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Abstract

This paper explores the link between exports and total factor productivity in Brazilian manufacturing firms over the period 2000–08. The Brazilian experience is instructive, as it is a case of an economy that expanded aggregate exports significantly, but with stagnant aggregate growth in total factor productivity. The paper first estimates firm-level total factor productivity under alternative assumptions (exogenous and endogenous law of motion for productivity) following a GMM procedure. In turn, the analysis uses stochastic dominance techniques to assess whether the ex ante most productive firms are those that start exporting (self-selection hypothesis). Finally, the paper tests whether exporting boosts firms' total factor productivity growth (learning-by-exporting hypothesis) using matching techniques to control for the possibility that selection into exports may not be a random process. The results confirm the self-selection hypothesis and show that starting to export yields additional growth in total factor productivity that emerges since the firm's first year of exporting but lasts only one year. Further, this extra total factor productivity 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.

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The Export-Productivity Link in Brazilian Manufacturing Firms[1]

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1. Introduction

Over the past 30 years, growth in Brazil has been characterized by periods of stagnation punctuated by short bursts of moderate growth. The low trend rate of growth corresponds to a low trend growth of productivity, while the bursts of growth often correspond to a greater absorption of factors of production, particularly labor. The most recent burst of growth occurred between 2003 and 2008, when growth averaged 4.7 percent annually. Since then, with the exception of 2010, when a rebound from the 2008-9 financial crisis produced growth of 7.5 percent, growth averaged little less than 2 percent annually (see Clarke et al. 2014).

This sluggish long-term growth of the Brazilian economy appears to be underpinned by low productivity growth, in spite of the economic reforms implemented since the late 1980s and early 1990s, which included a notable opening of the economy to international trade. Jorgensen (2011) reports estimates of aggregated total factor productivity (TFP, hereafter) growth for Brazil well below those of other large emerging markets since 1989. Clarke et al. (2014) suggest that aggregate TFP levels remained below their pre-reform levels until 2003, when the commodity boom began.

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. The Brazilian experience of reforms with subsequent sluggish productivity growth is puzzling if one believes that increases in exports should be associated with rising productivity. Our aim is more modest than solving Brazil's low-aggregate-productivity puzzle, but this paper takes another look at the link between exporting and subsequent productivity at the micro level. To the extent that aggregate productivity is a function of the sum of individual firm productivities, the findings should prove relevant for assessing whether the rise of exports helped, hindered or was irrelevant for country's aggregate productivity trends.

The literature analysing the relationship between exports and productivity using micro data has expanded to cover a wide range of different countries.[2] 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 most productive firms are able to sell abroad. If this mechanism dominates, then the rise of exports in the Brazilian economies might have yielded negligible effects on aggregate productivity.

At the same time, theory also suggests that once firms enter export markets they can also experience further productivity gains (Clerides *et al*., 1998): this is the so-called learning-by-exporting hypothesis (LBE, hereafter).[3] On theoretical grounds, the potential productivity gains arise from growth in sales that allows firms to profit from economies of scale, knowledge flows 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 improve their efficiency. The evidence for the learning by exporting effect is, however, less compelling in the existing literature.

[2] 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.

[3] 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.

The first empirical attempts to analyze 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.[4] However, the growing international evidence in favor 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. [5]

Also, the empirical evidence within the matching literature 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, 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

[4] 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, the Republic of 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.

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

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 analyze 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 labor 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 Sub-Saharan and Slovenian manufacturing, Manjón *et al.* (2013) do provide evidence from Spain.

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 certain 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). However, our found learning-by-exporting effect that only appears in the first year after the start of exporting is somehow poor. One would expect learning to have more dynamics than a one period hike in productivity in the initial year of exporting. This may be pointing out to a short term nature of learning from foreign markets for Brazilian firms and/or to the nature of exports and product markets where they operate (and the possibilities of learning from these markets).

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 analyze 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 analyze firms' productivity and trade exposure we use a data set 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. Important efforts have been made to minimize attrition and to annually incorporate new firms so that the sample of firms remains representative over time. In total PIA covers more than 40,000 firms. For exports we use a data set created by the foreign trade office, SECEX (*Secretaria Comercio Exterior*). SECEX provides the universe of registered trade flows at the firm level.[6]

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 specific producer price indices supplied by the Instituto Brasileiro de Geografia e Estatistica (IBGE) to deflate the variables in the production function and wages, with the exception of labor. The digits level of the sector deflators corresponds to the 2 digits CNAE classification. Unfortunately, the survey PIA *empresa* has not information on firms' prices to be able to construct firm specific deflators. As can be observed in Table 3, exporters are larger in terms of output, labor, 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:

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

[6] 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 data set are surveyed in PIA claiming not to export. We used SECEX as the most reliable source of information for exporters since exports are adequately registered by the customs authority.

where y_{it} is the log of production of firm i at time t, l_{it} is the log of labor, 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.

As timing assumptions for estimation, it is assumed that capital in period t was actually decided in period $t-1$ and, contrarily, that labor 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 labor and materials (correlated with current productivity) and the one dealing with the law of motion for productivity (required for identification purposes).[7]

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

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

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:

[7] 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 labor coefficient in the first equation, pointed out by Ackerberg *et al.* (2006).

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

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

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

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 endogenizing 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:

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

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

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

It is worth mentioning that by allowing the functions H_E and F_E to be different for exporters and non-exporters in Model 2, we also take into account that exporters' prices can be different to non-exporters' prices within a given industry. For instance, since we do not observe firm-level physical output and use industry specific deflators, unobserved firm-level price variation inside the industry can potentially bias the *tfp* estimates. The extent to which differences in output prices between exporters and non-exporters are present, we control for them. Still, if output prices differ across exporter firms and/or across non-exporter firms within an industry, our *tfp* estimates can be subject to some potential bias (Van Beveren, 2012). Unfortunately, without available information on firms individual prices, little can be done on this final concern. Therefore, we proceed under the assumption (like in De Loecker, 2007, and in many other papers in the related literature) that market conditions are, on the one side, common to all exporters within a given industry and, on the other side, common to all non-exporters within a given industry.

Additionally, in this literature there is also a concern about selection bias or "endogeneity of attrition" in the sample of firms. Traditionally, *tfp* estimation was obtained on a balanced panel subsample from the original sample and, therefore, omitting all firms entering or exiting over the sample period. In that case, for instance, because exiting firms tend to be less productive than their continuing counterparts, omitting them may generate a bias in the estimates (Van Beveren, 2012). However, the literature is nowadays more keen on employing for estimation unbalanced samples, in which entry and exit are implicitly taken into account in the analysis (something already stressed by OP). Provided OP show that once they move to an unbalanced panel, their explicit selection correction does not change their results, and LP found that selection corrections made little difference once the simultaneity correction (between productivity and some input choices) was in place, we simply notice that our sample is unbalanced, and that we do not focus here on selection issues. Further, our data set would not allow us to distinguish properly between firm death, survey non-response, etc.

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:

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

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).[8]

[8] 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.

Table 4 reports the results for the KS tests based both on productivities estimated when 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).[9] 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?

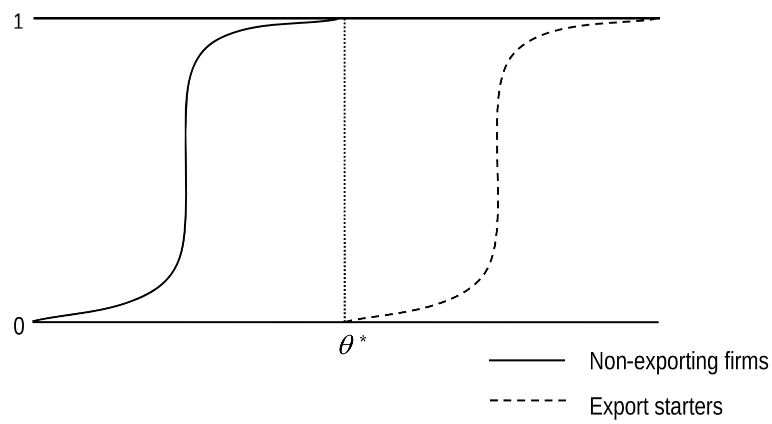
According to self-selection, only the more efficient firms self-select into exporting. The self-selection hypothesis can be benchmarked within Melitz (2003) model that allows for within-industry heterogeneous productivity firms. According to this model, there is a threshold of productivity, θ^*, which 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

[9] For these industries the distribution of exporters does not dominate that of non-exporters, but the opposite. Similar results will appear when testing for self-selection. It could be that in sectors with a high degree of technological intensity or sophistication, productivity driven self-selection into export markets is not so relevant.

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 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.[10] 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

[10] 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.

for at least two years. Thus, we compare,

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

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 analyze 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).[11] Therefore, in most sectors firms self-select into exporting.

[Table 5 around here]

6. Does export entry boost productivity growth?

To analyze 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

[11] 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,

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

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 the appropriate variables to match firms (and 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 a scalar that is the predicted probability of becoming an exporter. 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,

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

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.[12]

[Table 6 arround here]

[12] See Table A.2 in the Appendix for the quality of the matching analysis.

To construct the counterfactual we use the nearest neighbors matching procedure (Becker and Ichino, 2002).[13] 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 with similar characteristics as the 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

[13] Abadie and Imbens (2008) show that due to the extreme non-smoothness of nearest neighbors 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).

exporting to productivity 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 analyzing LBE.

Using the estimates in Table 7, we get that the effect of starting to export on the cumulative extra productivity growth along the whole period from t to (t+4) is 7.1% in Model 2, when using an endogenous Markov process (1.6% when using an exogenous Markov process, Model 1). 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 by 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.[14]

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 analyzing the relationship between exports and productivity has concluded that exporters are generally more

[14] 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.

productive than non-exporters and that only the ex-ante more efficient firms enter into export 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: firm self-selection into export markets is an important part of the story. Interestingly, we also find some evidence of learning-by-exporting, but of modest magnitude and of short duration. These findings thus imply that the export surge in the Brazilian economy probably helped productivity growth, but to a lesser extent than expected, may be due to the importance of the self-selection mechanism or to the nature of exports and the possibilities of learning in export markets.

References

Abadie, A., Drukker, D., Herr, J and G. W. Imbens. 2004, “Implementing Matching Estimators for Average Treatment Effects in Stata.” *The Stata Journal* 4(3): 290-311.

Abadie, A. and G.W. Imbens. 2008. “On the Failure of the Bootstrap for Matching Estimators.” *Econometrica* 76(6): 1537-1557.

Ackerberg, D. A., K. Caves and G. Frazer. 2006. “Structural Identification of Production Functions.” Working Paper, Department of Economics, UCLA.

Ackerberg, D., L. Benkard, S. Berry and A. Pakes. 2007. “Econometric Tools for Analyzing Market Outcomes,” in J. Heckman and E. Leamer (Eds.), *Handbook of Econometrics*, Vol. 6A. Amsterdam: North Holland.

Arnold, J. and K. Hussinger. 2005. “Export Behavior and Firm Productivity in German Manufacturing: A Firm-level Analysis.” *Review of World Economics* 141(2): 219–43.

Aw, B.Y. and A. Hwang. 1995. “Productivity and the Export Market: A Firm-Level Analysis.” *The World Bank Economic Review* 14: 1-65.

Baldwin, J.R. and W. Gu. 2004. “Trade Liberalisation: Export-market Participation, Productivity Growth and Innovation.” *Oxford Review of Economic Policy* 20: 372–92.

Becker, S., and A. Ichino. 2002. “Estimation of Average Treatment Effects Based on Propensity Scores.” *Stata Journal* 2: 358-377.

Bernard, A. B. and J. B. Jensen. 1999. “Exceptional Exporter Performance: Cause, Effect, or Both?” *Journal of International Economics* 47(1): 1–25.

Bernard, A. and J. Wagner. 1997. “Exports and Success in German Manufacturing.” *Review of World Economics* 133: 134–57.

Castellani, D. 2002. “Export Behaviour and Productivity Growth: Evidence from Italian Manufacturing Firms.” *Review of World Economics* 138: 605-628.

Clarke, R., M. A. Dutz, C. H. Hollweg, D. Lederman, and L. Zoratto. 2014. *Brazil’s Productivity Challenge: Selected Issues for Understanding and Improving Productivity*. World Bank Report No. ACS9943, Washington, DC. Downloaded on May 26, 2014, from: http://imagebank.worldbank.org/servlet/WDSContentServer/IW3P/IB/2014/06/26/000333

037_20140626110304/Rendered/PDF/ACS94430ESW0wh030Box385264B00OUO090.pdf.

Clerides, S. K., S. Lach and J.R. Tybout. 1998. "Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco." *Quarterly Journal of Economics* 113(3): 903–947.

Damijan, J.P. and C. Kostevc. 2006. "Learning-by-Exporting: Continuous Productivity Improvements or Capacity Utilization Effects?" *Review of World Economics* 142: 599–614.

De Loecker, J. 2007. "Do Exports Generate Higher Productivity? Evidence from Slovenia." *Journal of International Economics* 73(1): 69–98.

De Loecker, J. 2013. "Detecting Learning by Exporting." *American Economic Journal: Microeconomics* 5(3): 1-21.

De Loecker, J. and F. Warzynski. 2012. "Markups and Firm-Level Export Status." *American Economic Review* 102 (6): 2437-71.

Delgado, M.A., J.C. Fariñas and S. Ruano. 2002. "Firm Productivity and Export Markets: A Non-Parametric Approach." *Journal of International Economics* 57: 397-422.

Doraszelski, U. and J. Jaumandreu. 2013. "R&D and Productivity: Estimating Endogenous Productivity." *Review of Economic Studies* 80(4): 1338-1383.

Girma, S., D. Greenaway and R. Kneller. 2004. "Does Exporting Increase Productivity? A Microeconometric Analysis of Matched Firms." *Review of International Economics* 12(5): 855–66.

Greenaway, D. and R. Kneller. 2004. "Exporting and Productivity in the UK." *Oxford Review of Economic Policy* 20(3): 358–71.

Greenaway, D. and R. Kneller. 2007a. "Firm Heterogeneity, Exporting and Foreign Direct Investment." *Economic Journal* 117(517): 134–61.

Greenaway, D. and R. Kneller. 2007b. "Industry Differences in the Effect of Export Market Entry: Learning by Exporting?" *Review of World Economics* 143(3): 416–32.

Greenaway, D. and R. Kneller. 2008. "Exporting, Productivity and Agglomeration." *European Economic Review* 52(5): 919–39.

Hansson, P. and N. Lundin. 2004. “Exports as Indicator on or a Promoter of Successful Swedish Manufacturing Firms in the 1990s.” *Review of World Economics* 140(3): 415–45.

Heckman, J., H. Ichimura and P. Todd. 1997. “Matching as an Econometric Evaluation Estimator.” *Review of Economic Studies* 65: 261-294.

International Study Group on Exports and Productivity (ISGEP). 2008. “Understanding Cross-Country Differences in Exporter Premia: Comparable Evidence for 14 Countries.” *Review of World Economics* 144: 596-635.

Jorgensen, D. W. 2011. “Innovation and Productivity Growth: T.W. Schultze Lecture.” *American Journal of Agricultural Economics* 93(2): 276–296.

Kraay, A. 2002. “Exports and Economic Performance: Evidence from a Panel of Chinese Enterprises,” in *China and its Regions: Economic Growth and Reform in Chinese Provinces*, M.F. Renard (Ed.), Elgaronline, DOI: 10.4337/9781843765523.

Leuven, E, and B. Sianesi. 2003. “PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing.” *Statistical Software Components S432001*, Boston College, Department of Economics, revised 28 Dec 2006.

Levinsohn, J. and A. Petrin. 2003. “Estimating Production Functions Using Inputs to Control for Unobservables.” *Review of Economic Studies* 70: 317–342.

Manjón, M., J.A. Máñez, M.E. Rochina-Barrachina and J.A. Sanchis-Llopis. 2013. “Reconsidering Learning by Exporting.” *Review of World Economics* 149(1): 5-22.

Mánez-Castillejo, J.A., M.E. Rochina-Barrachina and J.A. Sanchis-Llopis. 2010. “Does Firm Size Affect Self-Selection and Learning-by-Exporting?” *The World Economy* 33 (3): 315-346.

Martins, P.S. and Y. Yang. 2009. “The Impact of Exporting on Firm Productivity: A Meta-Analysis of the Learning-by-Exporting Hypothesis.” *Review of World Economics* 145 (3): 431-445.

Melitz, M. 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” *Econometrica* 71 (6): 1695–1725.

Olley, G. S. and A. Pakes. 1996. “The Dynamics of Productivity in the Telecommunications Equipment Industry.” *Econometrica* 64(6): 1263–1297.

Rosenbaum, P.R. and D.B. Rubin. 1985. “Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score.” *The American Statistician* 39(1): 33 - 38.

Serti, F., and C. Tomasi. 2008. “Self-Selection and Post-Entry Effects of Exports: Evidence from Italian Manufacturing Firms.” *Review of World Economics* 144 (4): 660–694.

Silva, A., A.P. Africano and Ó. Afonso. 2010. “Learning-by-Exporting: What We Know and What We Would Like to Know.” Universidade de Porto FEP Working Papers No. 364, Portugal.

Singh, T. 2010. “Does International Trade Cause Economic Growth? A Survey.” *The World Economy* 33: 1517-1564.

Van Beveren, I. 2012. “Total Factor Productivity Estimation: A Practical Review.” *Journal of Economic Surveys* 26(1): 98–128.

Van Biesebroeck, J. 2005. “Exporting Raises Productivity in Sub-Saharan Manufacturing Plants.” *Journal of International Economics* 67(2): 373–91.

Wagner, J. 2002. “The Causal Effects of Export on Firm Size and Labour Productivity: First Evidence from a Matching Approach.” *Economics Letters* 77(2): 287–92.

Wagner, J. 2007. “Exports and Productivity: A Survey of the Evidence from Firm Level Data.” *The World Economy* 30(12): 60–82.

Wagner, J. 2012. “International Trade and Firm Performance: A Survey of Empirical Studies since 2006.” *Review of World Economics* 148: 235-267.

Wooldridge, J.M. 2009. “On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables.” *Economics Letters* 104: 112–114.

Table 1. Variables description

Production function variables and wages	
Output	Gross output deflated
Labor	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, labor as number of workers)

		2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Exporters	Output	60.47	68.60	76.29	69.55	65.71	74.43	76.59	78.04	97.93	74.18
		(384.02)	(596.70)	(677.40)	(439.23)	(397.72)	(530.77)	(768.60)	(538.37)	(1547.06)	(653.32)
	Labor	342.76	334.48	341.99	337.81	357.74	368.18	380.99	412.29	421.78	366.45
		(858.28)	(929.93)	(934.39)	(940.21)	(1054.34)	(1128.26)	1216.46)	(1363.28)	(1516.87)	(1104.67)
	Capital	84.19	87.98	95.62	77.09	65.95	74.50	87.77	118.46	131.34	91.43
		(695.80)	(916.36)	(1129.51)	(591.47)	(550.71)	(619.43)	1192.79)	(1796.40)	(3335.95)	(1203.16)
	Materials	42.86	49.19	56.17	53.49	48.60	56.78	55.49	55.11	67.14	53.87
		(226.43)	(369.54)	(475.00)	369.00)	(293.73)	(416.26)	479.03)	(349.19)	(815.62)	(421.53)
	Wages	15.39	16.48	16.33	15.25	13.34	14.87	14.72	14.41	16.33	15.24
		(26.49)	(38.70)	(40.58)	(36.08)	(22.11)	(29.06)	31.44)	(22.01)	(52.40)	(33.21)
Non-exporters	Output	5.27	5.10	4.91	4.47	4.40	4.31	4.37	4.86	4.93	4.74
		(16.62)	(22.01	(19.30)	(22.91)	(17.46)	(16.56)	(15.38)	(17.87)	(19.13)	(18.58)
	Labor	83.58	79.25	78.56	75.40	78.29	76.01	78.30	83.41	80.89	79.30
		(129.25)	(129.83	(126.45)	(126.54)	(126.67)	(128.77)	(143.26)	(156.40)	(158.93)	(136.23)
	Capital	7.57	6.48	5.78	4.50	4.49	4.63	5.08	5.38	13.95	6.43
		(52.09)	(38.56	(30.37)	(24.07)	(22.58)	(29.52)	(36.40)	(31.81)	(352.53)	(68.66)
	Materials	3.96	3.77	3.64	3.33	3.25	3.17	3.16	3.48	3.60	3.48
		(12.57)	(16.52	(15.71)	(18.05)	(13.75)	(13.40)	(12.01)	(14.69)	(17.04)	(14.86)
	Wages	7.76	7.97	7.72	7.16	6.87	7.14	7.14	7.20	7.20	7.35
		(12.73)	(14.22)	(14.60)	(15.22)	(14.15)	(13.12)	(11.86)	(11.64)	(10.39)	(13.10)

Notes: 1. Standard Errors are in parenthesis.
2. 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

			Model 1				Model 2			
Industry	Non-exporters	Exporters	S_1	*p-val*	S_2	*p-val*	S_1	*p-val*	S_2	*p-val*
10-14	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

Note: S_1 and S_2 are the one-sided and two-sided K-S tests, respectively.

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

			Model 1				Model 2			
Industry	Non-exporters	Exporters	S_1	*p-val*	S_2	*p-val*	S_1	*p-val*	S_2	*p-val*
10-14	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

Note: S_1 and S_2 are the one-sided and two-sided K-S tests, respectively.

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

		Not controlling for export status in TFP estimation (Model 1)		Controlling for export status in TFP estimation (Model 2)	
Period	Observations	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.

Appendix

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

		Model 1			Model 2		
	Industry Classification (CNAE 2 digits)	Labor	Capital	Materials	Labor	Capital	Materials
10-14	Mining and extractive industries	0.192	0.084	0.503	0.170	0.098	0.539
		(0.009)	(0.015)	(0.079)	(0.092)	(0.017)	(0.078)
15	Food and Beverage Manufacturing	0.124	0.041	0.745	0.124	0.039	0.735
		(0.003)	(0.005)	(0.033)	(0.003)	(0.005)	(0.031)
17	Textile Product Manufacturing	0.133	0.045	0.389	0.152	0.042	0.373
		(0.006)	(0.009)	(0.049)	(0.006)	(0.009)	(0.048)
18	Apparel Manufacturing	0.357	0.036	0.375	0.369	0.035	0.372
		(0.006)	(0.005)	(0.028)	(0.006)	(0.005)	(0.028)
19	Leather processing, Leather products, Luggage and Footwear Manufacturing	0.273	0.063	0.414	0.301	0.063	0.404
		(0.006)	(0.008)	(0.037)	(0.006)	(0.008)	(0.035)
20	Wood Products Manufacturing	0.177	0.065	0.568	0.184	0.065	0.548
		(0.008)	(0.009)	(0.040)	(0.008)	(0.009)	(0.037)
21	Pulp, Paper and Paper Products Manufacturing	0.093	0.045	0.595	0.110	0.044	0.596
		(0.009)	(0.009)	(0.062)	(0.009)	(0.009)	(0.054)
22	Publishing, Printing and Reproduction of Recordings	0.178	0.102	0.414	0.195	0.094	0.458
		(0.009)	(0.014)	(0.069)	(0.009)	(0.014)	(0.062)
23	Coal Products Manufacturing, Petroleum Refining,	0.07	0.018	0.985	0.074	0.027	0.964
	Nuclear Combustibles Processing and Alcohol Production	(0.008)	(0.018)	(0.074)	(0.008)	(0.019)	(0.081)
24	Chemical Products Manufacturing	0.132	0.043	0.762	0.142	0.045	0.74
		(0.004)	(0.007)	(0.042)	(0.005)	(0.007)	(0.038)
25	Rubber and Plastics Product Manufacturing	0.159	0.048	0.589	0.167	0.048	0.578
		(0.005)	(0.008)	(0.044)	(0.005)	(0.008)	(0.045)
26	Non-metallic Mineral Product Manufacturing	0.143	0.05	0.616	0.146	0.052	0.59
		(0.006)	(0.007)	(0.034)	(0.006)	(0.007)	(0.032)

27	Metals Production and Basic Processing	0.146	0.037	0.702	0.153	0.042	0.68
		(0.007)	(0.010)	(0.071)	(0.007)	(0.010)	(0.063)
28	Metal Product Manufacturing (excluding machinery and equipment)	0.247	0.057	0.517	0.263	0.057	0.499
		(0.006)	(0.007)	(0.030)	(0.006)	(0.007)	(0.031)
29	Machinery and Equipment Manufacturing	0.244	0.063	0.547	0.265	0.057	0.531
		(0.005)	(0.009)	(0.041)	(0.005)	(0.008)	(0.038)
30	Office Machinery and Data Processing Equipment Manufacturing	0.144	-0.001	0.900	0.172	-0.008	0.921
		(0.016)	(0.022)	(0.084)	(0.014)	(0.022)	(0.081)
31	Electrical Machinery, Equipment and Supplies Manufacturing	0.202	0.044	0.681	0.216	0.046	0.661
		(0.008)	(0.044)	(0.065)	(0.008)	(0.010)	(0.057)
32	Electronic Component and Communication Apparatus and Equipment Manufacturing	0.195	0.052	0.828	0.196	0.061	0.773
		(0.012)	(0.018)	(0.061)	(0.011)	(0.018)	(0.061)
33	Medical and Therapeutic Equipment, Optical and Precision Instruments,	0.229	0.067	0.745	0.253	0.072	0.653
	Equipment for Industrial Automation and Watch and Clock Manufacturing	(0.011)	(0.015)	(0.080)	(0.012)	(0.014)	(0.069)
34	Motor Vehicle Assembly and Motor Vehicle, Engine, Trailer and Body Manufacturing	0.216	0.037	0.625	0.218	0.035	0.619
		(0.008)	(0.007)	(0.052)	(0.008)	(0.006)	(0.049)
35	Other Transportation Equipment Manufacturing	0.251	0.091	0.507	0.273	0.076	0.498
		(0.014)	(0.024)	(0.070)	(0.014)	(0.020)	(0.059)
36	Furniture and Miscellaneous Manufacturing	0.197	0.063	0.474	0.207	0.059	0.471
		(0.007)	(0.008)	(0.051)	(0.008)	(0.008)	(0.049)

Table A.2. Quality of the matching analysis.

A.2.1. Probit pseudo R^2.(1)

	Exogenous Markov Process		Endogenous Markov Process	
	Before	After	Before	After
t/t+1	0.118	0.006	0.118	0.006
t/t+2	0.131	0.016	0.131	0.013
t/t+3	0.136	0.025	0.136	0.024
t/t+4	0.131	0.034	0.132	0.029

A.2.2. Median bias in the Probit regression.(2)

	Exogenous Markov Process		Endogenous Markov Process	
	Before	After	Before	After
t/t+1	9.609	2.683	9.610	2.321
t/t+2	9.921	5.611	10.275	3.643
t/t+3	9.486	7.374	9.486	7.489
t/t+4	12.365	7.921	12.365	8.886

Notes:

(1) Probit pseudo R^2 for export starters on covariates before matching and in matched samples (after matching).

(2) Median bias refers to median absolute standardised bias before and after matching.