Technological strategies and learning by exporting: the case of Brazilian manufacturing firms, 2006-2008

Abstract

This article assesses the relationship between learning by exporting and technological strategies for Brazilian manufacturing firms from 2006-2008. Technological strategies are characterised by the importance placed on innovation activities, sources of information and cooperation for innovation, and the location of these sources. Combining factor analysis with regression analysis, we find that (i) new exporters become more productive and larger than non-exporters; (ii) technological strategies improve the productivity and size of all firms; and (iii) the differentiated technological strategies of new exporters are generally not correlated with learning by exporting. Learning by exporting might be related to factors that are not captured by the Brazilian Technological Innovation Survey, and the absence of correlation between learning by exporting and technological strategies might reflect some missed opportunities for technological learning from international trade.

Keywords: *learning by exporting*, technological strategies, innovation, Brazilian industry

1. Introduction

The economics and business literature has dedicated much attention to international trade studies at the firm level to examine not only motivations for internationalisation but also firms' productive and technological dynamics when they decide to engage in international markets. This stream of literature has given rise to a number of stylised facts. One finding is that exporting firms are larger and more productive than non-exporting firms and that they sell more in the domestic market; thus, they have more favourable competitiveness indicators than do non-exporting firms (Tybout, 2003). Furthermore, these differences appear to be greater in developing countries, as shown in Table 1.

Table 1. Differences between exporters and non-exporters: Brazil and selected countries (in %)

	Brazil[a]	Sub-Saharan Africa[b]	United States[b]	Germany[b]	Colombia[b]
Average wages	16.3	34.1	9.3	1.7	17.3
Labour productivity	50.2	56.0	15.8	21.6	46.1

Total sales	169.1	312	110	95.7	123.7
Employment	83.5	212.6	93.6	71.7	197.2
Number of observations	45,996	3,800	190,000	4,200	70,000

Sources: (a) Araújo (2006); (b) Van Biesebroeck (2005), Bernard and Jensen (1999), Bernard and Wagner (1998) and Isgut (2001). All differences are significant at the 1% level.

Two non-mutually exclusive hypotheses can be used to explain why exporting firms perform better than non-exporters (Wagner, 2007). The first is that only larger and more productive firms begin to export because exporting involves entry costs for transportation, distribution, specialised personnel to handle international distribution networks and costs to adapt existing products to international standards (Wagner, 2007). Accordingly, many size, efficiency and productivity gains occur **before** a firm begins to export. Thus, most competitive firms self-select into exporting activities. Indeed, the self-selection of better firms for exporting is a well-documented phenomenon in the literature.

The second hypothesis that can explain the differences between exporters and non-exporters is that exporters **become** more competitive after entering international markets. The literature defines these *ex-post* gains as learning by exporting, which may derive from several sources:

- Economies of scale fostered by exports;
- Greater competitive pressure in international markets, which leads to production and management improvements;
- Quality improvements, either to meet international customers' demands or due to better access to state-of-the-art machinery and inputs;
- Improvements in innovation capabilities due to better access to technology and the possibility of cooperation with foreign firms in the productive chain (Wortzel & Wortzel, 1981; World Bank, 1993; Aw & Hwang, 1995; Clerides et al., 1998). Moreover, economies of scale derived from international trade dilute the fixed costs of innovation, especially R&D projects (Aw et al., 2008).

Nevertheless, the international business literature has paid increased attention to knowledge-seeking motivations for internationalisation, either through interactions with foreign firms or even through mergers and acquisitions (Kogut & Chang, 1991; Shan & Song, 1997; Garcia et al., 2012).

An overview of the literature supports the conclusion that more competitive firms become exporters, but exporters do not necessarily become more competitive (Wagner, 2007; López, 2005). Learning effects following entry into the international market, when they exist at all, tend to occur only in developing countries. One possible explanation is that learning effects may be marginally more important in developing countries, where firms tend to be further from the technological frontier (Blalock & Gertler, 2004).

In any case, the relationship among the possible learning effects of exportation through innovation has rarely been assessed directly. In other words, many studies test the export-productivity link, and some test the export-innovation link, but very few test the export-innovation-productivity link. Some exceptions are the studies by Crespi et al. (2008), Salomon and Shaver (2005) and Love and Ganotakis (2013). Crespi et al. (2008) reported that UK firms that had exported in the past and had used their overseas customers as an information source for innovation experience faster productivity growth. Studying a panel of Spanish firms between 1990 and 1997, Salomon and Shaver (2005) found that firms that had exported in the recent past tended to introduce more product innovations and to file more patents. More recently, Love and Ganotakis (2013) studied the effects of exportation on subsequent innovation in small and medium-sized high-tech companies in the UK. The basic argument in these studies is that exports induce innovation and that innovation fosters productivity. However, it is very difficult to identify how much of the impact of innovation on productivity is actually induced by foreign trade.

Thus, the main contribution of this article is its direct assessment of the relationship among exports, performance and technological strategies in the large emerging country of Brazil. This article tests three hypotheses:

> **H1**: Did learning by exporting occur in Brazilian new exporters in 2006-2008?
>
> **H2**: Are some technological strategies—expressed by innovation activities, information sources for innovation and cooperation—related to firms' productivity, size and market share?
>
> **H3**: Is learning by exporting related to entrants' differentiated technological strategies?

Using data from different sources on Brazilian manufacturing firms, we compare the trajectories and technological strategies of firms that began to export in 2004-2005 with those of non-exporters with similar characteristics in 2006-2008. We use quasi-experimental selection on observables techniques to ensure comparability between the groups, and the technological strategies are characterised using factor analysis.

The remainder of the paper proceeds as follows. The next section describes the data and defines the variables, and the third section details the empirical strategy. Section four describes the factor analysis that we use to characterise technological strategies, and the fifth section details the control of the self-selection of entrants. The sixth section discusses the regression results, and the seventh section concludes.

2. Data and description of variables

We used data from several sources (Portuguese acronyms in parentheses): the Annual Industrial Survey (PIA) and the Technological Innovation Survey (PINTEC), both from the Brazilian Institute of Geography and Statistics (IBGE); the Foreign Trade database from the Ministry of Development, Industry and Foreign Trade (SECEX/MDIC); and the Annual List of Social Information (RAIS), an annual census of all formal employees provided by the Ministry of Labour and Employment (MTE). All of these databases were

merged using the single tax identification code (CNPJ) for each firm. These datasets were linked by the Institute for Applied Economic Research (IPEA) at a secrecy room for confidential data at IBGE.[1]

The period of analysis was 2002-2008; accordingly, firms were classified as entrants in exporting activities if they entered in 2004 or 2005, exported for at least two consecutive years after entry, and were non-exporters in the two previous years. The period from 2006-2008 is covered by PINTEC's fourth edition, and non-monetary information, such as innovation activities, is for this period. Companies had to be included in the PINTEC and the PIA databases in all years from 2005-2008, which effectively restricted the analysis to companies with more than 30 employees. Identifying those firms in the RAIS and SECEX databases from 2002-2008 was not a major restriction because those databases are composed of administrative records.

Our analysis was restricted to innovative manufacturing firms during the period 2006-2008, regardless of whether those firms were entrants or non-exporters. Using the PINTEC restricted the sample to industrial firms because it covers industrial firms but very few service firms.

Only technological innovators responded to the part of the PINTEC questionnaire that allowed us to characterise their technological strategies according to the importance placed on innovation activities, the sources of information and cooperation for innovation and the location of these sources. For example, using the PINTEC data makes it impossible to assess the importance of sources of information for innovation for non-innovators. This restriction implies that learning by exporting through innovation could not be analysed for non-innovators in our research design. After addressing all of these concerns, our sample consisted of 18,977 firms, of which 892 (4.9%) were entrants according to the above definition.

The PINTEC variables used to characterise firms' technological learning strategies were the importance of innovation activities, the sources of information for innovation and cooperation and the location of these sources of information and cooperation. The PINTEC questionnaire is comparable to the Community Innovation Survey (CIS), for example, because it follows the Oslo Manual (OECD, 2005) for innovation surveys. In all cases, importance was assessed on a 1-4 Likert scale.

The positive effects of the entry of industrial firms into the international market were evaluated based on productivity, employment, net sales revenue (NSR) and market share. We used three productivity measures. The first measure is labour productivity, which is the ratio of a firm's aggregated value to its average number of employees during the year, i.e., a measure of value added per worker. The other two are measures for Total Factor Productivity (TFP). Both measures of TFP are firm-level residuals of the estimations of modified versions of the Cobb-Douglas function, which is a standard procedure in the literature (Bernard & Jensen, 1999; Delgado et al., 2002; García et al., 2012). The first measure is based on a fixed-effects OLS regression of value added by labour and physical capital, including sector and year dummies (TFP-FE). The second measure is based on

[1] It should be noted that the IPEA is not the owner of these databases and must comply with many confidentiality clauses. We are not allowed to keep a copy of the database files used in this paper; hence, in practice we must go to the secrecy room to run the tabulations and models.

the algorithm suggested by Levinsohn and Petrin (2003) (TFP-LP). The essential difference between these two estimation techniques of production functions is that the Levinsohn and Petrin (2003) algorithm addresses the endogeneity between choice of inputs usage and unobserved productivity shocks: since the latter are computed as residuals in production functions, and consequently, as a measure of TFP, they must be correlated with input levels because firms expand their inputs usage in response to positive productivity shocks. Levinsohn and Petrin (2003) propose using intermediate inputs as a proxy for those productivity shocks.

The turnover of a firm was represented by its NSR. This variable was also used to construct the market share variable at the three-digit National Classification of Economic Activities (CNAE) sector level. It should be noted that the creation of the market share variable preceded the restriction of the database to innovative companies: that is, market share refers to industry totals.

All of the financial variables, such as NSR and value added, were deflated by the Wholesale Price Index—Global Supply (IPA-OG) from the Getulio Vargas Foundation (FGV) at the CNAE three-digit level. Whenever there was no three-digit deflator, the two-digit deflator was used instead. Special attention was paid to the deflation procedure because the terms-of-trade appreciation of Brazilian exports during the first decade of the 2000s could mistakenly lead us to consider pure export price effects as learning by exporting.

The descriptive statistics of the impact variables are shown in Table 2. At first glance, the entrant firms are already larger and more productive than non-entrants in the entry year, suggesting some self-selection. Furthermore, the entrants seem to grow more quickly and to increase their productivity and expand their market share at higher rates than non-entrants, suggesting some learning-by-exporting. More precisely, the entrants' productivity grew 16.5 percentage points (pp) more quickly than that of the non-entrants. The differences in growth rates in NSR and number of employees between entrants and non-entrants were 34.5 pp and 12.5 pp, respectively. As a result, the differences between entrants and non-entrants were even higher in 2008.

In turn, the outcome indicators for innovation (product or process innovation for the company or market) indicate that non-entrant innovative companies innovated more for themselves by introducing products that already existed on the international market; conversely, they showed a smaller proportion of new-to-the-market innovation than did the entrants.

It should be noted, however, that all of these differences will be examined in more detail because these results are partially due to exporters' inherent self-selection.

Table 2. Differences between innovative entrant and non-entrant companies in international trade: Brazil, 2005-2008

Variable	Non-entrants	Entrants
Number of companies	18,085	892
Average number of employees—2005	71.96	208.47
Growth in the number of employees—2005-2008	3.07%	15.63%
Average NSR (2010 thousand R$)—2005	8,652.30	47,837.89
Growth in NSR—2005-2008	5.75%	40.32%

Labour productivity (added value/employee—2010 BRL, in thousands)—2005	42.46	102.49
Growth in labour productivity—2005-2008	8.99%	25.52%
Average market share (CNAE3)—2005	0.08%	0.31%
Growth in market share (CNAE3)—2005-2008	-8.09%	16.43%
Share of net sales exported—2005	-	7.63%
Share of net sales exported—2008	-	8.98%
New-to-the-firm product innovation	40.5%	36.8%
New-to-the-market product innovation	6.96%	21.17%
New-to-the-firm process innovation	72.42%	69.82%
New-to-the-market process innovation	5.23%	8.56%

Source: Prepared from the PINTEC, PIA and SECEX

3. Empirical strategy

We test the relationship between technological strategies and learning-by-exporting using a regression model:

$$performance_i = \beta_0 + \beta_1 export_i + \mathbf{activities_i \beta_a} + \mathbf{sources_i \beta_s} + \mathbf{location_i \beta_l} + \mathbf{cooperation_i \beta_c} + export_i * \mathbf{activities_i \beta_{ea}} + export_i * \mathbf{sources_i \beta_{es}} + export_i * \mathbf{location_i \beta_{el}} + export_i * \mathbf{cooperation_i \beta_{ec}} + \varepsilon_i \quad (1)$$

where $performance_i$ is the performance variable (productivity, employment, NSR or market share); $export_i$ is a binary variable (0 or 1) for entrant; $\mathbf{activities_i}$ is the set of factors or variables that represents the importance of innovation activities; $\mathbf{sources_i}$ is the set of factors or variables concerning the importance of the sources of information for innovation; $\mathbf{location_i}$ is the set of factors or variables regarding the location of the sources; and $\mathbf{cooperation_i}$ is the set of factors or variables that represents cooperation in innovation. The details regarding these factors and variables that represent technological strategies are detailed in the next section. $\mathbf{B}_a$, $\boldsymbol{\beta}_s$, $\boldsymbol{\beta}_l$ and $\boldsymbol{\beta}_c$ are the coefficient vectors for the factors or variables for innovation activities, sources, location and cooperation, respectively. $\boldsymbol{\beta}_{ea}$, $\boldsymbol{\beta}_{es}$, $\boldsymbol{\beta}_{el}$ and $\boldsymbol{\beta}_{ec}$ are the coefficient vectors for the interactions between these factors or variables and the export dummy.

This model should be interpreted as a series of correlation tests: if the factors or variables' coefficients are significant, then they have some correlation with the dependent variable. The interpretation of the coefficients is as follows:

(i) The coefficient β_1 for the entry dummy relates to the hypothesis of *learning-by-exporting*. If β_1 is positive and significant, the interpretation is that beginning to export positively affects the performance variable of interest (productivity, NSR, employment or market share);

(ii) The coefficients $\mathbf{B}_a$, $\boldsymbol{\beta}_s$, $\boldsymbol{\beta}_l$ and $\boldsymbol{\beta}_c$ indicate whether the technological strategies expressed by the factors or variables have an overall relationship with the performance variable for both entrant and non-entrant firms;

(iii) The coefficients $\boldsymbol{\beta_{ea}}$, $\boldsymbol{\beta_{es}}$, $\boldsymbol{\beta_{el}}$ and $\boldsymbol{\beta_{ec}}$ indicate whether there is any statistical correlation between the technological strategies and performance that is specific to entrants. In other words, these coefficients indicate whether learning-by-exporting has any relationship with technological strategies.

It should be noted, however, that better firms self-select to export. In this sense, the correlation tests provided by equation (1) may be biased because entrants were already better than non-entrants even before they began to export. Therefore, one must consider this self-selection in the estimation of equation (1).

Whenever the determinants of self-selection are known and sufficient—in this case, when we know which variables lead a firm to enter the export market—we can employ quasi-natural experimental techniques. We employ a "selection on observables" technique called *inverse probability weighting* (IPW) (Wooldridge, 2002, chapter 18).

IPW consists of weighting equation (1) by the following factor:

$$w_i = \frac{export_i}{p(X_i)} + \frac{1-export_i}{1-p(X_i)} \qquad (2)$$

where $export_i$ is as defined above and $p(X_i)$ denotes the estimated probability of entry. Intuitively greater weights are given to firms that did not enter the market despite their high estimated probability of doing so—representing good counterfactuals for the entrants—and to firms that did enter the market despite their low estimated probability—representing good counterfactuals for non-entrants (Hirano & Imbens, 2001; Abadie, 2005).

Thus, the first step in the IPW correction for self-selection is to estimate a model for $p(X_i)$, the probability of becoming an exporter. The literature suggests some determinants of exporting activities at the firm level: productivity, size, technology, sectoral factors, location and other determinants such as network factors (for example, being a multinational company) and firm age, among others (Greenway & Kneller, 2007). The *logit* model that estimates the probability of becoming an exporter is described in section 5.

4. The characterisation of technological strategies through factor analysis

The PINTEC questionnaire is divided into sections that allow firms to be characterised based on how they engage in innovation, in terms of their innovation activities, their sources of information and their degree of cooperation in innovation.

The original questionnaire contained 7 variables to reflect the importance of innovation activities, 14 to reflect the importance of sources of information and 8 to reflect a firm's sources of cooperation. Currently, there are 12 variables measuring the importance of sources of information and 8 for a firm's sources of cooperation. Accordingly, we sought to condense these variables through factor analysis. This condensation:

(i) Facilitates the characterisation and interpretation of different technological strategies as latent constructs, such as "R&D-driven innovation", "formal sources innovation" and others; and

(ii) Reduces the number of variables in the econometric model because many of these variables have low frequencies in the sample. For example, few firms cooperate with agents overseas, and this frequency is even lower when we categorise this cooperation by agent type.

In our specific case, factor analysis involves several technical aspects. First, our data are either ordinal or binary, which violates the continuity and normality of variables. This data structure requires the use of polychoric correlation matrices (Jöreskog and Moustaki, 2001), which take the inherent latent structure of the data into consideration (Holgado-Tello et al., 2010). In practice, the polychoric correlation matrices showed more relevant correlations than the Pearson correlation matrices, and therefore, the quality of the factor analysis was improved substantially. As a matter of example, a comparison among correlation matrices for the importance of innovation activities is available in the appendix. For the other sets of variables, Pearson correlation matrices are available under request.

The second aspect is the choice between principal components and common factor analysis. The difference between the two is that principal components analysis takes into consideration the total variance of the variables in the factor extraction, whereas common factor analysis takes into consideration only the common variance among the variables. In common factor analysis, the main diagonal of the correlation matrix to be factored is composed of some measure of communality between the variables, such as, e.g., the square of the multiple correlation (SMC). In principal components analysis, this main diagonal is composed of 1s.

According to Hair et al. (2005, chapter 3), although the literature is not conclusive regarding the choice between component and common factor analysis, common factor analysis may be appropriate when the researcher is interested in identifying latent constructs in a dataset and/or has little knowledge about the distribution of the variables' variances among common, specific and error components. In any case, Velicer and Jackson (1990) argue that empirical research has shown analogous results between component and common factor analysis in many situations.

Nevertheless, there are some particularities in the interpretation of common factor analysis. Because factors aim to explain only the common variance of the variables in a dataset, popular criteria for the choice of the number of factors—such as eigenvalues greater than one—may not fit in common factor analysis. Moreover, it is not uncommon to have negative eigenvalues for factors. The reason for this particularity is that the correlation matrix is not necessarily full rank or positive-definite because the elements on the main diagonal are communality measures that are less than 1. These negative eigenvalues may be interpreted as a limit on the dimensionality of latent constructs. For example, if the third and subsequent factors have negative eigenvalues, one should only consider two constructs in the common factor analysis.

After addressing all of these concerns, factor analysis was applied to three variable sets: (i) the importance of innovation activities; (ii) the importance of sources of information for innovation; and (iii) the location of these sources of information. Cooperation for innovation was treated separately. In all factor analyses, the factor extraction method was the iterated principal axis, the communality measure was the squared multiple correlations (SMC), and a Varimax orthogonal rotation was applied. Initially, the number of factors was limited by negative eigenvalues; later, we chose the factors with positive eigenvalues according to the scree plot.

4.1. The importance of innovation activities

The 7 PINTEC variables that capture the importance of innovation activities were originally evaluated on a 1-4 Likert scale. The polychoric correlation matrix (in the appendix) shows that there are two sets of correlated variables (>0.40): one set is composed of intramural and external R&D and market introductions of innovations, and the other set is composed of the acquisition of machinery and equipment and training. Kaiser's Measure of Sample Adequacy (MSA) is 0.65 on average, which is above the recommended 0.5 cut-off (Hair et al., 2005).

We chose two factors to condense the importance of innovation activities (preliminary eigenvalues and scree plots are shown in the appendix). These factors are summarised in Table 3:

- The first factor is named "R&D-driven innovation" because it is highly correlated with intramural and external R&D, market introductions of innovations and industrial projects. This factor indicates a strategy to develop new products or processes endogenously or from the purchase of R&D, followed by investments in industrial projects to further the release of these innovations on the market;
- The second factor is called "machinery-driven innovation" because it is highly correlated with the importance attributed to the acquisition of machinery and equipment and training. This factor reflects a strategy of acquiring embodied technology in machinery and equipment and training personnel to operate these machines, which enables convergence towards the technological frontier of the sector.

Table 3. Factor analysis of the importance of innovation activities

Importance of innovation activities (1-4 scale)	Factor loadings after iteration of the principal axis		Factor loadings after Varimax rotation		Communalities
	Factor 1	Factor 2	Factor 1	Factor 2	
Intramural R&D	0.692	-0.363	**0.781**	-0.035	0.611
Extramural R&D	0.587	-0.276	**0.649**	-0.001	0.421
Acquisition of other external knowledge	0.311	-0.010	0.286	0.123	0.097
Acquisition of machinery and equipment	0.185	0.411	-0.007	**0.451**	0.203
Training	0.614	0.738	0.244	**0.929**	0.923
Market introductions of innovations	0.515	-0.157	**0.533**	0.076	0.290
Industrial projects	0.424	-0.077	**0.417**	0.110	0.186
Sum of eigenvalues after iteration of the principal axis	2.730				-
Eigenvalues of factors	1.778	0.953	1.630	1.101	-
Proportion of the common variance explained by the factor	65.1%	34.9%	59.7%	40.3%	-
Standardised Cronbach's alpha	-	-	0.693	0.830	-

Source: PINTEC. Factor loadings above 0.40 are displayed in bold.

We built factor scores from the rotated factor loadings, which are simply the product of the factor loadings and the original values of the variables for each observation. Then, we created two variables that summarise the importance of innovation activities. However, a final assessment of the reliability of these new variables is necessary. One popular measure of reliability is Cronbach's alpha (Hair et al., 2005). The variable created from the first factor was close to the recommended lower bound of 0.70, and the second factor created a variable with a standardised Cronbach's alpha of 0.83.

4.2. The importance of sources of information

Of PINTEC's original 14 sources of information variables, the effect of four of these variables—intramural R&D, other internal sources, other enterprises of the same group and machinery and equipment suppliers—is already captured by the importance of innovation activities. Patents were not an important source of information for any firm in the sample. Moreover, the importance of clients, customers and competitors as sources of information for innovation were excluded from the factor analysis because these variables were not correlated with any other variable. Thus, these variables were entered as separate regressors in the regression models.

Therefore, from the remaining 7 variables, there are two sets of correlated variables. The first set is related to formal sources of knowledge (universities, research centres, and training and testing institutions), whereas the second set is related to informal sources

(conferences, fairs and computerised information networks). Kaiser's MSA is 0.82 on average.

Two factors characterise the importance of the sources of information for innovation, as shown in Table 4:

- The first factor is named "Formal sources of information"; it relates to universities, testing institutions, training centres and consulting firms, in that order of importance. The standardised Cronbach's alpha for this factor is 0.80;
- The second factor is called "Informal sources of information"; it is related to trade fairs, conferences and electronic information networks. The standardised Cronbach's alpha for this factor is 0.83.

Table 4. Factor analysis of the importance of sources of information for innovation

Importance of innovation activities (1-4 scale)	Factor loadings after iteration of the principal axis		Factor loadings after Varimax rotation		Communalities
	Factor 1	Factor 2	Factor 1	Factor 2	
Consultants	0.544	0.544	**0.590**	0.132	0.365
Universities	0.744	0.744	**0.755**	0.246	0.630
Training centres	0.706	0.706	**0.701**	0.253	0.555
Testing institutions	0.698	0.698	**0.730**	0.204	0.575
Conferences	0.718	0.718	0.400	**0.651**	0.584
Trade fairs	0.640	0.640	0.087	**0.919**	0.852
Electronic information networks	0.468	0.468	0.218	**0.477**	0.275
Sum of eigenvalues after iteration of the principal axis	3.836				-
Eigenvalues of factors	2.979	0.858	2.157	1.68	-
Proportion of the common variance explained by the factor	77.7%	22.3%	56.2%	43.8%	-
Standardised Cronbach's alpha	-	-	0.808	0.834	-

Source: PINTEC. Factor loadings above 0.40 are displayed in bold.

4.3. The importance of sources of information abroad

The PINTEC provides the location of sources of information for innovation, whether in Brazil or abroad. For the purposes of this paper, it is important to determine whether entrants use more information sources abroad than non-exporters and the possible impacts of these sources on entrants' performance variables.

Therefore, we created a dummy interaction variable that takes the value of 1 if the firm attributes medium or high importance to a particular source of information and that source is located abroad and 0 otherwise.

As discussed above, there are several sources of information, and in principle, there is an interaction variable for each source. However, few sources located abroad were used in a relevant way. In fact, when located overseas, only machinery and equipment suppliers, competitors, conferences, trade fairs and electronic information networks were used by more than 200 firms in the sample. Among these variables, competitors had a Kaiser's MSA below 0.40, so that variable was excluded from the factor analysis.

Therefore, the four remaining variables form only one general factor (because the other three factors have negative eigenvalues) that is related to all of the variables. It is not possible to rotate only one factor. The standardised Cronbach's alpha of this single factor is 0.79.

Table 5. Factor analysis of the importance of sources of information abroad

High or medium importance of the source located abroad (binary)	Factor loadings after iteration of the principal axis	Communalities
Machinery and equipment suppliers	**0.505**	0.255
Conferences	**0.879**	0.772
Trade fairs	**0.815**	0.665
Electronic information networks	**0.728**	0.530
Factor eigenvalue	2.221	-
Standardised Cronbach's alpha	0.79	-

Source: PINTEC. Factor loadings above 0.40 are displayed in bold.

4.4. Cooperation for innovation

Very few companies assigned high or medium importance to the various cooperation arrangements for innovation. Thus, to represent cooperation for innovation, we chose to use a dummy indicating whether a firm had any cooperation agreement for innovation. Cooperation agreements were found in 1,816 firms. PINTEC also provides information about cooperation abroad. However, only 21 firms cooperated abroad.

4.5. Descriptive statistics

Table 6 shows the averages and 10% confidence intervals of the factors for entrants and non-exporters. The entrants have higher factors than the non-exporters, and the only factor for which this difference is not significant at the 10% level is the "Machinery-driven innovation" factor (this is the only factor for which the confidence intervals cross for entrants and non-exporters). Regarding cooperation, entrants tend to have more cooperation agreements than non-exporters, although the number of firms that have

cooperation agreements abroad is very low (9 non-exporters and 12 exporters). Table 6 shows that on average, entrants have more proactive technological strategies than do non-exporters.

Table 6. Descriptive statistics of factors: entrants versus non-exporters

	Factors	Average	Confidence interval Lower 95% limit	Upper 95% limit
Non-exporters	R&D-driven innovation	4.39	4.33	4.45
	Machinery-driven innovation	4.29	4.22	4.36
	Formal sources of innovation	6.06	5.96	6.16
	Informal sources of innovation	6.44	6.34	6.53
	Sources of information abroad	0.06	0.05	0.07
	% of firms that cooperate for innovation	9.33%	-	-
	% of firms that cooperate abroad	0.05%	-	-
Entrants	R&D-driven innovation	5.02	4.82	5.22
	Machinery-driven innovation	4.44	4.26	4.62
	Formal sources of innovation	6.46	6.19	6.74
	Informal sources of innovation	7.30	7.07	7.53
	Sources of information abroad	0.26	0.20	0.33
	% of firms that cooperate for innovation+	14.35%	-	-
	% of firms that cooperate abroad+	1.35%	-	-

Source: PINTEC. + - Chi-squared tests of the distribution of cooperating firms among entrants and non-exporters reject the null hypothesis at the 1% significance level, which indicates that entrants tended to cooperate more than non-exporters.

5. Control of self-selection of entrants

Before proceeding to the regression analysis that relates entry into the international market to technological strategies, it is necessary to present the results of the *logit* model used to control self-selection.

In the model presented in Table 7, entering the export business in 2004 or 2005 and continuing to export for at least two consecutive years are regressed on the logarithm of employees and productivity, the age of the firm (quadratic form), the log of technical scientific employees, the market share in quadratic form and whether the company has foreign or mixed capital. Sectoral controls were also added to the model (firms were categorised according to Organization for Economic Cooperation and Development (OECD) categories of technological intensity - labour intensive, natural resources, low, medium and high technological intensity) , as well as regional controls (North, Northeast, Midwest, Southeast and South). These sectoral and regional controls are not reported in Table 7. All of the variables are in 2005 values. This specification is based on the literature on the micro-determinants of exports (Greenway & Kneller, 2007).

Technical-scientific employees—that is, employees in technical-scientific occupations according to the Brazilian Classification of Occupations—are a good proxy

for investments in technology because of a high correlation with firms' R&D (Araújo et al., 2009). Age and market share are in quadratic form because the literature argues that older companies are more likely to enter the international market than are younger companies, but only to a certain extent. The same reasoning applies to market share: a greater market share means a larger scale, but a very large market share means little competitive pressure, which can create a disincentive to seek out foreign markets. In both cases, a positive sign is expected for the coefficient for the variable in level, and a negative sign is expected for the coefficient of the squared variable, which indicates the existence of a maximum point.

In general, the results of the model coefficients are as expected. Productivity and size positively affect the likelihood of a company engaging in international trade, as does the log of technical-scientific employees. However, age has no relationship to entry into foreign markets, and market share seems to negatively affect the probability of becoming an exporter, even though only one of the coefficients is significant at the 10% level. Transnational companies have a higher probability of becoming exporters, whereas the opposite occurs with mixed capital firms (national and foreign).

The Wald test indicates that the model as a whole is statistically significant, and the acceptance of the null hypothesis of the Hosmer-Lemeshow test indicates that the model predicts the distribution of entrants and non-exporters adequately. Indeed, the per cent concordant statistic—an informal test indicating how many companies with an estimated probability higher than 0.5 actually began to export and vice-versa—is 77.3%.

Table 7. *Logit* model of the probability of entering international trade in 2004 or 2005

Independent variables	Coefficient	Standard error	Significance
Intercept	-10.533*	1.1533	<0.0001
Log (employees)	0.390*	0.0948	<0.0001
Log (productivity)	0.618*	0.0850	<0.0001
Age	0.003 n.s.	0.0172	0.8767
Age^2	0.000 n.s.	0.0003	0.3512
Log (technical-scientific employees) $_t$	0.508*	0.1302	<0.0001
Market share	-30.221***	16.7778	0.0717
Market share^2	103.600 n.s.	107.8000	0.3367
Foreign capital company	1.244*	0.4423	0.0049
National and foreign capital company	-1.557**	0.7312	0.0332
N (without sampling weights)	1,959	-	-
-2 Log likelihood—all variables	1342.77	-	-
-2 Log likelihood—intercept only	1592.95		
Wald test (H_0: all coefficients are null)	196.45	-	<0.0001
Pseudo R^2	0.157	-	-
Hosmer-Lemeshow test	5.60		0.69
Per cent concordant	77.3	-	-

Source: PINTEC, PIA and SECEX; * - significant at the 1% level, ** - significant at the 5% level, *** - significant at the 10% level; n.s. - not significant at the 10% level. The balancing condition was satisfied: dividing the sample according to five quintiles of estimated probability, the model's variables for entrants and non-entrants were not significantly different at the 5% level of significance, meaning that the

groups are comparable. The common support condition resulted in limiting the sample of regression models to firms whose *p(X)* was between 0.0042223 and 0.7346017.

Having obtained the estimated probabilities, we proceeded to the regression analysis using IPW. Six models of weighted regression were estimated with the logarithms of labour productivity, the two measures of TFP, NSR, number of employees and market share for 2007-2008 as the dependent variables. These models did not include controls by sector or by region because they were in the first stage.

6. Regression models: is learning by exporting related to technological strategies?

6.1. Productivity

The regression models are displayed in Table 8, and the first three columns show the productivity models (labour productivity, TFP-LP and TFP-FE).

One may notice that the R^2, a traditional goodness-of-fit measure, is rather low in all of the models. There are two explanations for this result. The first is that micro-econometric models typically have a low R^2. Generally, the heterogeneity of individuals increases as the number of observations increases, and micro-level databases have thousands (sometimes millions) of observations. The second reason is that our models are very parsimonious: dimensions such as productivity and revenue are "explained" only by exports and some innovation variables. For example, if we attempted to "explain" revenue by inputs such as raw materials, capital and labour, one would expect the R^2 value to increase substantially; however, estimating production functions is not the aim of this paper. In any case, the models in Table 8 are statistically valid because the F test under the null hypothesis that the coefficients are not significantly different from zero is rejected at less than 0.1% significance. We focus our analysis on the significance of the coefficients, which indicates a correlation between firms' performance variables and technological strategies.

The first set of results, concerning the entry into foreign markets dummy, indicates a general learning-by-exporting effect of 67.4% on labour productivity and an effect of 6.1% on TFP-LP. This percentage difference is not exactly equal to the coefficient of the model because the variable in log form was regressed on a dummy variable. Thus, to determine the percentage difference, it is necessary to apply the transformation $\exp(\beta)$-1. However, the dummy coefficient is not significant in the case of TFP when using the OLS-FE technique.

The second set of results concerns the impact of technological strategies on productivity, regardless of whether the firm is an entrant or a non-exporter. Regarding innovative activities, "R&D-driven innovation" is positive and significant at the 10% level in all three of the models. This result means that technological strategies that rely on endogenous capability building, such as intramural R&D, have some correlation with a firm's productivity. Conversely, the coefficients for the "Machinery-driven innovation" factor are not significant in the three models.

Regarding the sources of information for innovation, the factor that indicates the importance of formal sources is significant in the models for simple labour productivity and TFP-LP, whereas the "informal sources of information" factor is significant only in the simple labour productivity model, with a negative sign. The importance of clients and customers as information sources is not significant in any of the models (in fact, this source is not significant in any of the models in this article), and the use of competitors as a source of information shows a significant negative sign in all of the estimated productivity models. One possible explanation for these negative signs is that firms that attribute a high degree of importance to competitors as sources of information are in a less favourable competitive position and need to converge at the technological frontier of the industry.

The use of information sources abroad positively affects productivity because the coefficient related to this general factor is positive and significant at the 1% level for all of the productivity models, demonstrating a positive association between performance and the search for innovation information abroad. In turn, cooperation, even with agents located abroad, is not significant in any of the productivity models.

The third set of results—related to the interaction between the innovation factors and variables and the entry dummy—point in different directions. In general, factors related to innovation activities are not significant, except for the "R&D-driven innovation" factor in the model for TFP-LP, which is negative and significant at the 1% level.

The coefficients for the sources of information are not significant in the labour productivity model, but the first factor (formal sources) shows a negative and significant coefficient in both of the TFP models. Conversely, the second factor (informal sources) shows a positive and significant sign in the TFP models.

The use of clients and customers as sources of information for innovation is only significant in the model for labour productivity, with a positive sign. The interaction between the use of competitors as an information source and exporting activity is not significant in any of the models.

For entrants, the coefficient relating to sources of information abroad is negative. This result virtually offsets the positive overall effect observed for all firms. Finally, cooperation has a positive effect for entrants only in the TFP-LF model, and cooperation abroad has no relationship with the productivity of entrants in any of the estimated models.

In summary, productivity gains were demonstrated for entrants in two of the three estimated models. In all firms, these gains were related to innovative activities, to the use of sources of information for innovation (especially knowledge-intensive activities such as R&D) and to the use of formal sources for innovation, such as universities and research centres. In addition, the use of information sources abroad had a positive relationship with productivity. However, there seemed to be no special relationship between the technological strategies of entrants and productivity gains. Thus, the hypothesis of learning by exporting via technological learning was not confirmed, at least with respect to productivity measures.

Table 8. Regression models

Explanatory variables	Log of labour productivity		Log of TFP (Levinsohn-Petrin)		Log of TFP (OLS-FE)		Log of Net Sales Revenue		Log of the number of employees		Market share	
	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|
Intercept	9,863*	<.0001	2,435*	<.0001	2,431*	<.0001	14,549*	<.0001	3,813*	<.0001	0,0008 n.s.	0,267
Export dummy	0,516**	0,014	0,059*	0,003	0,028	0,143	1,178*	0,000	0,400**	0,032	0,0002 n.s.	0,885
Innovation activities, sources of information for innovation and cooperation – general impact												
	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|
R&D-driven innovation	0,075*	0,002	0,005**	0,016	0,004***	0,065	0,163*	<.0001	0,083*	<.0001	0,0000 n.s	0,8144
Machinery-driven innovation	0,021 n.s.	0,333	0,003 n.s.	0,124	0,003 n.s.	0,119	0,014 n.s.	0,668	0,004 n.s.	0,821	0,0001 n.s.	0,5990
Formal sources of information	0,045**	0,014	0,003***	0,056	0,002 n.s.	0,179	0,014 n.s.	0,617	-0,026 n.s.	0,111	0,0001 n.s.	0,4460
Informal sources of information	-0,035***	0,081	-0,003 n.s.	0,112	-0,002 n.s.	0,388	-0,001 n.s.	0,962	0,036**	0,046	-0,0001 n.s.	0,3213
Importance of clients and customers as sources of information	-0,018 n.s.	0,466	-0,001 n.s.	0,549	-0,002 n.s.	0,328	-0,027 n.s.	0,478	-0,031 n.s.	0,168	0,0000 n.s.	0,8459
Importance of competitors as sources of information	-0,066*	0,007	-0,004***	0,089	-0,004***	0,072	-0,083**	0,021	-0,027 n.s.	0,212	-0,0001 n.s.	0,4378
Sources of information abroad	0,426*	<.0001	0,030*	0,001	0,037*	<.0001	0,579*	<.0001	0,245*	0,004	0,0017*	0,0012
Cooperation (dummy)	0,041 n.s.	0,656	0,003 n.s.	0,745	0,003 n.s.	0,707	0,183 n.s.	0,184	0,100 n.s.	0,230	0,0012**	0,0192
Cooperation abroad (dummy)	0,611 n.s.	0,352	0,080 n.s.	0,195	0,075 n.s.	0,207	1,359 n.s.	0,162	0,719 n.s.	0,219	0,0022 n.s.	0,5624

Innovation activities, sources of information for innovation and cooperation – specific impact for entrants (variable*export dummy)														
		Parameter	**Pr > |t|**	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**
R&D-driven innovation		-0,044 n.s.	0,213	-0,011*	0,001	-0,002 n.s.	0,582	-0,184*	0,001	-0,145*	<.0001	0,0002 n.s.	0,2238
Machinery-driven innovation		-0,032 n.s.	0,392	-0,001 n.s.	0,854	-0,002 n.s.	0,593	0,047 n.s.	0,391	0,090*	0,006	-0,0001 n.s.	0,5016
Formal sources of information		-0,045 n.s.	0,123	-0,005***	0,069	-0,005**	0,047	-0,064 n.s.	0,139	0,010 n.s.	0,693	-0,0001 n.s.	0,5390
Informal sources of information		0,006 n.s.	0,874	0,010*	0,003	0,008**	0,019	0,017 n.s.	0,748	-0,052 n.s.	0,110	0,0001 n.s.	0,6563
Importance of clients and customers as sources of information		0,151*	0,001	-0,004 n.s.	0,324	0,003 n.s.	0,384	0,122***	0,057	0,104*	0,007	0,0001 n.s.	0,7862
Importance of competitors as sources of information		0,006 n.s.	0,885	0,006 n.s.	0,134	0,003 n.s.	0,408	0,067 n.s.	0,268	0,060 n.s.	0,100	0,0000 n.s.	0,8533
Sources of information abroad		-0,425*	0,000	-0,041*	0,000	-0,045*	<.0001	-0,672*	0,000	-0,289*	0,006	-0,0015 n.s.	0,0287
Cooperation (dummy)		0,239 n.s.	0,123	0,030**	0,042	0,015 n.s.	0,296	0,512**	0,026	0,270***	0,051	-0,0006 n.s.	0,4736
Cooperation abroad (dummy)		0,393 n.s.	0,668	0,090 n.s.	0,294	0,108 n.s.	0,194	1,850 n.s.	0,172	1,535***	0,060	0,0291*	<.0001
Model statistics	**R^2**	0,0873		0,0919		0,1074		0,1257		0,0843		0,0649	
	Adjusted R^2	0,0775		0,0821		0,0978		0,1163		0,0744		0,0549	
	F statistic	8,91		9,42		11,2		13,39		8,57		6,46	
	Pr > F	<,0001		<.0001		<.0001		<,0001		<,0001		<,0001	
	N	18.977		18.977		18.977		18.977		18.977		18.977	

Source: PINTEC, PIA and SECEX; * - significant at the 1% level, ** - significant at the 5% level, *** - significant at the 10% level; n.s. - not significant at the 10% level.

6.2. Size: Net sales revenue and number of employees

Regression models of the two size measures—NSR and the number of employees—are shown in the fourth and fifth columns of Table 8. In both cases, entry positively affects firms' size: the NSR of entrants was 224% higher than that of non-exporters in 2007-2008, and the number of employees was 50% higher. It should be noted that revenue grows more quickly than employment, which helps to explain the labour productivity gain shown in the previous section.

With respect to the general influence of technological strategies on size, the first factor of innovative activities (R&D-driven innovation) showed a positive and significant sign, whereas the second factor (Machinery-driven innovation) was not statistically significant. Formal sources of information did not significantly affect the scale, whereas informal sources affected only the number of employees. The importance of clients and customers as sources of information for innovation was not significant in either model, and the use of competitors as sources of information negatively and significantly affected firms' NSR. As noted above, the use of information sources abroad positively affected firms' size in both models, but the cooperation variables were not significant in either model.

With specific regard to the effect of technological strategies on entrants, negative and significant signs for two of the variables—the R&D-driven innovation factor and the use of sources of information for innovation abroad—offset the positive effects for firms in general. The use of clients and customers as sources of information for innovation positively affected the scale of entrants, but it did not affect the scale of firms in general. Finally, cooperation positively affected entrants' size, and cooperation agreements abroad had a positive and significant relationship with the number of employees.

Therefore, the specific effect of technological strategies on entrants' size is ambiguous. On the one hand, the general positive effects of technological strategies such as investment in R&D and the use of informal sources of information were offset by negative coefficients specific to entrants. On the other hand, cooperation in innovation was positively related to entrants' size. This pattern does not support the hypothesis that the different technological learning strategies of entrants explain the gains in scale derived from entry into international markets.

6.3. Market share

The last column of Table 8 displays the regression model for the market share of firms. Because the calculation of the market share variable took place prior to the restriction of the database to innovative firms, entrants' revenue growth due to exports does not necessarily imply increased market share. Put another way, the model captures the effects of entry into the international market on the industry's competition conditions as a whole.

Nevertheless, the model indicates that entry into the international market does not significantly alter firms' market share in the domestic market. Furthermore, the

innovation factors and variables do not seem to have a very strong relationship to that growth. The only significant coefficients for firms in general were sources of information abroad (1% significance level) and the cooperation dummy (5% significance level). The only significant variable specific to entrants was the interaction between cooperation agreements abroad and the export dummy.

7. Discussion and Conclusions

This article tested the following three hypotheses:

(i) Did learning by exporting occur in Brazilian new exporters in 2006-2008?

(ii) Are some technological strategies—in the form of innovation activities, information sources for innovation and cooperation—related to firms' productivity, size and market share?

(iii) Is learning by exporting related to the differentiated technological strategies of entrants?

To answer these questions, entrants in foreign markets in 2004-2005 were compared with non-exporting innovators in 2006-2008 in terms of performance and innovation variables. This comparison took into account entrants' self-selection. Learning by exporting was measured based on three measures of productivity: sales, number of employees and market share.

First, the results of this study are in line with the literature on learning by exporting for developing countries. Productivity differentials between exporters and non-exporters in two of three measures were 6.1% (TFP-LP) and 67.4% (labour productivity). NSR differentials were 224%, and the difference in the number of employees was 50%. In summary, exporters are more productive, earn more revenue and are larger than non-exporters. However, we did not find significant differences in the domestic market share between entrants in international trade and non-exporters.

Second, technological strategies such as reliance on endogenous knowledge creation through intramural R&D and the extensive use of formal (universities, research centres, etc.) and informal (conferences, trade fairs, etc.) sources of information for innovation had a positive impact on the performance of all firms. Nevertheless, this impact was even higher when firms sought this information abroad.

However, these results are general for all firms. By analysing the specific impact of entrants' technological strategies, we find no evidence of additional impacts; on the contrary, in some cases, the specific impact was negative. Thus, learning by exporting was not related to the differentiated technological strategies of international markets entrants in Brazil from 2006-2008.

These findings can be discussed using two approaches. The first is to attempt to understand what aspect of learning by exporting could not be captured by the Brazilian Technological Innovation Survey. We argue that entrants may successfully improve their efficiency. This efficiency improvement may result from scale efficiency gains—in our case, revenue grows much more quickly than employment, which may indicate improved

economies of scale—or from the adoption of better management techniques and adaptation to international standards, i.e., improved production efficiency, which may result from international trade. These effects are not well captured by innovation surveys if the surveys do not measure production or process technological innovation.

The second way to examine the findings is to attempt to explain why the results "do not support a significant relationship between technological strategies and the learning by exporting of entrants. One explanation is that the time span of the analysis might be too short to capture the relevant changes in new exporters' technological strategies. In this sense, the absence of correlation between technological strategies and learning by exporting may simply be a matter of timing. Unfortunately, this short time span is an unavoidable problem of the Brazilian innovation survey because a panel of more than one edition of the survey would include only large firms (more than 500 employees).

Another possible explanation is that this article's sample was restricted to innovative firms in order to verify differences in technological learning strategies – in other words, differences in **how** entrants innovate. It may be necessary to further investigate the effects of exporting activities on the decision to innovate and the *ex-post* impacts of innovation on productivity, with a specific focus on identifying the export-innovation-productivity link.

The literature states that the technological dimension of learning by exporting is related to knowledge spillovers from interactions with foreign agents; access to state-of-the-art technology, better equipment and materials; and the possibility of technological cooperation with other firms. These mechanisms may be even more important in today's international trade scenario, which is characterised by the emergence of global value chains (GVCs) that correspond to more than half of global trade, even when accounting for possible double counting of GVCs' trade (UNCTAD, 2013).

According to UNCTAD (2013), despite being the fourth largest foreign direct investment (FDI) host in 2011, Brazil is only the 22nd of 25 emerging countries in terms of firms' insertion in GVCs. One possible explanation is inconsistencies between trade and investment policies. Brazil poses few restrictions on FDI, but it is still a relatively closed country compared to its WTO counterparts. One may argue that protection fosters FDI targeted to the domestic market, but such protection may backfire with respect to Brazilian firms' insertion into GVCs.

Thus, one policy implication of this discussion is that Brazil should review its contextual conditions for international trade. Brazilian firms face high tariffs, even for some intermediate goods used to manufacture exported goods. Additionally, there are problems in Brazil's international trade infrastructure, and a very complex tax system makes the deduction of all domestic taxes through exports impossible. Brazil should improve its tariff policy, infrastructure and tax system not only to foster innovation through trade by industrial firms but also to bring major benefits to the country's economic structure as a whole.

Deeper insertion of Brazilian firms into GVCs may result in knowledge spillovers, but as García et al. (2012) note, firms must have the capability to absorb these knowledge spillovers. UNCTAD (2013) warns that trade in GVCs may lock firms into low value-added stages if they cannot proceed along the productive chain. Accordingly,

strengthening the national innovation system becomes a policy recommendation because it provides benefits in addition to simply preparing firms to learn from exporting.

Finally, the results also provide managerial implications. It is clear that internationalisation helps to improve firms' performance. Nevertheless, it is also clear that Brazilian firms anchor international trade in commodities such as mineral ore, agriculture and basic industrial products. A managerial approach to take better advantage of international insertions should focus on improvements in innovation capabilities in association with attempts to obtain better positions in GVCs.

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Appendix A. Correlation Matrices

Table 1A – Pearson correlation matrix – Importance of innovation activities

Importance of innovation activities (1-4 Scale)	Intramural R&D (1)	Extramural R&D (2)	Acquisition of other external knowledge (3)	Acquisition of machinery and equipment (4)	Training (5)	Market introduction of innovations (6)	Industrial Project (7)
Average	1.365	1.111	1.394	3.159	2.885	1.859	2.063
Std. Deviation	0.948	0.538	0.954	1.190	1.270	1.225	1.304
N	2,411	2,411	2,411	2,411	2,411	2,411	2,411
(1)	**1**						
(2)	0.25	**1**					
(3)	0.06	0.08	**1**				
(4)	-0.01	0.02	0.01	**1**			
(5)	0.10	0.05	0.11	0.30	**1**		
(6)	0.25	0.11	0.12	0.01	0.15	**1**	
(7)	0.16	0.09	0.09	0.02	0.14	0.20	**1**

Source: PINTEC.

Table 2A – Polychoric correlation matrix – Importance of innovation activities[+]

Importance of innovation activities (1-4 Scale)	Intramural R&D (1)	Extramural R&D (2)	Acquisition of other external knowledge (3)	Acquisition of machinery and equipment (4)	Training (5)	Market introduction of innovations (6)	Industrial Project (7)
Average	1.365	1.111	1.394	3.159	2.885	1.859	2.063
Std. Deviation	0.948	0.538	0.954	1.190	1.270	1.225	1.304
N	2,411	2,411	2,411	2,411	2,411	2,411	2,411
(1)	**1**	0.49	-0.08	-0.12	0.12	0.29	0.12
(2)	**0.55**	**1**	0.18	0.07	-0.03	0.02	0.08
(3)	0.13	0.23	**1**	-0.06	0.15	0.13	0.06
(4)	-0.04	0.04	0.02	**1**	0.44	-0.02	-0.02
(5)	0.18	0.14	0.19	**0.42**	**1**	0.08	0.11
(6)	**0.42**	0.28	0.21	0.02	0.19	**1**	0.16
(7)	0.29	0.25	0.16	0.04	0.20	0.29	**1**
a priori communalities (SMC)	0.41	0.34	0.11	0.20	0.26	0.23	0.15
Kaiser's Measure of sample adequacy (MSA)	0.62	0.65	0.67	0.46	0.58	0.75	0.82

Source: PINTEC. [+] - In polychoric correlation matrices, partial correlations controlling all other variables are displayed above the main diagonal.

Table 3A – Polychoric correlation matrix – Importance of sources of information for innovation

	Importância das fontes de informação								
Importance of the source (1-4 Scale)	Clients and customers (1)	Comp-etitors (2)	Cons-ultants (3)	Univer-sities (4)	Training centres (5)	Testing institu-tions (6)	Conf-erences (7)	Trade fairs (8)	Electronic information networks (9)
Average	2.994	2.357	1.779	1.494	1.723	1.767	2.114	2.698	3.094
Std. Deviation	1.199	1.209	1.142	0.971	1.106	1.146	1.218	1.234	1.150
N	2,411	2,411	2,411	2,411	2,411	2,411	2,411	2,411	2,411
(1)	**1**	-	-	-	-	-	-	-	-
(2)	**0.40**	**1**	-	-	-	-	-	-	-
(3)	0.20	0.26	**1**	0.26	0.18	0.11	0.03	0.00	-0.02
(4)	0.30	0.29	**0.50**	**1**	0.25	0.29	0.15	0.00	0.04
(5)	0.32	0.31	**0.46**	**0.58**	**1**	0.30	0.03	0.06	0.12
(6)	0.33	0.30	**0.43**	**0.59**	**0.58**	**1**	0.23	-0.12	0.02
(7)	0.25	0.27	0.31	**0.47**	**0.41**	**0.46**	**1**	0.54	0.07
(8)	0.24	0.25	0.19	0.29	0.30	0.23	**0.64**	1.00	0.29
(9)	0.28	0.26	0.17	0.28	0.31	0.24	0.39	0.46	**1**
a priori communalities (SMC)	-	-	0.31	0.50	0.46	0.47	0.53	0.46	0.25
Kaiser's Measure of sample adequacy (MSA)	-	-	0.88	0.85	0.86	0.83	0.77	0.69	0.86

Source: PINTEC.

Table 4A – Tetrachoric correlation matrix – Importance of sources of information abroad

High or medium importance of the source located abroad (binary)	Machine and equipment suppliers (1)	Conferences (2)	Trade fairs (3)	Electronic information networks (4)
Average	0.037	0.019	0.041	0.082
Std. Deviation	0.190	0.138	0.198	0.275
N	2411	2411	2411	2411
(1)	**1**	0.16	0.11	0.13
(2)	**0.43**	**1**	0.54	0.35
(3)	**0.40**	**0.73**	**1**	0.22
(4)	0.39	**0.64**	**0.59**	**1**
a priori communalities (SMC)	0.22	0.61	0.56	0.45
Kaiser's Measure of sample adequacy (MSA)	0.90	0.72	0.75	0.83

Source: PINTEC.

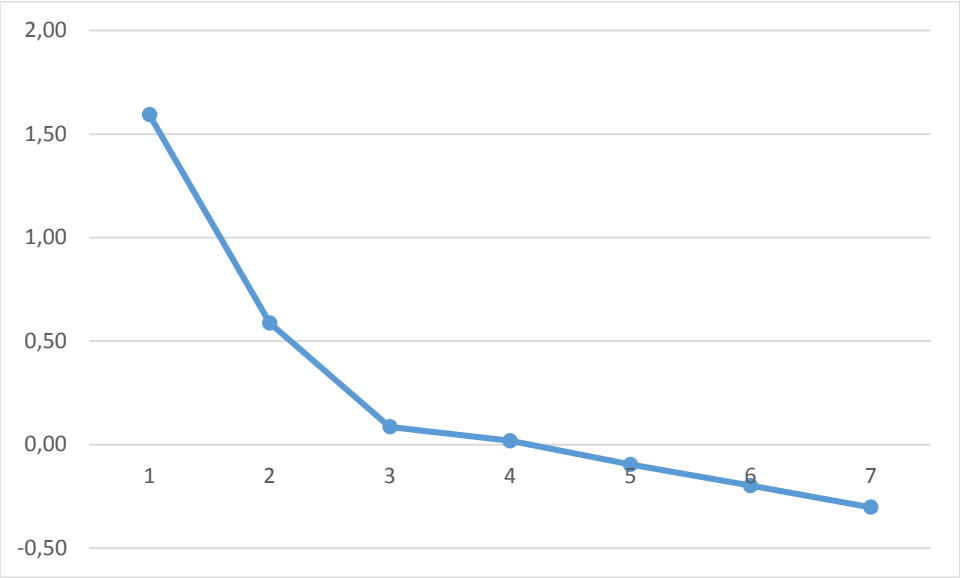
Appendix B. Preliminary eigenvalues of common factor analysis and Scree Plots

Table 1B – Preliminary eigenvalues of the importance of innovation activities

Preliminary Eigenvalues: Total = 1.689				
Average = 0.241				
	Eigenvalue	**Difference**	**Proportion**	**Cumulative**
1	1.59	1.01	0.94	0.94
2	0.59	0.50	0.35	1.29
3	0.09	0.07	0.05	1.34
4	0.02	0.11	0.01	1.35
5	-0.10	0.10	-0.06	1.30
6	-0.20	0.10	-0.12	1.18
7	-0.30		-0.18	1.00

Source: PINTEC.

Graph 1B - Scree plot of preliminary eigenvalues of factors - innovation activities



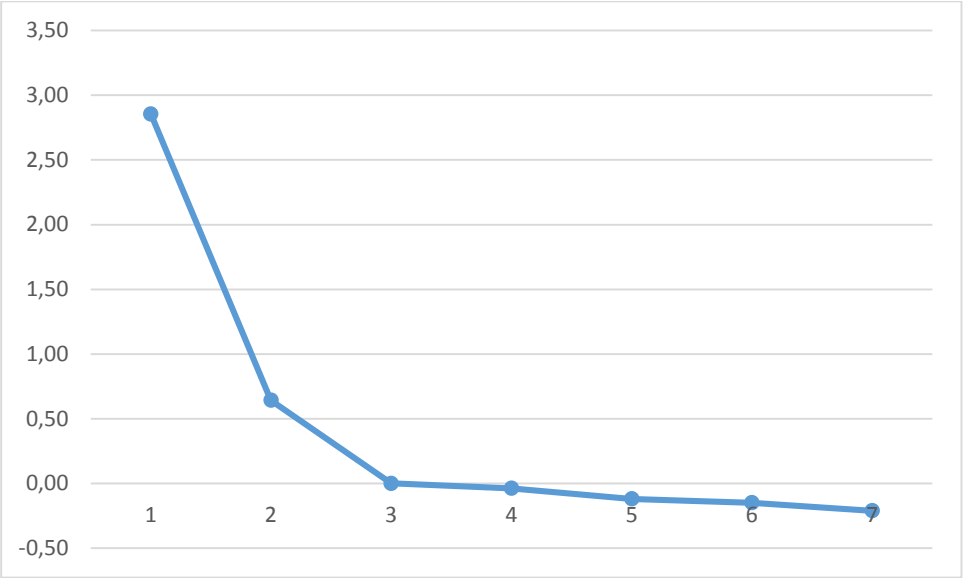
Source: PINTEC.

Table 2B – Preliminary eigenvalues of the importance of sources of information

Preliminary Eigenvalues: Total = 2.980				
Average = 0.426				
	Eigenvalue	**Difference**	**Proportion**	**Cumulative**
1	2.86	2.21	0.96	0.96
2	0.64	0.64	0.22	1.17
3	0.00	0.04	0.00	1.17
4	-0.04	0.08	-0.01	1.16
5	-0.12	0.03	-0.04	1.12
6	-0.15	0.06	-0.05	1.07
7	-0.21		-0.07	1.00

Source: PINTEC.

Graph 2B - Scree plot of preliminary eigenvalues of factors – sources of information for innovation



Source: PINTEC.

Table 3B – Preliminary eigenvalues of the importance of sources of information abroad

Preliminary Eigenvalues: Total = 1.826				
Average = 0.457				
	Eigenvalue	**Difference**	**Proportion**	**Cumulative**
1	2.11	2.15	1.15	1.15
2	-0.04	0.05	-0.02	1.13
3	-0.09	0.06	-0.05	1.08
4	-0.15		-0.08	1.00

Source: PINTEC.