The Export-productivity Link for Brazilian Manufacturing Firms

Xavier Cirera, Daniel Lederman, Juan A. Máñez, María E. Rochina, and Juan A. Sanchis

Abstract

This paper explores the link between exports and total factor productivity (TFP) for Brazilian manufacturing firms over the period 2000–2008, both under the assumption of an exogenous or an endogenous law of motion for productivity. The authors first obtain TFP estimates under each alternative assumption following Wooldridge (*On estimating firm-level production functions using proxy variables to control for unobservables*, 2009) GMM procedure. Second, using stochastic dominance techniques they analyse whether the ex-ante most productive firms are those that start exporting (self-selection hypothesis). Finally, the authors test whether exporting boosts firms TFP growth (learning-by-exporting hypothesis) using matching techniques, to control for the possibility that selection into exports may not be a random process. Their results confirm the self-selection hypothesis and show that starting to export yields firms an extra TFP growth that emerges since the first year exporting but lasts only from this year to the next. Further, this extra TFP growth is much higher under the assumption of an endogenous law of motion for productivity, which reinforces the importance of accounting for firm export status to study the evolution of productivity.

(Published in Special Issue Micro-econometric Analyses of International Firm Activities)

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1. Introduction.

The Brazilian economy has undergone radical changes in the last two decades. Brazil has emerged as a significant rising power. Yet, despite this process of structural transformation, estimates of aggregated total factor productivity (TFP, hereafter) suggest that this remains at best at productivity levels similar to the late 1970s and early 1980s. This result is puzzling. In addition to macro stability and economic reforms in Brazil in the last two decades, the Brazilian economy is far more integrated in global markets than in the 1980s. The value of exports more than tripled in the period 2000-2008 and manufacturing exports represented around 52% of total merchandised exports during the period. As a result, in this paper we aim to examine whether exporting has played a major role in increasing productivity by Brazilian firms.

The literature analysing the relationship between exports and productivity using microdata has expanded to cover a wide range of different countries.[1] Two important findings arise from this literature: exporters are generally more productive than non-exporters, and there is self-selection into export markets. According to the self-selection mechanism firms need to reach a minimum productivity threshold to enter the more competitive foreign markets (Melitz, 2003). Thus, only the ex ante more productive firms are able to sell abroad.

At the same time, theory also suggests that once firms enter export markets they should also experience further productivity gains (Clerides *et al.*, 1998): this is the so-called learning-by-exporting hypothesis (LBE, hereafter).[2] On theoretical grounds, the potential productivity gains arise from growth in sales that allows firms to profit from economies of scale, knowledge flows

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[1] See Greenaway and Kneller (2007a) and Wagner (2007 and 2012) for thorough reviews of this literature. Further, ISGEP (2008) provides an international comparison across 14 countries.

[2] Silva *et al.* (2010) provide a detailed survey of the learning by exporting literature. Further, Martins and Yang (2009) provide a meta-analysis of 33 empirical studies. Singh (2010) concludes that studies supporting self-selection overwhelm studies supporting learning-by-exporting.

from international customers (that provide information about process and product innovations, reducing costs and improving quality) and from increased competition in export markets that forces firms to behave more efficiently. The evidence for the learning by exporting effect is, however, less compelling.

The first empirical attempts to analyse the post-entry effects of exporting were made without controlling properly for the mixed effect of self-selection when testing for LBE. Many of these works failed to produce any conclusive evidence on LBE. [3] However, the growing international evidence in favour of the self-selection hypothesis (following Bernard and Jensen, 1999) has substantially modified the approach to test for the potential post-entry effects of exporting. In this sense, more recent studies recognize that new exporters have many of the characteristics to become exporters (as compared to non-exporters) and, consequently, selecting into exporting is not a random process (i.e., only the higher productivity firms enter into the export markets). In order to account for this non-random selection process recent papers use matching techniques when testing for LBE. [4]

Also, the empirical evidence within the matching literarature is also far from conclusive. Whereas some studies do not find any evidence of post-entry productivity changes (see Wagner, 2002, Arnold and Hussinger, 2005, and Hansson and Lundin, 2004), those studies that find evidence, differ in the time span of the productivity changes associated to exporting. For the UK,

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[3] For example, Bernard and Jensen (1999), Bernard and Wagner (1997), Clerides *et al.* (1998) and Aw and Hawng (1995) do not find any evidence of LBE for the US; Germany; Colombia, Mexico and Morocco; and, Korea, respectively. Furthermore, evidence in Delgado *et al.* (2002), for Spanish firms, is far from conclusive (they only find supporting evidence for young firms). However, Baldwin and Gu (2004) for Canada, find that export-market participation is associated with increases in plant productivity growth, and Kraay (2002) and Castellani (2002) for China and Italy, respectively, find that exporting has a positive and significant effect on productivity growth.

[4] Van Biesebroeck (2005) argues that not controlling for self-selection could lead to over-estimate the effects of learning for new-exporters.

Greenaway and Kneller (2004, 2008) and Girma *et al.* (2004) show that productivity growth for new exporters is faster than for non-exporters only one or, at most, two years after entry. Also for the UK, Greenaway and Kneller (2007b), using different data, extend the period of extra productivity growth to three years. De Loecker (2007) for Slovenia and Serti and Tomassi (2008) for Italy report evidence of a longer period of extra-productivity growth (four and at least six years, respectively). Finally, Máñez *et al.* (2010) show that starting to export yields firms an extra-productivity growth that emerges since the first (second) year exporting and lasts at least for two (one) years more in the case of Spanish small (large) firms.

As De Loecker (2013) showed, however, most previous tests on the existence of the LBE mechanism could be flawed. The usual empirical strategy is to look at whether a productivity estimate, typically obtained as the residual of a production function estimation, increases after firms enter in the export market. But for such an estimate to make sense, past export experience should be allowed to impact future productivity. Yet, some previous studies (implicitly) assume that the productivity term in the production function specification is just an idiosyncratic shock (Wagner, 2002; Hansson and Lundin, 2004; Greenaway and Kneller, 2004, 2007b, 2008; Girma *et al.*, 2004; Máñez *et al.*, 2010), while others assume that this term is governed by an exogenous Markov process (Arnold and Hussinger, 2005; Serti and Tomassi, 2008). It is this sort of assumptions, often critical to obtain consistent estimates (Ackerberg *et al.*, 2007), what makes these tests of the existence of LBE to lack internal consistency.

Van Biesebroeck (2005) is probably the first study to extend the estimation framework developed by Olley and Pakes (1996, OP hereafter) to include lagged export participation status as a state variable in the estimation of productivity. Somehow differently, De Loecker (2010) allows the law of motion for productivity over time to depend on past export status. In this paper we address the aforementioned drawback of internal inconsistency by obtaining TFP estimates both under the assumption of an exogenous or a more general process (endogenous) driving the

law of motion for productivity over time. In particular, we explore the potential role that firm export status might have had in shaping firm's productivity evolution. Further, we incorporate these features into the GMM framework recently proposed by Wooldridge (2009).

Then, we analyse whether allowing or not for past export status to affect productivity has any impact in the analysis of the self-selection and LBE hypotheses. To the best of our knowledge De Loecker (2013) and Manjón *et al.* (2013), for Slovenian and Spanish manufacturing firms, respectively, are the only two papers that use quite a similar method to the one in this paper.

However, although closely related, the estimation method in our study differs at some points to that in De Loecker (2013). De Loecker (2013) relies for estimation in Ackerberg *et al.* (2006) while we implement the GMM framework proposed by Wooldridge (2009). Wooldridge (2009) argues that both OP, Levinsohn and Petrin (2003, LP hereafter) or Ackerberg *et al.* (2006) two–step estimation methods can be reconsidered as consisting of two equations which can be jointly estimated by GMM in a one-step procedure. This joint estimation strategy has the advantages of increasing efficiency relatively to two-step procedures, making unnecessary bootstrapping for the calculus of standard errors, and also solving the identification problem of the labour coefficient in the first estimation step (noted by Ackerberg *et al.*, 2006).

We also differ from De Loecker (2013) in that he uses investment as a proxy variable (and so does Van Biesebroeck, 2005) whereas we use intermediate materials. In this way we avoid possible concerns about zero-investment observations (LP, 2003) and the invertibility of the investment function (Van Biesebroeck, 2005).

However, our methodological procedure in this paper is closer to the one in Manjón *et al.* (2013) for Spanish firms. Although Van Biesebroeck (2005) and De Loecker (2013) also provide evidence from developing countries, Manjón *et al.* (2013) do provide evidence from a developed country.

To anticipate our results, we find, in general, that both exporters are more productive than non-exporters and that the most productive firms self-select into export markets (evidence on the self-selection hypothesis). We also find evidence on learning-by-exporting: the productivity of firms that start exporting grows more than that of non-exporters the first year they sell in international markets. Further, our results confirm the importance of accounting for firms export status on the TFP estimation when testing for learning-by-exporting. Not accounting for firm export status leads to underestimate the extra productivity growth of export starters vs. non-exporters (from 7.1% when accounting for firms export status to 1.6% when not accounting for it).

The remaining of the paper is organized as follows. Section 2 presents the data and provides empirical evidence on the differences between exporters and non-exporters in critical variables. Section 3 is devoted to the production function estimation method. Sections 4, 5 and 6 empirically analyse the relationship between firms' productivity and their export status (a non-causal relationship in Section 4, self-selection in Section 5 and learning-by-exporting in Section 6). Section 7 concludes.

2. Data and descriptive analysis of exporters *vs.* non-exporters.

In order to analyse firms' productivity and trade exposure we use a dataset that links firm characteristics, production and export data for Brazilian firms for the period 2000 to 2008. For production and firm characteristics, we use the survey PIA *empresa* (Pesquisa Industrial Anual). PIA is a firm level survey for manufacturing and mining sectors conducted annually by the Brazilian Statistical Institute, IBGE (Instituto Brasileiro de Geografia e Estatistica). Firms with 30 or more employees are included in the sample, while smaller firms of up to 29 workers are included randomly in the sample. In total PIA covers more than 40,000 firms. For exports we use

a dataset created by the foreign trade office, SECEX (*Secretaria Comercio Exterior*). SECEX provides the universe of registered trade flows at the firm level.[5]

Table 1 shows the main variables used in the analysis; and Tables 2 and 3 show, respectively, firms export activity, and average values for the main production function variables and wages, according to firms' exporting status during the sample period. From the figures in Table 2 we observe that the proportion of exporting firms in the sample is slightly below 30%. As regards the variables in Table 3, we proxy capital with assets, and include also electricity and energy as intermediate inputs. We use sector deflators provided by the IBGE to deflate the variables in the production function and wages, with the exception of labour. As can be observed in Table 3, exporters are larger in terms of output, labour, capital and materials and pay higher wages than non-exporters.

[Table 1 around here]

[Table 2 around here]

[Table 3 around here]

3. Production function estimation, firm trade status and TFP.

We assume that firms produce using a Cobb-Douglas technology:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + \omega_{it} + \eta_{it} \tag{1}$$

where y_{it} is the log of production of firm i at time t, l_{it} is the log of labour, k_{it} is the log of capital, m_{it} is the log of intermediate materials, and μ_t are time effects. As for the unobservables in estimation, ω_{it} is productivity and η_{it} is a standard *i.i.d.* error term.

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[5] The main source for identifying exporters is SECEX, since customs data is more reliable identifying exporters and because there are some differences between PIA and SECEX in identifying exporters. Around 600-700 firms are identified in PIA as exporters and not in SECEX. Also around 1,500 firms that are exporters in the SECEX dataset are surveyed in PIA claiming not to export. We consider these firms exporters in our data.

As timing assumptions for estimation, it is assumed that capital in period t was actually decided in period t-1 and, contrarily, that labour and materials are chosen in period t.

Under all these assumptions we follow the estimation method in Wooldridge (2009), who, differently to OP and LP, jointly estimates by GMM the equation tackling the problem of endogeneity of labour and materials (correlated with current productivity) and the one dealing with the law of motion for productivity (required for identification purposes).[6]

Let us consider first the problem of endogeneity. We follow here the approach by LP and use the demand for materials, $m_{it} = m_E(k_{it}, \omega_{it})$, as an invertible function in productivity to get:

$$\omega_{it} = h_E(k_{it}, m_{it}) \tag{2}$$

where, following De Loecker (2007, 2013), the export status subscript, E, denotes different demands of intermediate inputs for exporters and non-exporters. They justify this extension to filter out differences in market structures between domestic and exporting firms within a given industry, such as the mode of competition, demand conditions and exit barriers, which may potentially affect optimal input demand choices. Further, it also corrects for unobserved productivity shocks correlated with export status.

Then, substituting (2) into (1) and acknowledging that the capital and materials coefficients in the production function cannot be identified, we get our first estimation equation:

$$y_{it} = \beta_0 + \beta_l l_{it} + \mu_t + H_E(k_{it}, m_{it}) + \eta_{it} \tag{3}$$

where $H_E(k_{it}, m_{it}) = 1(non-\exp)H_0(k_{it}, m_{it}) + 1(\exp)H_1(k_{it}, m_{it}, E_{it})$, and $1(non$-exp$)$ and $1(\exp)$ are indicator functions that take value one for non-exporters and exporters, respectively. We end

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[6] According to the timing assumptions the appropriate instruments and moment conditions are employed for each equation. This joint estimation strategy has several advantages: i) it increases efficiency; ii) it makes unnecessary the use of bootstrapping for standard errors; and, iii) it solves the identification problem of the labour coefficient in the first equation, pointed out by Ackerberg *et al.* (2006).

up with two different unknown functions, H_0 and H_1, that will be proxied by second degree polynomials in their respective arguments.

Our second estimation equation in the GMM-system deals with the law of motion for productivity and relays on the following endogenous Markov process:

$$\omega_{it} = E\left[\omega_{it}|\omega_{it-1}, E_{it-1}\right] + \xi_{it} = f\left(\omega_{it-1}, E_{it-1}\right) + \xi_{it} \tag{4}$$

where productivity in t depends on productivity and the firm export decision in t-1 and on ξ_{it} (innovation term by definition uncorrelated with k_{it}).

De Loecker (2013) stresses the importance of endogenising the law of motion for productivity. An exogenous Markov process is only appropriate when productivity shocks are exogenous to the firm but not if future productivity is determined endogenously by firm choices, such as the firm export decision. Therefore, those methods not incorporating an endogenous Markov process suffer from an internal inconsistency as do not accommodate endogenous productivity processes like learning by exporting. The same arguments are put forward in De Loecker and Warzynski (2012).

Substituting (4) into the production function (1), and using (2) for period t-1, our second estimation equation is given by:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + F_E\left(k_{it-1}, m_{it-1}\right) + u_{it} \tag{5}$$

where $u_{it} = \xi_{it} + \eta_{it}$ and $F_E\left(k_{it-1}, m_{it-1}\right) = 1(non - \exp)F_0\left(k_{it-1}, m_{it-1}\right) + 1(\exp)F_1\left(k_{it-1}, m_{it-1}, E_{it-1}\right)$. The unknown functions F are proxied by second degree polynomials in their respective arguments.

Therefore, (3) and (5) are our two main estimation equations. However, in order to assess the impact, on the export-productivity link for Brazilian manufacturing firms, of considering export status in TFP estimation, we should compare our main results (Model 2) with the ones obtained when restricting the functions H_E and F_E to be identical for exporters and non-exporters (Model 1).

Both for Models 1 and 2, we estimate the production function in (1) separately for firms in each one of 22 industries (see Table A.1 in the Appendix). Using the estimates of the production function coefficients, we define the log of measured TFP of firm i at time t for each industry s, denoted tfp_{it}^{s}, as

$$tfp_{it}^{s} = y_{it} - \beta_0 - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} - \mu_t \tag{6}$$

4. Productivity and export status.

To provide a first picture of the export-productivity link, prior to we test for self-selection and LBE, we check for each industry whether exporters are more productive than non-exporters using stochastic dominance techniques.

For this comparison we define as exporters those firms that export at least one year during the years they are in the sample and as non-exporters those firms that do not export in any of the sample years. Also, since the Kolmogorov-Smirnov one and two-sided tests of stochastic dominance (KS, hereafter) require independence of observations both between the two samples under comparison and among the observations in a given sample, analogously to Doraszelski and Jaumandreu (2013) for R&D, for each industry j we compare:

$F_{E,j}$ (productivity) vs. $F_{NE,j}$ (productivity) (7)

where $F_{E,j}$ is the cumulative distribution function of the average productivity for exporters in sector j (calculated as the average over the years they export) and $F_{NE,j}$ is the cumulative distribution function of the average productivity for non-exporters in sector j (calculated as the average over the years they are in the sample).[7]

Table 4 reports the results for the KS tests based both on productivities estimated when

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[7] See Delgado *et al.* (2002) for a more detailed description of the application of the KS tests for stochastic dominance. Máñez *et al.* (2010) provide an application with panel data, which is analogous to the tests carried out in this paper.

not considering the export status in the TFP estimation procedure (Model 1) and when considering it (Model 2). Our results show that irrespectively of the model, we reject the null hypothesis of equality of the two distributions, and we do not reject the null that the productivity of exporters is higher than that of non-exporters for 18 out of 22 industries (except for industries 23, publishing and printing, 30, office machinery, 32, electrical components and communication apparatus and 33, medical equipment).[8] Therefore, our results suggest that, in general, the productivity distribution for exporters stochastically dominates that of non-exporters.

[Table 4 around here]

5. Do firms self-select into exporting?

According to self-selection, only the more efficient firms self-select into exporting. The self-selection hypothesis can be benchmarked within Melitz (2003) model that allows for within-industry heterogeneous productivity firms. According to this model, there is a threshold of productivity, θ^*, which defines the decision rule for a firm to export or to sell in the domestic market only. Thus, firms with productivity below (above) this threshold will not export (will export). This threshold can be interpreted as the lowest level of productivity that allows firms to obtain positive discounted expected profits over future periods. The exporting threshold θ^* defines a separating line between the productivity distribution functions of exporting and non-exporting firms.

Therefore, according to Melitz (2003) the previous productivity distributions of export starters should lie at the right of θ^* and those of non-exporters at the left. Although this productivity threshold is not directly observable, it implicitly poses a testable prediction; that is, the previous (to start exporting) productivity distribution of export starters should dominate that of non-exporters. Figure 1 illustrates graphically this testable prediction by showing the positions for

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[8] For these industries the distribution of exporters does not dominates that of non-exporters, but the opposite.

the ex-ante productivity distributions of export starters and non-exporting firms when there exists an exporting threshold at θ^*.

Figure 1: TFP distributions and self-selection.
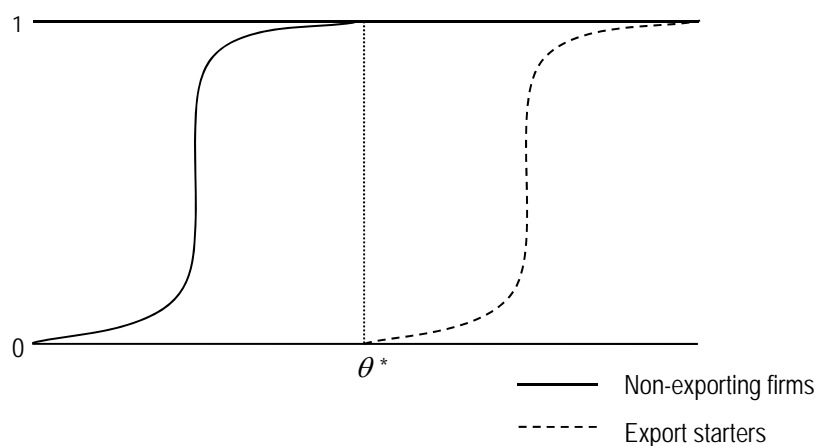
To test this hypothesis, we compare TFP previous to starting to export for export starters and non-exporters. To classify a firm as an export starter in year t we require two conditions: i) the firm has not exported in the sample period previous to year t and it exports in year t; and, ii) for at least two years previous to t, we observe the firm in the sample.[9] To classify a firm as a non-exporter in year t we require: i) that the firm has not exported in year t and in previous years of the sample; and, ii) that for a minimum of two years previous to t, we observe this firm in the sample.

However, the small size of export starter cohorts between 2002 and 2008 in our industry-by-industry analysis advises not carrying out year-by-year stochastic dominance tests as their results would not be reliable. To overcome this limitation we apply this test jointly for the whole sample period for each one of the industries. Therefore, we re-define as non-exporters those firms that do not export during the whole sample period and for which we have information in the sample for at least two years. Thus, we compare,

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[9] Accomplishment of these two criteria implies that we cannot include the 2000 and 2001 cohorts of export starters in our sample, as we do not know whether or not those firms exported in the two previous years.

$$F_{ES,j} \ (\textit{productivity}) \ vs. \ F_{NE,j} \ (\textit{productivity}) \tag{8}$$

where $F_{ES,j}$ is the TFP distribution in year t - 1 of the seven cohorts of export starters (for t = 2002-2008) in industry j, and $F_{NE,j}$ is the yearly average TFP distribution over the period 2002-2008 for non-exporters in industry j.

In this section, we analyse whether the results on self-selection are robust to the inclusion of firms export status into the TFP estimation. This again implies a pairwise comparison of Models 1 and 2.

The results of formal KS tests of stochastic dominance (see Table 5) confirm that, both for Models 1 and 2, for a large majority of industries the previous TFP distribution of export starters dominates that of non-exporters (except for industries 23, 30, 32 and 33, which are those sectors where exporters are not found to be more productive than non-exporters).[10] Therefore, in most sectors firms self-select into exporting.

[Table 5 around here]

6. Does export entry boost productivity growth?

To analyse the LBE hypothesis implies testing whether export participation has any impact on export productivity growth. However, as explained before, comparing the productivity growth of export starters and non-exporters, after the former start to export, does not allow assessing if the observed differences are due to LBE or to self-selection. To properly control for the direction of causality from exporting to productivity growth, we would need to compare the actual productivity

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[10] For industries 23, 32 and 33 the pre-entry TFP distribution of export starters does not dominate that of non-exporters, but the opposite. For industry 30 neither one nor the other distribution dominates (they are statistically the same).

growth of export starters after starting to export with the productivity growth of the same firms should they have not started to export. The problem is that we do not have information about the counterfactual situation (the productivity growth of export starters should they have not started to export). To solve this problem we use matching techniques to construct this counterfactual.

More formally, let $\Delta y_{i(t+1)}^{D_{it}}$ denote the growth rate of productivity from *t* to *t+1* and $D_{it} \in \{0, 1\}$ be an indicator of whether firm *i* is an export starter (i.e., a firm that exports for the first time in the sample years) in period *t* (as opposed to a non-exporter). Thus, we can use $\Delta y_{i(t+s)}^1$ to define the TFP growth between (*t+s-1*) and (*t+s*), $s \geq 1$, for firm *i* classified as an export starter in *t*, and $\Delta y_{i(t+s)}^0$ as the TFP growth for firm *i* should it had not exported. Using this notation, the causal effect of exporting, in terms of TFP growth, from period (*t+s-1*) to (*t+s*) for firm *i* that starts exporting in *t*, can be defined as,

$$\Delta y_{i(t+s)}^1 - \Delta y_{i(t+s)}^0 \tag{9}$$

Following the policy/treatment evaluation literature (see Heckman *et al.*, 1997), we can define the average causal effect of exporting for firms that start to export in *t* as follows,

$$E\left(\Delta y_{i(t+s)}^1 - \Delta y_{i(t+s)}^0 \middle| D_{it} = 1\right) = E\left(\Delta y_{i(t+s)}^1 \middle| D_{it} = 1\right) - E\left(\Delta y_{i(t+s)}^0 \middle| D_{it} = 1\right) \tag{10}$$

The main problem for making causal inference using (10) is that in observational studies, the counterfactual $\Delta y_{i(t+s)}^0$ for an export starter is not observed and, therefore, it has to be generated (notice that this is the average productivity growth that export starters would have experienced had they not started to export). To overcome this problem we use a matching procedure to identify, among the pool of non-exporters in *t*, those with a distribution of observable variables (*X* in *t-1*) affecting productivity growth and the probability of exporting, as similar as possible to that of export starters. It is then assumed that, conditional on *X*, firms with the same characteristics are randomly exposed to export activities. Thus, expression (10) can be rewritten as,

$$E\left(\Delta y^{1}_{i(t+s)}\Big|X_{it-1},D_{it}=1\right)-E\left(\Delta y^{0}_{i(t+s)}\Big|X_{it-1},D_{it}=0\right) \tag{11}$$

Since there are several observable variables that may potentially affect the firms' probability of exporting and their productivity growth, the question that arises is what is the appropriate variable to match firms (and in case of using more than one variable, what are the appropriate weights). We deal with this issue using the propensity score techniques proposed by Rosenbaum and Rubin (1985). Within the matching methodology, the propensity score is a method that allows combining all the information from a vector of variables driving the probability to start exporting into an scalar that is the predicted probability to become an export starter. The propensity score method preserves the same properties than matching directly on the vector of variables: firms with the same probability to become an export starter are randomly exposed to export activities. Thus, we will match firms on the basis of the probability to export for the first time.

Therefore, before performing the matching analysis, we obtain the probability of becoming an export starter (i.e., the propensity score) as the predicted probability in the following probit model,

$$P\left(D_{it}=1\right)=\Phi\left\{\omega_{it-1},k_{it-1},s_{it-1},industry,year\right\} \tag{12}$$

where $\Phi(\cdot)$ is the normal cumulative distribution function, and the set of observable characteristics included in the model are: lagged productivity, capital, size, industry dummies and year dummies. If it is the case that firms starting to export are previously more productive, larger and invest more in capital, to properly identify a causal relation from starting to export to productivity, we have to match export starters with a control group of non-export starters that share the same characteristics on these variables. Table 6 shows the results of these probit regressions.

[Table 6 arround here]

To construct the counterfactual we use the nearest neighbours matching procedure (Becker and Ichino, 2002).[11] In particular, matching is performed using the *psmatch2* Stata command (Leuven and Sianesi, 2003). For each of our two models, we compare, using matching techniques, the productivity growth of export starters and matched non-exporters for the periods t to $(t + 1)$, $(t + 1)$ to $(t + 2)$, $(t + 2)$ to $(t + 3)$ and $(t + 3)$ to $(t + 4)$.

Table 7 reports the results of this comparison. We get that the extra productivity growth (EPG, hereafter) of export starters over non-exporters after one year is 1.6% for Model 1 and 7.1% for Model 2. The former coefficient is statistically significant at a 10% confidence level and the latter at a 1%. Beyond one year the estimates suggest that there is no extra productivity growth of export starters over non-starters.

[Table 7 arround here]

The fact that the EPG is detected in the first year firms start exporting but lasts only from this year to the next, can be due to various reasons: on the one hand, learning is more important in the initial period of internationalization as firms are exposed to advanced foreign technologies and are faced with foreign competition for the first time; on the other hand, the increase of productivity in the first year of exporting may be the result of a better utilization of firms' capacity after getting access to foreign demand (Damijan and Kostevc, 2006). Therefore, if non-exporting firms equivalent to export starters had exported, they would have enjoyed a jump in productivity the first year exporting (measured by the statistically significant estimated EPG from t to $(t+1)$). In spite of not detecting statistically significant EPG the following years, the initial jump is enough to ensure a gap in productivity that remains in the future (in comparison to the alternative of continuing as non-exporters). This is the causal effect from exporting to productivity

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[11] Abadie and Imbens (2008) show that due to the extreme non-smoothness of nearest neighbours matching, the standard conditions for bootstrapped standard errors are not satisfied, leading the bootstrap variance to diverge from the actual variance. This may be corrected using the Stata *nnmatch* command (Abadie *et al.*, 2004).

that has been identified after controlling for self-selection, through the use of matching techniques. Further, the fact that the EPG of export starters in sub-period t to $(t+1)$ is much higher when considering an endogenous Markov process than when considering an exogenous one highlights the importance of allowing past export status to affect productivity when analysing LBE.

Table 8 shows the effect of starting to export on the cumulative productivity growth along the whole period from t to $(t+4)$. To put these results in context, the cumulative EPG estimates for Model 2 are low if we compare them with the estimates obtained by Manjón *et al.* (2013) for Spain and De Loecker (2007) for Slovenia, who estimate productivity in a similar manner and also use matching methods for testing LBE. In particular, for periods $(t+s)$, with s = 1, 2, 3 and 4, Manjón *et al.* (2013) cumulative EPG estimates are 3.6, 5.4, 10.8 and 14.4%, respectively, whereas those in De Loecker (2007) for $(t+s)$, with s = 1, 2, 3 and 4, are 14.7, 27.3, 41.4 and 30.6%, respectively.[12]

[Table 8 arround here]

7. **Concluding remarks.**

This paper has examined both self-selection into export markets and post-entry productivity changes for Brazilian manufacturing firms over the period 2000-2008. The literature analysing the relationship between exports and productivity has concluded that exporters are generally more productive than non-exporters and that only the ex-ante more efficient firms enter into export

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[12] We compare our results with those of these two papers, as the methodologies are quite similar. Both Manjón *et al.* (2013) and De Loecker (2007) consider an endogenous Markov process for the law of motion of productivity. Further, De Loecker (2007) considers different demand of investment for exporters and non-exporters, and Manjón *et al.* (2013), who use as control function the demand of intermediate materials, consider different demands of intermediate materials for exporters and non-exporters. Additionally, both papers use matching techniques to calculate the EPG of export starters.

markets (i.e., there is self-selection into export markets). However, the higher productivity of exporters could be also the result of LBE. Recent research has shown that previous empirical studies impose strong assumptions about the evolution of productivity and the role of export status in TFP estimation, which may have biased the estimates towards the rejection of the LBE hypothesis.

In this paper we address this drawback by obtaining TFP estimates both under the assumption of an exogenous or a more general process driving the law of motion for productivity. In particular, we explore the potential role that previous export status might have in shaping firm's productivity. Moreover, in the specification of the production function we also acknowledge that exporters and non-exporters may have different demands of intermediate inputs.

Our results suggest that with the exception of a few sectors, exporters are more productive than non-exporters, and firms self-select into exporting. These results are robust for both TFP estimates under the assumption of exogenous and endogenous Markov process for the law of motion of productivity.

In addition, we find some evidence of learning by exporting. Starting to export yields firms an extra 1.6% (according to Model 1) and 7.1% (according to Model 2) TFP growth that emerges since the first year exporting but lasts only from this year to the next. This extra TFP growth is, however, lower than comparable estimates in other countries. These patterns of post-entry extra productivity growth are compatible with a faster learning process, low cumulative learning opportunities over time, or a fast imitation of good practices in terms of efficiency by non-exporters.

Overall, our results confirm for the case of Brazil the main finding in the literature, the importance of firm self-selection into export markets. Interestingly, we also find some evidence of learning-by-exporting.

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Table 1. Variables description.

Production function variables and wages	
Output	Gross output deflated
Labour	Number of employees
Capital	Value of assets deflated
Materials	Intermediate inputs, including electricity and energy, deflated
Wages	Wages per worker deflated

Table 2. Firms by export status.

		2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Exporters	Number of firms	7,404	7,738	7,882	8,501	9,097	9,131	9,050	8,998	8,968	8,530
	%	30.51	29.59	28.76	29.53	30.70	28.87	27.36	27.29	26.00	28.73
Non-exporters	Number of firms	16,859	18,410	19,527	20,289	20,533	22,501	24,023	23,969	25,522	21,293
	%	69.48	70.41	71.25	70.47	69.30	71.13	72.63	72.71	74.00	71.26

Source: Authors' own elaboration from SECEX and PIA.

Table 3. Firms' characteristics by export status (R$ million, labour as number of workers).

		2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Exporters	Output	6.03E+07	6.86E+07	7.63E+07	6.95E+07	6.56E+07	7.43E+07	7.66E+07	7.82E+07	9.79E+07	7.43E+07
	Labour	3.43E+02	3.34E+02	3.42E+02	3.38E+02	3.58E+02	3.68E+02	3.81E+02	4.12E+02	4.22E+02	3.68E+02
	Capital	8.43E+07	8.80E+07	9.57E+07	7.71E+07	6.61E+07	7.46E+07	8.79E+07	1.18E+08	1.32E+08	9.16E+07
	Materials	4.28E+07	4.92E+07	5.63E+07	5.35E+07	4.86E+07	5.69E+07	5.56E+07	5.51E+07	6.71E+07	5.42E+07
	Wages	1.54E+04	1.65E+04	1.63E+04	1.52E+04	1.33E+04	1.49E+04	1.47E+04	1.44E+04	1.63E+04	1.52E+04
Non-exporters	Output	3.45E+06	3.26E+06	3.25E+06	3.15E+06	3.21E+06	3.17E+06	3.15E+06	3.55E+06	3.58E+06	4.72E+06
	Labour	8.36E+01	7.92E+01	7.86E+01	7.54E+01	7.83E+01	7.60E+01	7.83E+01	8.34E+01	8.09E+01	7.93E+01
	Capital	7.57E+06	6.48E+06	5.78E+06	4.50E+06	4.49E+06	4.63E+06	5.08E+06	5.38E+06	1.40E+07	6.50E+06
	Materials	3.96E+06	3.77E+06	3.64E+06	3.33E+06	3.25E+06	3.17E+06	3.16E+06	3.48E+06	3.60E+06	3.46E+06
	Wages	7.76E+03	7.98E+03	7.71E+03	7.16E+03	6.87E+03	7.14E+03	7.14E+03	7.21E+03	7.19E+03	7.33E+03

Source: Authors' own elaboration from SECEX and PIA.

Table 4. Productivity levels: not controlling (Model 1) and controlling (Model 2) for export status in TFP estimation.

Industry	Non-exporters	Exporters	Model 1				Model 2			
			S_1	*p-val*	S_2	*p-val*	S_1	*p-val*	S_2	*p-val*
10	494	227	3.396	0.000	0.000	1.000	4.120	0.000	0.059	0.993
15	2853	1284	12.996	0.000	0.524	0.578	19.309	0.000	0.473	0.640
17	871	623	9.991	0.000	0.000	1.000	10.716	0.000	0.000	1.000
18	2812	842	11.011	0.000	0.054	0.994	12.725	0.000	0.054	0.994
19	1139	897	11.42	0.000	0.039	0.997	13.302	0.000	0.039	0.997
20	846	922	10.619	0.000	0.068	0.991	13.410	0.000	0.068	0.991
21	580	285	7.009	0.000	0.000	1.000	8.419	0.000	0.000	1.000
22	767	259	6.423	0.000	0.143	0.960	7.124	0.000	0.143	0.960
23	74	120	0.847	0.000	2.077	0.000	0.756	0.134	1.105	0.087
24	781	1088	6.243	0.000	0.078	0.988	10.485	0.000	0.098	0.981
25	1479	946	10.051	0.000	0.520	0.582	12.691	0.000	0.381	0.748
26	1576	558	11.304	0.000	0.202	0.921	14.127	0.000	0.099	0.980
27	359	383	6.307	0.000	0.071	0.990	8.480	0.000	0.038	0.997
28	1840	859	8.923	0.000	0.043	0.996	10.942	0.000	0.000	1.000
29	1044	1472	7.881	0.000	0.056	0.994	12.502	0.000	0.000	1.000
30	56	72	0.457	0.079	1.203	0.055	0.401	0.074	1.214	0.053
31	406	510	3.76	0.000	0.132	0.966	7.554	0.000	0.205	0.919
32	142	222	0.498	0.000	4.317	0.000	0.409	0.000	3.614	0.000
33	130	294	0.618	0.000	2.776	0.000	3.013	0.000	1.358	0.025
34	463	543	7.419	0.000	0.565	0.528	8.467	0.000	0.486	0.623
35	151	132	2.195	0.000	0.223	0.906	3.484	0.000	0.207	0.918
36	1207	1000	8.762	0.000	0.000	1.000	11.247	0.000	0.000	1.000

Table 5. Self-selection: not controlling (Model 1) and controlling (Model 2) for export status in TFP estimation.

Industry	Non-exporters	Exporters	Model 1				Model 2			
			S_1	*p-val*	S_2	*p-val*	S_1	*p-val*	S_2	*p-val*
10	472	44	2.469	0.000	0.070	0.990	2.473	0.000	0.043	0.996
15	2819	332	6.748	0.000	0.220	0.908	6.446	0.000	0.195	0.926
17	846	129	4.799	0.000	0.000	1.000	4.504	0.000	0.000	1.000
18	2776	352	6.103	0.000	0.151	0.956	6.035	0.000	0.243	0.888
19	1124	188	3.024	0.000	0.103	0.979	2.261	0.000	0.166	0.946
20	788	149	3.133	0.000	0.150	0.956	2.964	0.000	0.150	0.956
21	642	81	2.907	0.000	0.000	1.000	2.762	0.000	0.000	1.000
22	665	88	4.000	0.000	0.200	0.923	3.974	0.000	0.200	0.923
23	75	42	0.371	0.000	2.031	0.000	0.371	0.000	2.031	0.000
24	753	209	2.341	0.000	0.184	0.935	2.446	0.000	0.167	0.946
25	1385	245	5.408	0.000	0.398	0.728	5.158	0.000	0.415	0.708
26	1559	116	4.757	0.000	0.332	0.803	4.632	0.000	0.364	0.767
27	358	83	2.075	0.000	0.525	0.577	2.125	0.000	0.143	0.960
28	1795	230	3.441	0.000	0.046	0.996	3.423	0.000	0.003	1.000
29	997	295	2.342	0.000	0.640	0.440	2.290	0.000	0.392	0.735
30	48	18	0.779	0.471	0.628	0.454	0.452	0.288	0.905	0.195
31	391	120	1.092	0.152	0.305	0.830	1.284	0.058	0.159	0.951
32	122	46	0.251	0.000	2.929	0.000	0.204	0.000	2.882	0.000
33	139	53	0.306	0.000	3.009	0.000	0.000	0.000	2.246	0.000
34	457	94	3.228	0.000	0.840	0.244	3.303	0.000	0.857	0.230
35	159	34	1.636	0.005	0.000	1.000	1.769	0.002	0.000	1.000
36	1171	248	4.430	0.000	0.058	0.993	4.432	0.000	0.045	0.996

Table 6. Probit for the propensity score (Probability of becoming an export starter).

Models			
Model 1	Variables	Marginal effect	s.e.
	TFP_{t-1}	0.007***	0.001
	Capital per worker$_{t-1}$	0.011***	0.000
	Size$_{t-1}$	0.021***	0.000
	Number observations: 75958		
Model 2	Variables	Marginal effect	s.e.
	TFP_{t-1}	0.008***	0.000
	Capital per worker$_{t-1}$	0.009***	0.000
	Size$_{t-1}$	0.017***	0.000
	Number observations: 75958		

Notes:
(1) All the estimations include year and industry dummies.
(2) *, **, *** Significance at 10 %, 5 % and 1 % level, respectively.

Table 7. Estimates of EPG for export starters.

Period	Observations	Not controlling for export status in TFP estimation (Model 1)		Controlling for export status in TFP estimation (Model 2)	
		EPG	s.e.	EPG	s.e.
t/t+1	1691 (72762)	0.016*	0.009	0.071***	0.010
t+1/t+2	1064 (72762)	0.008	0.013	0.010	0.013
t+2/t+3	737 (72762)	0.021	0.015	0.023	0.016
t+3/t+4	539 (72762)	0.021	0.017	0.028	0.017

Notes:
(1) EPG stands for extra productivity growth of export starters over matched non-exporters.
(2) In the column observations we report the number of export starters and number of control observations in parentheses imposing common support.
(3)*, **, *** Significance at 10 %, 5 % and 1 % level, respectively.

Table 8. Cumulative EPG over the period t/t+s (for s = 1,…,4).

	Cumulative productivity growth			
	t/t+1	t/t+2	t/t+3	t/t+4
Model 1	1.6%	1.6%	1.6%	1.6%
Model 2	7.1%	7.1%	7.1%	7.1%

To calculate the cumulative EPG over the period t/t+s (with s=1,…,4) we add up the EPG of export starters over non exporters for a given sub-period $t+i/t+j$ (for i=0,…,3 and j=1,…,4) if the EPG of this period is statistically significant (at least at a 10% level).

Appendix

Table A.1. Coefficients of the production function (not controlling, Model 1, and controlling, Model 2, for export status in TFP estimation)

Industry Classification (CNAE 2 digits)	Model 1			Model 2		
	Labour	Capital	Materials	Labour	Capital	Materials
10-14 Mining and extractive industries	0.192	0.084	0.503	0,170	0,098	0,539
15 Food and Beverage Manufacturing	0.124	0.041	0.745	0,124	0,039	0,735
17 Textile Product Manufacturing	0.133	0.045	0.389	0,152	0,042	0,373
18 Apparel Manufacturing	0.357	0.036	0.375	0,369	0,035	0,372
19 Leather processing, Leather products, Luggage and Footwear Manufacturing	0.273	0.063	0.414	0,301	0,063	0,404
20 Wood Products Manufacturing	0.177	0.065	0.568	0,184	0,065	0,548
21 Pulp, Paper and Paper Products Manufacturing	0.093	0.045	0.595	0,110	0,044	0,596
22 Publishing, Printing and Reproduction of Recordings	0.178	0.102	0.414	0,195	0,094	0,458
23 Coal Products Manufacturing, Petroleum Refining, Nuclear Combustibles Processing and Alcohol Production	0.070	0.018	0.985	0,074	0,027	0,964
24 Chemical Products Manufacturing	0.132	0.043	0.762	0,142	0,045	0,740
25 Rubber and Plastics Product Manufacturing	0.159	0.048	0.589	0,167	0,048	0,578
26 Non-metallic Mineral Product Manufacturing	0.143	0.050	0.616	0,146	0,052	0,590
27 Metals Production and Basic Processing	0.146	0.037	0.702	0,153	0,042	0,680
28 Metal Product Manufacturing (excluding machinery and equipment)	0.247	0.057	0.517	0,263	0,057	0,499
29 Machinery and Equipment Manufacturing	0.244	0.063	0.547	0,265	0,057	0,531
30 Office Machinery and Data Processing Equipment Manufacturing	0.144	-0.001	0.900	0,172	-0,008	0,921
31 Electrical Machinery, Equipment and Supplies Manufacturing	0.202	0.044	0.681	0,216	0,046	0,661
32 Electronic Component and Communication Apparatus and Equipment Manufacturing	0.195	0.052	0.828	0,196	0,061	0,773
33 Medical and Therapeutic Equipment, Optical and Precision Instruments, Equipment for Industrial Automation and Watch and Clock Manufacturing	0.229	0.067	0.745	0,253	0,072	0,653
34 Motor Vehicle Assembly and Motor Vehicle, Engine, Trailer and Body Manufacturing	0.216	0.037	0.625	0,218	0,035	0,619
35 Other Transportation Equipment Manufacturing	0.251	0.091	0.507	0,273	0,076	0,498
36 Furniture and Miscellaneous Manufacturing	0.197	0.063	0.474	0,207	0,059	0,471

Please note:

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