Direct and Indirect Exporting and Productivity: Evidence from Firm-Level Data

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This paper examines the separate productive impacts of direct and indirect exporting to further our understanding of the mechanisms underlying learning-by-exporting effects by utilizing a method that allows us to check the robustness of the results to the selection on unobservables. We found that the productivity effects of exporting are mainly associated with direct exporting, indicating that knowledge spillover, and thus, productive impact of exporting grows with increased interaction with international firms and consumers. Indirect exporters are unlikely to be able to efficiently exploit the productive capacity of foreign technology and knowledge. Copyright © 2013 John Wiley & Sons, Ltd.

INTRODUCTION

Exporting has been advocated as a significant channel for transferring foreign knowledge and technology from international markets, especially in developing countries. For instance, models advocated by Krugman (1979) and Jovanovic and Lach (1991) show that exporting can enhance firm productivity by means of the following: (1) exporting firms learning about and adopting the best international production, distribution, and management methods; and (2) such firms receiving feedback from international customers, suppliers, and competitors that may improve their product standards, as well as benefiting from other knowledge spillovers (Yasar and Morrison Paul, 2007). This theory behind the impact of exporting on firm productivity is referred to in the literature as the ‘learning-by-exporting’ hypothesis (Clerides et al., 1998). Recently, several studies (e.g., Yeaple 2005; Atkeson and Burstein, 2007; Bustos, 2007, 2008; Constantini and Melitz, 2008; Verhoogen, 2008; Aw, Roberts, and Xu, 2008; Lileeva and Trefler, 2010) show that access to international markets provides firms with incentives to export and invest in innovation and skills simultaneously, as they realize that it makes it easier to contend with aggravated competition and that access to these markets augments the returns to innovation.

Given this conceptual mechanism that international engagement provides firms with incentives to transfer and adapt latest technologies and to directly invest in innovation and skills to develop new products and technologies, various empirical studies have addressed the question of whether exporting does in fact increase the productivity of plants or firms. However, only a few studies tend to support this so-called learning-by-exporting theory. Most empirical studies have shown that the more dominant causation is in the opposite direction: the more productive firms self-select...
into export markets. Recently, Lileeva and Trefler (2010) claimed that the weak evidence for the productive impact of exporting may partially arise from the fact that the previous studies do not consider both the heterogeneity in initial productivity as in Melitz (2003), and the heterogeneity in the productivity gains from investing. Once one addresses both kinds of the heterogeneity, ‘negative selection is an immediate consequence of the fundamental complementarity between exporting and investing in productivity.’

In this study, we highlight another dimension of heterogeneity that influences the productive impact of exporting. Specifically, we examine the separate productive impacts of direct and indirect exporting to further our understanding of the mechanisms that underlie learning-by-exporting effects. Exporting can cause higher productivity because of the exposure of exporting firms to new knowledge, technology, and skills from their international counterparts and consumers. According to the theory pioneered by Rosenberg (1982), ‘learning-by-using’ is knowledge that can be gained after a product or process has been used (Mukoyoma, 2004; Yaşar et al., 2006). In the exporting context, the knowledge spillover to firms grows with increased interaction with international firms and consumers; exporting firms learn over time through these types of interactions. Direct exporting may be considered as a mechanism that facilitates face-to-face interactions of business people and consumers, which is especially needed to transfer this sort of disembodied knowledge that is tacit in nature (Howells, 1996).

Thus, one would expect direct but not indirect exporting to result in improvements to productivity, because the direct exporting requires closer interaction between customers and firms in the international market. Indirect exporting, by contrast, is carried out through an intermediary, and thus, the indirectly exporting firm does not engage closely with customers or firms in the international market. As Czinkota et al. (2011) emphasize:

Through direct participation in international markets, firms build relationships with customers and their trading counterparts, which can result in enhanced labor force skills, improved product offerings, and positive externalities from knowledge and technology produced by the firms in these markets (Wu et al., 2007; Czinkota et al., 2011), which can in turn have a significant impact on the firms’ economic performance. Consistent with Rosenberg (1982), the potential productive benefits of foreign technology and knowledge would thus be expected to be exploited more effectively through direct exporting.

The current study contributes to the literature on the exporting–productivity nexus by examining whether direct exporting firms and indirect exporting firms differ in their impact on productivity. To the best of our knowledge, this is the first paper that looks explicitly at the relationship between productivity and different modes of export, while at the same time controlling for other firm-level variables that may influence firm productivity (age, firm size, foreign ownership, importing, licensing, outsourcing, research and development (R&D), capacity utilization, etc.). We also check the robustness of the results to the potential selection problems using a method advocated by Altonji et al. (2005).

After controlling for a number of firm characteristics that represent firm heterogeneity and alternative mechanisms for knowledge spillovers that might enhance firm productivity, we find that direct exporting has a strong positive and statistically significant effect on the firm productivity. The impact of indirect exporting on productivity, however, is not statistically significant. Our sensitivity analysis shows that these findings are robust to the selection bias.

EMPIRICAL SPECIFICATION AND DATA DESCRIPTION

Empirical Model

Our goal in this paper is to explore whether direct exporters and indirect exporters have higher productivity (than non-exporters) for a sample of Brazilian manufacturing firms. To this end, we estimate a production function specification, \( Y = f (M, E, K, L, DE, IDE, R) \), representing the most output that is technologically producible from the given input vector and firm characteristics. For estimation, we assume that
this production function can be represented by a Cobb-Douglas approximation to the general function:

\[
\ln Y_i = a_0 + a_1 \ln M_i + a_2 \ln E_i + a_3 \ln L_i + a_4 \ln K_i + a_5 \ln D_{E_i} + a_6 \ln D_{E_i} + \sum_m \beta_m R_{m_i} + u_i, \tag{1}
\]

where \( i \) is a firm subscript; \( \ln Y \) is the log of gross output; \( \ln M, \ln E, \ln K, \) and \( \ln L \) are the log values of material, energy, capital, and labor inputs, respectively; \( DE \) is a binary variable that indicates whether the firm is a direct exporter (=1 if the firm exported directly and 0 otherwise); \( IDE \) is a dummy variable that represents whether the firm is an indirect exporter (=1 if the firm exported indirectly and 0 otherwise); and \( u \) is a stochastic error term. The \( R_{m_i} \) vector includes the variables for internal firm characteristics, which are as follows: age of the firm \( (AGE) \); the cost share of outsourcing in total costs \( (OS) \); capacity utilization \( (CU) \), defined as the amount of output actually produced relative to the maximum amount that could be produced with existing machinery and regular shifts; whether the firm has a foreign share \( (FDI) \); whether the firm has licensed any foreign technology \( (LIC) \); whether the firm imported material and supplies \( (IMP) \), defined as a binary variable that =1 if the firm imports, zero otherwise); the existence \( (RDUM) \) of internal R&D expenditures; and size \( (SD) \), industry \( (ID) \), and region \( (CD) \) dummies.9

The coefficients of interest are \( a_4 \) and \( a_5 \), which denote the productivity differences between firms in a particular exporting status relative to non-exporting firms. For example, an estimated \( a_4 \) shows whether direct exporters (those who exported directly) have higher unexplained contributions to output than non-exporters (those who did not export at all). Similarly, an estimated \( a_5 \) shows whether indirect exporters have higher productivity than non-exporters. Consistent with theoretical predictions, we expect the coefficient on both the direct export dummy and the indirect export dummy to be positive and statistically significant. Furthermore, we expect that statistical tests will show that \( a_4 > a_5 \), such that the productivity of the direct exporting firms will statistically be greater than that of indirect exporting firms.

The control variables included in Equation (1) represent either alternative mechanisms for knowledge spillovers that might boost firm performance or firm characteristics that should be controlled for to accommodate firm heterogeneity. The \( FDI, IMP, \) and \( LIC \) variables are included to reflect other knowledge spillovers from international technology transfer; these result from importing or licensing technology or indirectly from knowledge in a foreign country that spills over through foreign ownership (Blomström and Kokko, 1998; Yasar and Morrison Paul, 2007). For example, Caves (1974), Globerman (1979), and Aitken and Harrison (1999) find that industries and firms with higher foreign shares \( (FDI) \) are more productive. Coe and Helpman (1995), Keller (2009), Kugler and Verhoogen (2009), and Yaşar (2013) find significant productivity effects from importing technology at the country, industry, and firm levels, respectively. The variable that represents the licensing of foreign technology \( (LIC) \) is also expected to have a significant positive impact on firm productivity (Eaton and Kortum, 1996; Yasar and Morrison Paul, 2007). Own-firm R&D is included to capture internal knowledge creation. The firms’ age \( (AGE) \) is included in the specification as a measure of reputation/experience; we expect a positive and significant relationship between firms’ age and productivity. Outsourcing share \( (OS) \) is included because various studies show that outsourcing leads to higher performance, because the costs of producing inputs or services in-house are higher than subcontracting them, due to either production or transaction costs (Paul and Yasar, 2009). Capacity utilization \( (CU) \) is included to control for the average utilization of a firm’s fixed inputs. Firm size \( (SD) \) is included in the specification to capture differences in the production technology across plants of different sizes. Regional dummies \( (CD) \) are included to correct for the exogenous disparities in the productivity differences across the regions. Industry dummies \( (ID) \) are included to account for production differences across the industries in the pooled data.

Because we used cross-industry and cross-region firm-level data, we expect that firms in a single industry or region (or cluster) may have similarities not shared by firms in other industries or regions. That is, firms within industries and regions will be more homogeneous than firms across industries and regions, because of both observable and unobservable factors. One might therefore expect correlations among the residuals of the equation of interest for different firms in the same industry or region. Not controlling for such dependencies may result in biased standard errors.10 We thus compute and report the standard errors that are robust to potential within-cluster (within-industry and region group) correlation.

Furthermore, we check the robustness of our results to the selection on unobservables. Without controlling for the selection on unobservables inherent in the data, it would be difficult to assess whether exporting leads to higher performance. If the differences
in some unobserved firm characteristics affect the differences in the productivity of exporters and non-exporters, we cannot conclude that differences in productivity are due to exporting. Several approaches have been used in the literature to control for this selection bias and thus to improve causal inferences. For instance, one can use the propensity score-matching method and a difference-in-difference estimator to control for selection on observables and time-invariant unobservables (Girma et al., 2003). Or, we could estimate a one-step procedure and include the exporting variable in the production function estimation model using a dynamic generalized method of moments approach (proposed by Arellano and Bond, 1991, Arellano and Bover, 1995, and Blundell and Bond, 1998), or using the semiparametric Olley and Pakes (1996) model (Van Biesebroeck, 2005; Yasar and Morrison Paul, 2007). A better way to control for potential selection problems is to find instrumental variables that explain the full random variation in our exporting variables. Unfortunately, our data do not allow us to implement these approaches. However, as illustrated in the next section, we use a recently developed method that allows us to examine whether our results are robust to the selection bias and thus whether they can be interpreted as reflecting a genuine causal effect.

SELECTION ON UNOBSERVABLES: A SENSITIVITY ANALYSIS

We check the robustness of our results to the selection bias by using a method that was advocated by Altonji et al. (2005). Based on this method, if the set of observable control variables in Equation (1) is randomly chosen from the set of all possible control variables affecting the firm productivity, and none of unobservable factors have a dominant impact on the distribution of the treatment (exporting) and outcome (productivity) variables, then the robustness of the productive impact of exporting can be checked by assessing how much the selection on unobservables is required or must be, relative to the amount of selection on observables, to entirely account for the estimated significant positive relationship between exporting and productivity. To reiterate the use of this approach, suppose we are interested in estimating the following model:

$$\ln Y_i = a_0 + X_\delta + \alpha_{DE} EXP_i + u_i,$$  

(2)

where $EXP$ is a dummy variable indicating whether or not the firm is a direct exporter; $X$ represents all the observable variables in Equation (1) except for the export variables, industry dummies, and region dummies; and $\delta$ is the vector of the associated parameters. The error term $(u)$ in Equation (2) represents all the unobservable factors, including the group-fixed effects (Millimet, Tchernis and Husain, 2010). Thus, the error term $u$ contains the following three components: (1) a stochastic error term; (2) region-fixed effects that account for region-specific unobservable factors; and (3) the industry-fixed effects that represent the industry-level unobservable factors. We next derive the following relationship from Equation (2):

$$\frac{E[u EXP = 1] - E[u EXP = 0]}{\text{Var}(u)} = \frac{E[X \delta EXP = 1] - E[X \delta EXP = 0]}{\text{Var}(X \delta)}$$  

(3)

The left-hand side of Equation (3) is the amount of selection on unobservables, and the right-hand side is the amount of selection on observables. Assuming that the set of observable factors $(X)$ is a random subset of all factors affecting the firm productivity, where none of the unobservable factors have a dominant impact on the distribution of the treatment (exporting) and outcome (productivity) variables, this equation implies that the relationship between (exporting) and the mean of the distribution of the index of unobservables that determine (productivity) is the same as the relationship between (exporting) and the mean of the observable index, after adjusting for differences in the variance of these distributions. (Altonji et al., 2005)

Given these assumptions, the robustness of the productive impact of exporting can then be checked by assessing how much the selection on unobservables is required or must be, relative to the amount of selection on observables, to entirely account for the estimated positive relationship between exporting and productivity. To accomplish this, let us first write export participation as

$$EXP_i = X_i \pi + v_i.$$  

(4)

Substituting (4) into (2) results in

$$\ln y_i = X_i (\delta + \alpha_{DE} \pi) + \alpha_{DE} v_i + u_i$$  

(5)

Now, the probability limit of the ordinary least square (OLS) estimate of $\alpha_{DE}$ can be written as

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The first part is the productivity impact of exporting, and the second part is the bias.

Given the assumption that the amount of selection on unobservables is equal to the extent of selection on observables as illustrated in Equation (3), the bias term in (6) can be written as

\[
p \lim \delta_{DE} = \alpha_{DE} + \frac{\text{Cov}(\epsilon, u)}{\text{Var}(\epsilon)} \{E[u \mid \text{EXP} = 1] - E[u \mid \text{EXP} = 0]\}.
\]

(6)

Under the null of \( \alpha_{DE} = 0 \), we can consistently estimate \( \delta \) using Equation (5). Then, we compute the variance of the residual (\( \text{Var}(u) \)), the variance of the predicted value of the output (\( \text{Var}(\hat{\epsilon}) \)), \( E[X\delta \mid \text{EXP} = 1] \), and \( E[X\delta \mid \text{EXP} = 0] \). Next, we estimate Equation (4) and compute the corresponding variance of the residual (\( \text{Var}(\epsilon) \)). We then estimate the bias illustrated in Equation (7) by all of these terms and the variance of the EXP variable. Finally, we estimate the implied ratio by dividing the unconstraint estimate of \( \alpha_{DE} \) obtained from Equation (5) by the bias illustrated in Equation (7),

\[
\text{Implied Ratio} = \frac{\hat{\alpha}_{DE}}{\frac{\text{Cov}(\epsilon, u)}{\text{Var}(\epsilon)}},
\]

which indicates how large the selection on unobservables relative to the selection on observables needs to be in order to explain the entire exporting effect. For instance, if this ratio is 1.033, then the normalized shift in the distribution of the unobservables would have to be (1.033) times as large as the shift in the observables to explain away the entire (exporting) effect. (Altonji et al., 2005) If this ratio is greater than 1, we can then conclude that the impact of exporting on productivity is robust.

Data

To estimate our model of the productive impact of exporting for a sample of Brazilian manufacturing firms, we use a cross section of survey data from the Investment Climate Survey collected by the World Bank in 2003. The World Bank’s Enterprise Surveys use either simple random sampling or random-stratified sampling to confirm the randomness of their sample. Face-to-face interviews were performed with firm managers using a sampling method designed to guarantee sufficient representation of firms by industry, size, ownership, export orientation, and location. The firms in the survey are from 13 Brazilian regions: São Paulo, Rio de Janeiro, Minas Gerais, Santa Catarina, Rio Grande do Sul, Paraná, Goiás, Mato Grosso, Ceará, Paraíba, Maranhão, Bahia, and Amazonas. The industries represented are textiles, garments, shoes and leather products, chemicals, machinery, electronics, auto parts, and furniture. Our final sample includes 1427 firms after dropping the missing observations. About 22.90% of the firms surveyed were direct exporters and 8.3% were indirect exporters, while the rest produced only for the domestic market (i.e., non-exporters, which is the base group). Out of 1427 firms used in this paper, 348 are direct exporters (24.39%), 116 are indirect exporters (8.13%), and the rest are non-exporters (67.48%).

Before moving to the estimation of Equation (1), we analyze the means of the firm characteristics for direct exporters, indirect exporters, and non-exporters (base group, indirect exporters, and direct exporters). The results are reported in Table 1. For example, 15.7% of the direct exporting firms had a foreign partner, whereas only 7.5% of the indirect exporting firms and 1.7% of the non-exporters had a foreign partner. Furthermore, the mean age of the direct exporting firms is 26.74, whereas it is 19.38 and 15.16 for the indirect exporting firms and non-exporters. We also tested the statistical significance of the differences between mean values of the variables for firms that directly and indirectly export versus the base group. The null hypothesis, that the means are equal between pairs of groups, is rejected for almost all of the variables. For example, the mean difference for FDI between the base group and direct exporting firms is 0.140 (0.157–0.017), which is significant at 1% level as shown by the triple asterisks (***) on the 0.157 estimate, indicating significantly higher foreign ownership by firms that export directly. Exporting firms also have significantly higher output, inputs, and capacity utilization rates than that of the non-exporters. Furthermore, exporting firms are larger, invest more in R&D, and import significantly more material and equipment.

Using variance inflation factors (VIFs) and tolerance levels, we also checked to see if any of the variables included in the specification in (1) reveal very high degrees of correlation that can cause a multicollinearity problem. As illustrated in Table 2, none of the variables
and without exporting, conditional on the other variables in the model. That is, the estimates of these two coefficients in the production function allow us to test whether there is evidence of learning-by-exporting in the Brazilian manufacturing sector by examining the separate effects of direct and indirect exporting.

The OLS estimates reveal that among the two export status categories, direct exporters (Dexp) have the largest productivity difference over non-exporters. More specifically, direct exporters are around 19.2% significantly more productive than non-exporters, whereas indirect exporters are only 7.3% (insignificantly) more productive than non-exporters, conditional on other variables in the model. The coefficient estimates thus show that direct exporting is significantly associated with firm productivity and that indirect exporting is insignificantly associated with firm productivity. Based on these results, there seems to be statistically significant evidence of the learning-by-exporting effect through direct exporting but not indirect exporting. Productivity also tends to be significantly related (positively) to foreign ownership, outsourcing, size, own-R&D dummy, and (insignificantly) to imports and licensing. The estimated output elasticities with respect to input material, labor, capital, and energy are also illustrated in Table 3, which are consistent with those found in previous studies in developing countries. We also found that firms with a foreign share (FDI) and which invest in R&D have significantly higher productivity levels than those that are not involved in these activities. The capacity utilization, firm size, and outsourcing share variables are also significantly associated with firm productivity.

### RESULTS AND DISCUSSION

#### Ordinary Least Square Results

To evaluate the productivity contributions of the two groups of exporting firms (direct and indirect exporters), we now turn to the results from the OLS estimation of Equation (1), which are presented in Table 3. Because the output variable is expressed as logs, the parameter estimates $\alpha_3$ and $\alpha_5$ indicate the average percentage difference in terms of the productivity between firms with

![Table 1. Comparison of Firms with and without Export History to Non-Exporters (the Mean for Each Group and the Whole Sample)](raw_text_table_1)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Base group</th>
<th>Direct exporter</th>
<th>Indirect exporter</th>
<th>Total</th>
<th>OBS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log output ($LnY$)</td>
<td>13.928</td>
<td>16.495***</td>
<td>15.643***</td>
<td>14.650</td>
<td>1578</td>
</tr>
<tr>
<td>Log material input ($LnM$)</td>
<td>12.997</td>
<td>15.562***</td>
<td>14.935***</td>
<td>13.755</td>
<td>1516</td>
</tr>
<tr>
<td>Log energy input ($LnE$)</td>
<td>9.689</td>
<td>11.878***</td>
<td>11.142***</td>
<td>10.308</td>
<td>1561</td>
</tr>
<tr>
<td>Log capital input ($LnK$)</td>
<td>12.392</td>
<td>14.750***</td>
<td>13.760***</td>
<td>13.057</td>
<td>1527</td>
</tr>
<tr>
<td>Log total employment ($LnEMP$)</td>
<td>3.637</td>
<td>4.908***</td>
<td>4.536***</td>
<td>4.001</td>
<td>1536</td>
</tr>
<tr>
<td>Capacity utilization rate (CU)</td>
<td>73.604</td>
<td>75.041***</td>
<td>77.376***</td>
<td>74.239</td>
<td>1639</td>
</tr>
<tr>
<td>Foreign ownership dummy (FDI)</td>
<td>0.017</td>
<td>0.157***</td>
<td>0.075***</td>
<td>0.054</td>
<td>1642</td>
</tr>
<tr>
<td>Importing dummy (IMP)</td>
<td>0.369</td>
<td>0.612**</td>
<td>0.597***</td>
<td>0.443</td>
<td>1642</td>
</tr>
<tr>
<td>Licensing dummy (LIC)</td>
<td>0.044</td>
<td>0.157***</td>
<td>0.105***</td>
<td>0.075</td>
<td>1642</td>
</tr>
<tr>
<td>Outsourcing share (OS)</td>
<td>0.110</td>
<td>0.109***</td>
<td>0.117***</td>
<td>0.110</td>
<td>1594</td>
</tr>
<tr>
<td>Age of the firm (AGE)</td>
<td>15.163</td>
<td>26.742***</td>
<td>19.381***</td>
<td>18.158</td>
<td>1642</td>
</tr>
<tr>
<td>The existence of research and development expenditures (RDUM)</td>
<td>0.439</td>
<td>0.625**</td>
<td>0.656***</td>
<td>0.499</td>
<td>1642</td>
</tr>
<tr>
<td>Size dummy (SD)</td>
<td>0.154</td>
<td>0.569</td>
<td>0.493</td>
<td>0.277</td>
<td>1642</td>
</tr>
</tbody>
</table>

We tested the mean differences between the each treated group and the base group.

***Mean difference is significant at 1% level.

**Mean difference is significant at 5% level.

*Mean difference significant at 10% level.

### Table 2. Tests of Multicollinearity: Variance Inflation Factors (VIF) and Tolerance

<table>
<thead>
<tr>
<th>Variables</th>
<th>VIF</th>
<th>Tolerance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log material input ($LnM$)</td>
<td>3.960</td>
<td>0.253</td>
</tr>
<tr>
<td>Log energy input ($LnE$)</td>
<td>3.270</td>
<td>0.306</td>
</tr>
<tr>
<td>Log capital input ($LnK$)</td>
<td>2.970</td>
<td>0.337</td>
</tr>
<tr>
<td>Log total employment ($LnEMP$)</td>
<td>5.090</td>
<td>0.197</td>
</tr>
<tr>
<td>Capacity utilization rate (CU)</td>
<td>1.090</td>
<td>0.916</td>
</tr>
<tr>
<td>Foreign ownership dummy (FDI)</td>
<td>1.380</td>
<td>0.727</td>
</tr>
<tr>
<td>Importing dummy (IMP)</td>
<td>1.210</td>
<td>0.826</td>
</tr>
<tr>
<td>Licensing dummy (LIC)</td>
<td>1.240</td>
<td>0.805</td>
</tr>
<tr>
<td>Outsourcing share (OS)</td>
<td>1.080</td>
<td>0.923</td>
</tr>
<tr>
<td>Firm age (AGE)</td>
<td>6.790</td>
<td>0.147</td>
</tr>
<tr>
<td>Research and development dummy (RDUM)</td>
<td>1.130</td>
<td>0.888</td>
</tr>
<tr>
<td>Size dummy (SD)</td>
<td>3.120</td>
<td>0.320</td>
</tr>
<tr>
<td>Direct exporting (DE)</td>
<td>1.550</td>
<td>0.644</td>
</tr>
<tr>
<td>Indirect exporting (IDE)</td>
<td>1.230</td>
<td>0.810</td>
</tr>
<tr>
<td>Mean VIF</td>
<td>2.190</td>
<td></td>
</tr>
</tbody>
</table>

The rule of thumb in the econometric literature is that a VIF $> 10$ or a tolerance level $< 0.1$ are signs of severe multicollinearity problems.
Table 3. Production Function Estimates: Productive Impact of Direct Exporters and Indirect Exporters

<table>
<thead>
<tr>
<th>Variables</th>
<th>With industry and region dummies</th>
<th>Without industry and region dummies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log material input (LnM)</td>
<td>0.587*** (0.026)</td>
<td>0.604*** (0.024)</td>
</tr>
<tr>
<td>Log energy input (LnE)</td>
<td>0.090*** (0.015)</td>
<td>0.094*** (0.015)</td>
</tr>
<tr>
<td>Log capital input (LnK)</td>
<td>0.086*** (0.014)</td>
<td>0.089*** (0.014)</td>
</tr>
<tr>
<td>Log total employment</td>
<td>0.228*** (0.033)</td>
<td>0.191*** (0.031)</td>
</tr>
<tr>
<td>Capacity utilization (CU)</td>
<td>0.002* (0.001)</td>
<td>0.002* (0.001)</td>
</tr>
<tr>
<td>Direct export dummy (DE)</td>
<td>0.192*** (0.035)</td>
<td>0.210*** (0.039)</td>
</tr>
<tr>
<td>Indirect export dummy (IDE)</td>
<td>0.073 (0.045)</td>
<td>0.104** (0.047)</td>
</tr>
<tr>
<td>Size dummy (SD)</td>
<td>0.083* (0.047)</td>
<td>0.073 (0.047)</td>
</tr>
<tr>
<td>Foreign ownership dummy (FDI)</td>
<td>0.139** (0.058)</td>
<td>0.182*** (0.063)</td>
</tr>
<tr>
<td>Licensing dummy (LIC)</td>
<td>0.008 (0.051)</td>
<td>0.034 (0.057)</td>
</tr>
<tr>
<td>Importing dummy (IMP)</td>
<td>0.023 (0.025)</td>
<td>0.051** (0.025)</td>
</tr>
<tr>
<td>Outsourcing share (OS)</td>
<td>0.218*** (0.097)</td>
<td>0.189* (0.097)</td>
</tr>
<tr>
<td>Research and development</td>
<td>0.075*** (0.028)</td>
<td>0.076*** (0.028)</td>
</tr>
<tr>
<td>Firm age (AGE)</td>
<td>0.001 (0.002)</td>
<td>0.004** (0.002)</td>
</tr>
<tr>
<td>Firm age square (AGE^2)</td>
<td>-0.000 (0.000)</td>
<td>-0.000 (0.000)</td>
</tr>
<tr>
<td>Industry dummies</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Region dummies</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>1427</td>
<td>1427</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.945</td>
<td>0.942</td>
</tr>
<tr>
<td>P-value for $\alpha_4 &gt; \alpha_5$</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

The OLS regressions reported in the first column of this table include dummy variables that control for industry and region characteristics. The coefficients for these dummy variables are not reported here in the interest of space, but are available from the author upon request. The standard errors are clustered by industry and sector.

*Significant at 10% level.
**Significant at 5% level.
***Significant at 1% level.

Hypothesis test: test: $\alpha_4 > \alpha_5$.

Furthermore, based on the parameter estimates in Table 3, direct exporting firms tend to have higher productive impact than indirect exporting firms. This is validated by the hypothesis test where the coefficient associated with the direct exporting dummy ($\alpha_4$) is shown to be significantly larger than the coefficient associated with the indirect exporting dummy ($\alpha_5$) (see the bottom row in Table 3 for the hypothesis test: $\alpha_4 > \alpha_5$).

Table 4. Robustness of the Productive Impact of Direct Exporting to the Selection Bias due to Unobservable Factors: Direct Exporters versus Non-exporters and Indirect Exporters ($N = 1427$)

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\alpha}_{DE}$</td>
<td>$\frac{\text{Cov}(\alpha)}{\text{Var}(\alpha)}$</td>
<td>Implied ratio</td>
</tr>
<tr>
<td>0.188</td>
<td>0.182</td>
<td>1.033</td>
</tr>
</tbody>
</table>

$\hat{\alpha}_{DE}$ is the unconstrained parameter estimate of the productive impact of direct exporters, compared with non-exporters and indirect exporters. $\frac{\text{Cov}(\alpha)}{\text{Var}(\alpha)}$ is the bias of the unconstrained direct exporting effect under the assumption that the standardized selection on unobservables is equal to the standardized selection on observables. Implied ratio is the ratio of standardized selection on unobservables to standardized selection on observables under the hypothesis that there is no direct exporting effect. It is the ratio of selection on unobservables to selection on observables required to explain away the entire estimate of exporting effect.
the technology and knowledge spillover to exporting firms increases with greater interaction with international firms and consumers. This implies that the firms that are directly involved with exporting can acquire the knowledge through these interactions and thus consequently improve their productivity.

**Further Robustness Check**

The observable variables that we included in our estimating equations have been identified by the theoretical studies as significant determinants of the firm productivity, and they have large explanatory power, which can be considered a subset of many other factors that can potentially impact the productivity. Thus, the first assumption of the Altonji et al. (2005) method is reasonable in the case of this paper. Regarding the second assumption, one variable that may have a dominant impact on the distribution of the treatment (exporting) and outcome (productivity) variables is the export history of the firms in the data. For example, Das, Roberts and Tybout (2007) and Aw, Roberts and Xu (2011) suggest that past export experience is a highly important determinant of future export engagement. Lileeva and Treffler (2010) find that new exporters are more likely to have larger productivity improvements in response to exporting. Thus, not including the export history variable in the analysis may bias the results. We did not include this variable in Equation (1) so that we can use the non-exporters as a base group. To check the robustness of the results, we conducted the test by including this variable in the models, which is available for 458 direct and indirect exporting firms, to compare the direct exporters with the indirect exporters. The results from the Altonji et al. (2005) method are illustrated in Table 5. The unconstrained parameter estimate of the productive impact of direct exporters, compared with indirect exporters, is 0.112. The implied ratio is 2.67, indicating that the productive impact of direct exporting, compared with that of indirect exporting, is robust.\(^{15}\)

<table>
<thead>
<tr>
<th>(\hat{\alpha}_{DE})</th>
<th>(\text{Var}(\hat{\alpha}_{DE}))</th>
<th>Implied ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.112</td>
<td>0.042</td>
<td>2.677</td>
</tr>
</tbody>
</table>

\(\hat{\alpha}_{DE}\) is the unconstrained parameter estimate of the productive impact of direct exporters, compared with indirect exporters. \(\text{Var}(\hat{\alpha}_{DE})\) is the bias of the unconstrained direct exporting effect under the assumption that the standardized selection on unobservables is equal to the standardized selection on observables. Implied ratio is the ratio of standardized selection on unobservables to standardized selection on observables under the hypothesis that there is no direct exporting effect. It is the ratio of selection on unobservables to selection on observables required to explain away the entire estimate of exporting effect.

Guides us on which variables to include in our model as the main predictors of firm productivity. As illustrated in Table 2, the observable variables included in our model have strong explanatory power. Thus, the assumption that the amount of selection on unobservables is equal to the amount of selection on observables is reasonable in the case of this paper. It is not likely that the unobservable factors would explain away the entire large and significant positive impact of direct exporting on firm productivity.

**CONCLUSIONS**

Theoretical studies have advocated exporting as one of the significant determinants of firm productivity, especially in developing countries. Despite this recognition of the importance of exporting for productivity, however, the empirical evidence of learning-by-exporting has been mixed. Most empirical studies in the growing body of the literature on the exporting–productivity nexus provide no evidence that exporting improves the productivity of the firms. None of these studies, however, examines the relationship between productivity and the separate modes of exporting. This article makes a contribution to the literature as the first paper (to the best of our knowledge) that specifically investigates the separate productive impacts of direct and indirect exporting and checks the robustness of the results to the selection bias, thereby furthering our understanding of the mechanisms that underlie learning-by-exporting.

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15. It is dangerous to infer too much about selection on the unobservables from selection on the observables if the observables are small in number and explanatory power, or if they are unlikely to be representative of the full range of factors that determine an outcome. In our case, there is a solid foundation provided by the production theory and the endogenous growth theory that
Brazilian manufacturing firm data were analyzed using the OLS method and a recently introduced method that allows us to check the robustness of the results to unobserved heterogeneity. Our results support the notion that the productivity effects of exporting are associated with direct exporting. We found that direct exporters have more pronounced productivity effects than indirect exporters. Our results thus provide some evidence that productivity effects increase with greater interaction with international firms and consumers; indirect exporters are unlikely to be able to effectively exploit the productive power of foreign technology and knowledge.

On the policy side, direct exporting firms should be taken into consideration in policy prescriptions that aim to improve the economic performance of exporting firms, given that indirect exporters are unlikely to be able to exploit the productive capacity of foreign technology and knowledge. An understanding of which type of exporting has an impact on firm performance is important for entrepreneurs. Given that the productivity effects of exporting tend to be more pronounced through direct exporting, Brazilian exporting firms that now export through an intermediary may consider taking advantage of learning-by-exporting by shifting to exporting directly.

Although we control for the main determinants of firm productivity that have been identified in the literature and utilize a method that allows us to check the robustness of our results to unobserved heterogeneity caused by omitted variables, our results should still be interpreted cautiously, as our empirical analysis is restricted to cross-section data. The use of instrumental variables that explain the full random variation in our export variables would allow us to address more directly the potential selection issues and thus, check the robustness of the results even further.

In subsequent research, as more data become available, we hope to add a time series dimension to our cross-section analysis and use instrumental variable estimators to investigate this relationship to a greater degree. Examining this relationship for other countries and separate industries can also be a fruitful avenue for future research as richer data become available.

Acknowledgements

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NOTES

1. In a more general context, endogenous growth literature has predicted that international engagement can cause higher productivity through innovation (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991), technology transfer and adoption from leading nations (Eaton and Kortum, 1996, 2001; Barro and Sala-I-Martin, 1995; Parente and Prescott, 1994), and learning-by-doing gains (Lucas, 1988; Clerides et al., 1998).

2. See Keller (2009) and Wagner (2011) for a recent review of this literature.


5. The industry heterogeneity also matters for productive impact of technology and knowledge transfer (Aw, Chung, and Roberts, 2000; Yasar et al., 2007; and Salomon and Jin, 2008). For instance, Yasar et al. (2007 and Salomon and Jin (2008) provide evidence that firms in technologically lagging industries gain more from exporting activities than their counterparts in technologically advanced industries.

6. Lileeva and Trefler (2010) found that Canadian plants that were induced by US tariff reductions to start or increase exporting improved their labor productivity, engaged in more product innovation, and adapted more advanced technologies after they were exposed to the export market. These plants also increased their domestic market share. For the initially low productivity firms that started exporting as a result of tariff cuts, these gains were even larger, which implies a ‘negative selection’.

7. See Rauch and Watson (2004), Basker and Hoang Van (2008a,b), Akerman (2009), Antras and Costinot (2009), Bardhan et al. (2009), Blum et al. (2009), Bernard et al. (2010), Lu et al. (2010), and Ahn et al. (2011) for the role of intermediaries in international trade. The firms that are less efficient than the direct exporters sell their products in the export market through intermediaries. These indirect exporters’ characteristics do not allow them to deal with the costs associated with direct exporting. Our summary statistics for the Brazilian firms provide evidence for these predictions.

8. We use two sizes of dummies (representing small and medium firms with less than 100 employees and large firms with 100 or more employees) to capture differences in technology across different sizes of firms.

9. As shown by two recent influential papers, Katayama, Lu, and Tybout (2009) and De Loecker (2011), measured plant-level productivity may confound true plant-level productivity and differences in markups
across plants. The data on unit prices are not available, making it impossible to address this issue in this paper. Using concentration ratios does not change the results (Amiti and Konings, 2007).


12. See Millimet, Tchernis and Husain (2010) and Roy (2010) for a presentation and an application of this approach in different settings.

13. In this specification, the base group is the non-exporters and the indirect exporters; we lump the non-exporters and indirect exporters together and use a single dummy variable to represent them. This means that we now examine whether and to what extent firms classified as direct exporters are more productive than non-exporters and indirect exporters. This makes our test even stronger. The coefficient on the DE variable in Equation (1) was positive and significant after controlling for the observable factors that have been identified as the main determinants of the firm economic performance in the literature. Thus, it is useful to examine whether the positive selection due to unobservable factors is driving the large positive productive impact of the direct exporting. The coefficient on the variable that represents the indirect exporters in Equation (1), however, was not statistically significant, and thus, we did not perform the same sensitivity check for the productive impact of indirect exporters. However, we dropped the non-exporters and re-estimated Equation (1). Our results indicated that the productive impact of direct exporters is 11.7% higher than that of indirect exporters. We then examined whether this significant productivity difference between direct and indirect exporters is driven by unobservable factors using the Altonji et al. (2005) approach. We obtained an implied ratio of 2.61, indicating that the productive impact of direct exporting, compared with that of indirect exporting, is robust.

14. For an excellent discussion of these data, see Lederman (2007).

15. As highlighted in footnote 13, we conducted the same test without including the export history variable in the models and obtained an implied ratio of 2.61.

REFERENCES


