<td>20.8</td>
<td>9.40</td>
</tr>
<tr>
<td>Rubber and plastic products</td>
<td>LMTs</td>
<td>159</td>
<td>3528608</td>
<td>21.482</td>
<td>5.998</td>
<td>0.509</td>
<td>16.4</td>
<td>6.4</td>
<td>20.8</td>
<td>4.4%</td>
</tr>
<tr>
<td>Nonmetallic mineral products</td>
<td>LMTs</td>
<td>128</td>
<td>1742349</td>
<td>18.974</td>
<td>11.857</td>
<td>0.418</td>
<td>18.7</td>
<td>7.6</td>
<td>22.7</td>
<td>10.16</td>
</tr>
<tr>
<td>Ferrous and non ferrous metals</td>
<td>LMTs</td>
<td>141</td>
<td>1170016</td>
<td>11.769</td>
<td>5.745</td>
<td>1.246</td>
<td>21.0</td>
<td>9.1</td>
<td>24.6</td>
<td>9.93</td>
</tr>
<tr>
<td>Metal products</td>
<td>LMTs</td>
<td>268</td>
<td>2914336</td>
<td>21.221</td>
<td>6.523</td>
<td>0.611</td>
<td>20.5</td>
<td>9.3</td>
<td>22.8</td>
<td>5.60</td>
</tr>
<tr>
<td>Agricultural and industrial</td>
<td>HTs</td>
<td>73</td>
<td>6341058</td>
<td>73.636</td>
<td>5.521</td>
<td>0.949</td>
<td>31.4</td>
<td>21.2</td>
<td>26.9</td>
<td>9.59</td>
</tr>
<tr>
<td>Office machines and data</td>
<td>HTs</td>
<td>226</td>
<td>2681677</td>
<td>25.743</td>
<td>5.877</td>
<td>0.963</td>
<td>16.4</td>
<td>8.4</td>
<td>19.1</td>
<td>5.31</td>
</tr>
<tr>
<td>Machinery and electrical</td>
<td>HTs</td>
<td>206</td>
<td>39100000</td>
<td>50.455</td>
<td>3.964</td>
<td>0.750</td>
<td>21.3</td>
<td>9.3</td>
<td>25.3</td>
<td>8.25</td>
</tr>
<tr>
<td>Motor vehicles</td>
<td>HTs</td>
<td>72</td>
<td>82000000</td>
<td>223.398</td>
<td>1.438</td>
<td>0.580</td>
<td>47.6</td>
<td>47.4</td>
<td>27.6</td>
<td>16.67</td>
</tr>
<tr>
<td>Other transport equipment</td>
<td>HTs</td>
<td>95</td>
<td>432820.2</td>
<td>12.091</td>
<td>8.132</td>
<td>2.503</td>
<td>45.0</td>
<td>50.6</td>
<td>29.3</td>
<td>16.84</td>
</tr>
<tr>
<td>Furniture industry</td>
<td>LMTs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
As commented in the theoretical framework, few attempts have been performed in the literature in order to measure the technological innovation efficiency, limiting the comparative of our results with previous results since those studies uniquely considering innovation inputs and innovation outputs were performed analyzing 30 different countries (Wang, 2007; Wang & Huang, 2007) or twenty six regions of China (Guan & Chen, 2010). If the reader claims a point of reference we could say that Wang (2007) obtain a mean of the efficiency scores of 65% and a mean of 86% for the study of Wang & Huang (2007) and for the sample of the regions of China the mean of the efficiency scores is 45.3%.

Results presented in Table 2 also enable us to observe the heterogeneity of firms within industries. For example, the publishing and printing industry has the highest percentage of efficient firms (35.71%) but the mean and median of the efficiency scores are not the highest but the standard deviation is among the largest. This indicates that in this industry the firms tend to be in the poles, that is, highly efficient or highly inefficient. For the textiles and clothing industry there seems to be less variation but a clear tendency to inefficiency. Observe how the standard deviation, mean and median are the lowest and the how the percentage of efficient firms is very low. That is, there are very few firms in the best practice frontier and the rest are very far from the frontier.

**Stage II: Effect of Internationalization on Technological Innovation Efficiency**

In order to empirically test our hypothesis that, thanks to the knowledge gain in international markets, firm internationalization will have a positive effect on the technological innovation efficiency. In Table 3 we present the estimates of the random effects Tobit model.

In Model 1 we introduce the internationalization variable without the squared term. As observer, internationalization does not produce a significant effect on the technological innovation efficiency. Firms competing in dynamic markets seem to be more efficiency that those firms competing in stable or recessive markets. This indicates how completion demand firms to be more efficient in the transformation of innovation inputs into innovation outputs. Interestingly, firm size does produce a negative and significant effect indicating that larger firms trend to be more inefficient that SMEs.
One possible explanation of this behavior is that thanks to the flexibility that characterize SMEs, they are able to adapt and adjust their process easily and faster than large firms.

Table 3. Effect of internationalization on technological innovation efficiency

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internationalization</td>
<td>-0.0073</td>
<td>-0.2371**</td>
</tr>
<tr>
<td></td>
<td>(0.0371)</td>
<td>(0.1018)</td>
</tr>
<tr>
<td>Internationalization²</td>
<td></td>
<td>0.0027**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0011)</td>
</tr>
<tr>
<td>Firm age</td>
<td>-1.5795</td>
<td>-1.4905</td>
</tr>
<tr>
<td></td>
<td>(1.0788)</td>
<td>(1.0773)</td>
</tr>
<tr>
<td>Market Dynamism</td>
<td>2.571*</td>
<td>2.6406*</td>
</tr>
<tr>
<td></td>
<td>(1.4074)</td>
<td>(1.4072)</td>
</tr>
<tr>
<td>Number of Competitors</td>
<td>0.6505</td>
<td>0.5968</td>
</tr>
<tr>
<td></td>
<td>(0.7432)</td>
<td>(0.7427)</td>
</tr>
<tr>
<td>Firm size</td>
<td>-0.0049***</td>
<td>-0.0050***</td>
</tr>
<tr>
<td></td>
<td>(0.0015)</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>Constant</td>
<td>35.7598***</td>
<td>37.9087***</td>
</tr>
<tr>
<td></td>
<td>(4.2473)</td>
<td>(4.3272)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-10552.901</td>
<td>-10549.98</td>
</tr>
<tr>
<td>Wald chi²</td>
<td>17.53***</td>
<td>23.54***</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2315</td>
<td>2315</td>
</tr>
<tr>
<td>Number of firms</td>
<td>362</td>
<td>362</td>
</tr>
</tbody>
</table>

Notes: *** p-value <= 0.001; ** p-value <=0.05; * p-value <=0.1. Robust standard errors are in parentheses.

From Model 1, we can also observe that neither firm age nor the number of competitors affect significantly the technological innovation efficiency. This might indicate that the absorptive capacity needed to scan and integrate external knowledge, gained in international markets, is not necessarily linked to the firm organizational routines created through the years.

When introducing squared term of internationalization in Model 2 interesting results emerge that support our hypothesis and shed light on to a new discovery. Observe how the internationalization has a negative and significant effect on the technological innovation efficiency, but the internationalization-squared term has a positive and significant effect. This clearly indicates a “U” shape relationship between firm internationalization and technological innovation efficiency. That is, low levels of firm internationalization lead to lower rates of efficiency but higher rates of firm internationalization allows firms to gain knowledge, integrate it and increase the efficiency whereby
the technological innovation process is performed. The remaining variables of Model 2 remain unchanged in regards with Model 1.

CONCLUSIONS

It has been repeatedly emphasized in the literature that it is highly important to jointly consider internationalization and technological innovation when referring to firms’ competitiveness abroad (Cassiman & Golovko, 2010; Filipescu et al. 2009; Hitt et al., 1997; Monreal et al., 2012). Technological innovations are a source of competitive advantages for firms and help them become more competitive in new international markets (Kyläheiko et al., 2011; Lachenmaier & Wössmann, 2006; Pla & Alegre, 2007; Vila & Kuster; 2007). While firms are developing their activities abroad, they enter into contact with global and local competitors, different types of customers and other participants in the market and learn about them. This acquired knowledge makes firms develop more technological innovations, become more competitive and further increase their international market presence (Filipescu et al., 2009). However, it is important to see whether these internationalization advantages also help firms improve the efficiency of the technological innovation process. This was exactly the aim of this paper and, in order to fulfill it, we employed a firm-level panel dataset of Spanish innovating and non-innovating manufacturing firms covering the period from 1990 to 2005.

With regards to the methodology approach, we calculate an intertemporal output-oriented DEA bootstrap. The efficiency scores are calculated by each firm corresponding to a specific industry, which are classified in 19 different sectors according to the CNAE.Rev.1 classification. In the second stage of the study, we explain the obtained efficiency scores based on firms’ internationalization.

Results of the first stage of the analysis show that most Spanish manufacturing firms are operating at very inefficient rates. The most efficient industry is the Wood industry, followed by the Transport equipment industry, operating at the 49% and 48% of efficiency, respectively. On the contrary, the most inefficient industry is the Textiles and wearing apparel (10% of efficiency as a mean) followed by the Non-metallic mineral products industry. As for the second stage of the analysis, results indicate
that indeed high rates of internationalization register significant higher score of the technological innovation efficiency.

This research shows the importance of taking into consideration both inputs and outputs of technological innovation in order to measure how internationalization affects them. For a practitioner’s point of view, this research allows to observe that in order to become more efficient in terms of technological innovations firms should focus on international markets as the knowledge obtained from them is very valuable and can make them much more competitive in the global market.
REFERENCES


