Learning-by-exporting: do firm characteristics matter? Evidence from Argentinian panel data.

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Abstract

We identify characteristics that affect firms' ability to learn from their export activities. Our analysis employs propensity score matching (PSM) techniques and GMM regressions on a panel of Argentinian firms spanning 1992-2001. Characteristics we find important to learning-by-exporting are: foreign ownership, intensive use of imported inputs, a skilled workforce and small firm size. Finally, firms that are new to exporting seem to experience particularly high productivity gains but begin enjoying them before entering into the export market.

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1 Introduction.

Do domestic firms learn in foreign markets? Answering this question convincingly is of critical relevance for justifying export promotion. Arguably, this is even more important for developing economies. Yet, whether or not exporting firms gain a technological advantage remains one of the most controversial topics in the trade and development economics literature. Despite numerous empirical studies, no definitive consensus has emerged on the relevance of learning-by-exporting. If any, the consensus is against its existence based on the weak econometric evidence[1] and based on recent comparable micro-level panel data for 14 countries that provides no evidence in favor of the learning-by-exporting hypothesis (The International Study Group on Exports and Productivity (2007)).

However, anecdotal evidence and several case studies support the possibility of learning-by-exporting.[2] Moreover, the presumption that learning-by-exporting is relevant appears to be one of the main justifications behind government policies aimed at enhancing export activities.

The literature recognizes that learning-by-exporting is conditional on firm characteristics (i.e. firm heterogeneity). A small number of papers have identified some characteristics such as age of the firm (Delgado et al., 2002; Fernandes and Isgut, 2007), export intensity (Kraay, 1999; Castellani and Zanfei, 2007; Damijan et al., 2007; Girmaa et al., 2004), industry characteristics such as exposure to foreign firms (Greenaway and Kneller, 2003) and destination of exports (DeLoecker, 2007). Another strand of the literature argues that learning-by-exporting is conditional on the development level of destination markets. For instance, Trofimenko (2008) finds a learning-premium for Colombian exporters that target advanced economies and high-tech industries.[3] Unfortunately, no systematic pattern has yet emerged as to which mechanisms are important across countries and, therefore, more evidence is required. This paper is our contribution to this line of research.

We investigate the link between exports and productivity using data on

[1] See Wagner (2007) and Greenaway and Kneller (2007) for literature surveys.
[2] See Keller (2004) for a literature survey.
[3] DeLoecker (2007); Fernandes and Isgut (2007) offer similar results.

the performance of Argentinian manufacturing firms for the period 1992-2001. Exploiting the great level of detail on firm activities provided by this unique dataset, we are able to offer a thorough evaluation of the learning-by-exporting hypothesis. By using this particular dataset we can simultaneously analyze more characteristics than has been previously possible.

Exporting exposes firms to new knowledge that may improve their productivity but only if this knowledge is absorbed. As a consequence, learning-by-exporting is driven by firm characteristics that facilitate knowledge absorption. Among these characteristics, we explore the driving role played by ownership, size, export experience, R&D, labor force skills and use of imported inputs. The intuitive conjecture that some firms can learn more than others has, until recently, been overlooked in the literature. Once these characteristics are taken into account, a clearer picture emerges on their relevance to learning-by-exporting.

An underlying problem in investigating the link between productivity and exporting is identifying the direction of causality. Although the positive correlation between export status and productivity is well-established empirically, there is still a growing literature in the quest for identifying the direction of causality. Self-selection (i.e. exporting-by-learning) and learning-by-exporting are the main candidate explanations of the export-productivity link but these emphasize different causal paths. On the one hand, relatively more productive firms may self-select into international markets. Highly productive firms receive a relatively high return from exports because of either the existence of sunk export costs (Clerides et al., 1998; Melitz, 2003) or the combination of Ricardian technological differences and transport costs (Eaton et al., 2004; Bernard et al., 2005). On the other hand, firms may learn from their experience in international markets and the causality traverses from exporting to efficiency gains. As has been well recognized in the literature, both explanations need not to be mutually exclusive. As highly productive firms self-select into the export market, export dynamics feed back into firm-level learning, further altering the pattern of productivity over time. Lastly, it is possible that selecting into export markets may be a conscious process where firms begin to improve their productivity before exporting (Hallward-Driemeier et al., 2002; Alvarez and López, 2005).[4]

Many reasons for learning by exporting are possible: knowledge transfers from international purchasing agents, tacit knowledge acquired from interacting with them, incentives for innovation and organizational improvements achieved by serving highly competitive markets, among others. This channel may be all the more important for firms in developing countries as there might be much more to learn from more developed foreign markets. As discussed above and explored below, the extent to which a firm learns by exporting might also be conditional to the relative importance of its exports, skill of its labor force, R&D expenditures, size, imports and ownership.

Previous empirical studies on causality give more support to the export self-selection explanation. In a seminal paper, Clerides et al. (1998) find strong evidence of self-selection by Colombian, Mexican and Moroccan manufacturing establishments. Bernard and Jensen (1999) and Arnold and Hussinger (2005) find a similar result for US and German firms respectively. None of these studies find support for the learning by exporting explanation.

Evidence of causality going in the other direction, with export leading to productivity gains is given by Kraay (1999) for China, Fernandes and Isgut (2007) for Colombia and DeLoecker (2007) using data of Slovenian manufacturing firms. As mentioned above, this evidence notwithstanding, the consensus casts doubts on the existence of learning-by-exporting. Differences in data coverage, country export experiences, industrial development and methodology may account for the conflicting results.

We tackle the issue of causality by implementing propensity score matching (PSM) techniques. The use of PSM techniques to disentangle export-productivity causation was introduced into the microeconometrics of international trade literature by Wagner (2002), and is being increasingly implemented in the context of industrialized countries and to a lesser extent to developing economies.

In addition to the PSM technique, we adopt an instrumental variables approach using generalized method of moments (GMM) to identify those

[4]In a related paper, Iacovone and Javorcik (2007) show that Mexican plants undertake export-oriented investments prior to braking into foreign markets.

characteristics that are robust to both approaches. We find robust support for the self-selection explanation as well as for the existence of a learning-by-exporting process. Having established the effect of exports on productivity, we explore the way in which different firm characteristics shape the ability to learn by exporting.

Results that are robust to whether we use propensity score matching or GMM estimators emerge. The export experience of Argentinian firms improves their productivity. As we show that high-productivity firms self-select into foreign markets, our results support the statement according to which the relationship between exports and productivity is bi-directional. We join Hallward-Driemeier et al. (2002) and Alvarez and López (2005) by providing more evidence on how new exporters begin enjoying productivity gains during the process of preparing to export. We contribute to the literature in confirming that the skill structure of the labor force affects the export performance of Argentinian firms. Importantly, we make a contribution in identifying the role played by importing experience, foreign ownership and small size: Learning-by-exporting is more relevant for foreign-owned firms and those that make intensive use of imported inputs. This suggests that relatively more globally engaged firms make a more productive use of the learning opportunities associated with their activities in foreign markets. Finally, small firms appear to learn more through exporting which suggests easier knowledge absorbtion.

Of additional interest is the fact that this particular dataset spans an entire macroeconomic cycle of growth and downturn, thus allowing us to analyze the export behavior of firms in different macroeconomic environments.

The paper proceeds as follows, in the next Section the data are described and summarized. In Section 3 stylized facts on the export experience of the firms in the sample are illustrated and results on the PSM and GMM statistical analysis are reported. A final Section concludes.

Variable	Description.
L_tot	Labor: total number of employees.
L_manu	Labor: manual employees.
L_nonm	Labor: non-manual (professional and technical) employees.
L_tech	Labor: technical employees.
L_prof	Labor: professional employees.
Q	Output: total output.
I	Investment in capital equipment.
R&D_Ratio	Expenditure on R&D as a proportion of total output.
Skill_Ratio	Proportion of professional workers out of total workforce.
ForeignK_Ratio	Proportion of shares that are foreign-owned. Firm-level means for 1992-1996 and 1997-2001.
Exp_Ratio	Export sales as a proportion of total sales.
K	Capital equipment.

Table 1: Variable descriptions.

2 Data.

We explore a unique balanced panel of firm-level data comprising a representative set of Argentinian manufacturing firms that allows us to identify the link between firm characteristics and the learning opportunities that exporting generates.

Most of the data have been collected through the 1998 and 2003 surveys of the *National enquiry into the technological behaviour of Argentinian industrial enterprises*[5] conducted by the *Argentinian National Institute of Statistics and Censuses*[6] (INDEC). Between them, the surveys cover the period 1992-2001 and sample about 1250 firms about 680 of which appear on both surveys. The INDEC surveys are designed to cover all Argentinian firms with 10 or more employees at the time of the surveys. The data are a representative sample of Argentina's manufacturing sector and account for more than 50 percent of total manufacturing sales and employment and 60

[5] *Encuesta Nacional sobre la Conducta Tecnologica de las Empresas Industriales Argentinas.*

[6] *Instituto Nacional de Estadística y Censos.*

per cent of total exports.[7]

Though there are some minor differences between the 1998 and 2003 surveys, both provide consistent information on each firm's location, sector, age, ownership structure, investment flows, variation of capital stock, exports, imports of capital goods, imports of inputs, labor, skill structure, use of information and communication technologies, innovation activities such as R&D, innovation expenditures, product development, product innovation and organizational innovation. From the the 1998 and 2003 surveys we have constructed a balanced panel of 670 firms upon which much of the analysis is based. However, we have used the full unbalanced panel of 1229 firms to estimate the production function in order to overcome any selection bias due to firm attrition.[8]

Much of the data is obtained directly from the surveys with minor transformations. The one exception is the the firms' total factor productivity, the derivation of which is described in subsection 2.2. This, in turn, relies in part on calculations of the capital stock which are presented in subsection 2.1.

Table 1 gives the variable descriptions and Table 2 reports the summary statistics for the resulting dataset. The unbalanced panel is used in the estimation of the production function and to generate measures of total factor productivity. The balanced panel is used in the analysis of the learning by exporting hypothesis.

2.1 Measures of the capital stock.

Though measures of the labor force are readily available, measures of capital must be constructed. The capital stock is only available as the index variable `Capital` where 1992=100 but from this we can construct a capital growth rate $\dot{K}_{i,t}$ for each firm i:

$$\dot{K}_{i,t} = \frac{\texttt{Capital}_{i,t+1} - \texttt{Capital}_{i,t}}{\texttt{Capital}_{i,t}} \tag{1}$$

[7] For more discussion on the representativeness of the dataset see INDEC (2002).

[8] This last issue is an important one as the exclusion of firms that do not make it to the second survey and the exclusion of firms that only enter in the second survey would both generate upwardly biased estimates of firms' productivity.

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	9495	1996		1992	2001
L_tot	9495	252	480	10	5977
L_manu	9495	191	367	10	5693
L_nonm	9495	61	179	0	3285
L_tech	9495	41	131	0	2927
L_prof	9495	20	71	0	1472
Q	9495	33532129	107920909	29548	2.35×10^9
I	9495	2824040	22999247	0	1.37×10^9
R&D_Ratio	9495	0.01	0.03	0	0.69
Skill_Ratio	9495	0.06	0.09	0	1.00
ForeignK_Ratio	9495	0.11	0.29	0	1.00
Exp_Ratio	9495	0.10	0.20	0	1.00
K	9495	16854628	77266006	1021	3.02×10^9

1229 firms in unbalanced panel (9495 observations).
670 firms in balanced panel (6700 observations).
See Table 1 for the variable descriptions.

Table 2: Summary statistics.

We do have measures of gross investment in each period given by $I_{i,t}$. The initial capital stock at the start of 1992 can therefore be obtained by solving the following equation:

$$K_{i,1992} = \frac{I_{i,1992}}{\dot{K}_{i,1992} + \delta}, \quad \forall\ I_{i,1992} \neq 0 \tag{2}$$

where δ is the depreciation rate set to 11.3% following the work of Kydland and Zarazaga (2006).[9] For any firms where investment in 1992 is zero ($I_{i,1992} = 0$), equation (2) is re-applied using $t = 1993$ and the value for 1992 is then calculated using $K_{i,1992} = (K_{i,1993} - I_{i,1992})/(1-\delta)$. Having calculated these starting values of the capital stock in 1992, any remaining values are calculated using the standard equation:

$$K_{i,t} = K_{i,t-1} + I_{i,t-1} - \delta K_{i,t-1} \tag{3}$$

[9]Applying industry-specific measures of capital depreciation was not found to substantially alter the results.

2.2 Measures of Total Factor Productivity (TFP).

To obtain a measure of TFP we assume that production is described by a Cobb-Douglas function using labor, capital and technical progress. In order to mitigate the effects of attrition bias, the production function is estimated using the full unbalanced panel of 1229 firms. Estimates of the log-linearized production function are reported in Table 3. The results in columns (3.1) and (3.2) illustrate the typical simultaneity bias that is induced by estimating the production function directly by OLS. Our preferred estimate is given in column (3.3). In this estimation, we control for sample selection and for the simultaneity bias using the Olley and Pakes (1996) method as described in Arnold (2003). The estimate in column (3.3) is used to generate the natural logarithm of total factor productivity for each firm in each period (lnTFP_{it}). This lnTFP_{it} is used in the next section to analyze the linkages between export experience and total factor productivity.

3 Analysis.

In this section we use summary statistics to identify links between the export experience of firms and their productivity. As mentioned above, this productivity is measured by the total factor productivity (TFP) estimated from the production function in column (3.3) of Table 3. We begin in subsection 3.1 by offering a graphical analysis that already captures some of the salient features of the data. In subsection 3.2 we explain how the propensity-score-matching technique is applied in our analysis, then, we apply this technique by using firms that never export as a base-case to assess the productivity gains of firms that export in every period and firms that became exporters during the period. The results suggest that both self-selection into exporting and learning-by-exporting are important.

3.1 Graphical analysis.

Figure 1 illustrates how total factor productivity (TFP) evolves according to the export status of firms. We note that for all firm types, mean TFP

	(3.1)	(3.2)	(3.3)
Method:	OLS	OLS	Olley and Pakes[a]
Regressand: lnQ			
Regressors:			
lnK	0.324***	0.319***	0.484***
	(0.005)	(0.005)	(0.612)
lnL_manu	0.555***	0.552***	0.483***
	(0.009)	(0.009)	(0.009)
Trend		0.020***	0.051***
		(0.004)	(0.004)
Constant	8.945***	8.891***	-18.29***
	(0.068)	(0.068)	(5.259)
R^2	0.616	0.617	0.663
Observations:	9495	9495	9495
Constant returns to scale F-tests and probabilities in tail of distribution under the null hypothesis: H_0, $\beta_K + \beta_L = 1$.			
$F_{1,9502}$-statistic	297	285	n.a.[b]
Density in tail of F-statistic	0.000	0.000	
$\beta_K + \beta_L =$	0.868	0.871	0.967

Standard errors in (brackets).

[a] This is the method of Olley and Pakes (1996) as described by Arnold (2003).

[b] Not applicable because under Olley and Pakes (1996) the parameters on capital and labor are estimated under different regressions.

Table 3: Cobb-Douglass production function estimates.

increases up to 1998 with the peak in the economic cycle. With the economic downturn, TFP declines for all firm types to 2001.

Comparing firms who are exporters through the period (Type 1) to firms who never export (Type 2) we see the effects of both self-selection and learning by exporting. The self-selection effect can be seen by Type 1 firms having a higher TFP than Type 2 firms at the start of the sample period and the learning by exporting effect is reflected by this gap increasing over time.

The learning by exporting effect is even more evident when considering firms who became exporters at any time during the sample period (Type 3). This is illustrated by the rate at which mean TFP increases much more rapidly for Type 3 firms than for either Type 1 or Type 2 firms. By 1998 the mean TFP of Type 3 firms is very close to mean TFP of Type 1 firms.

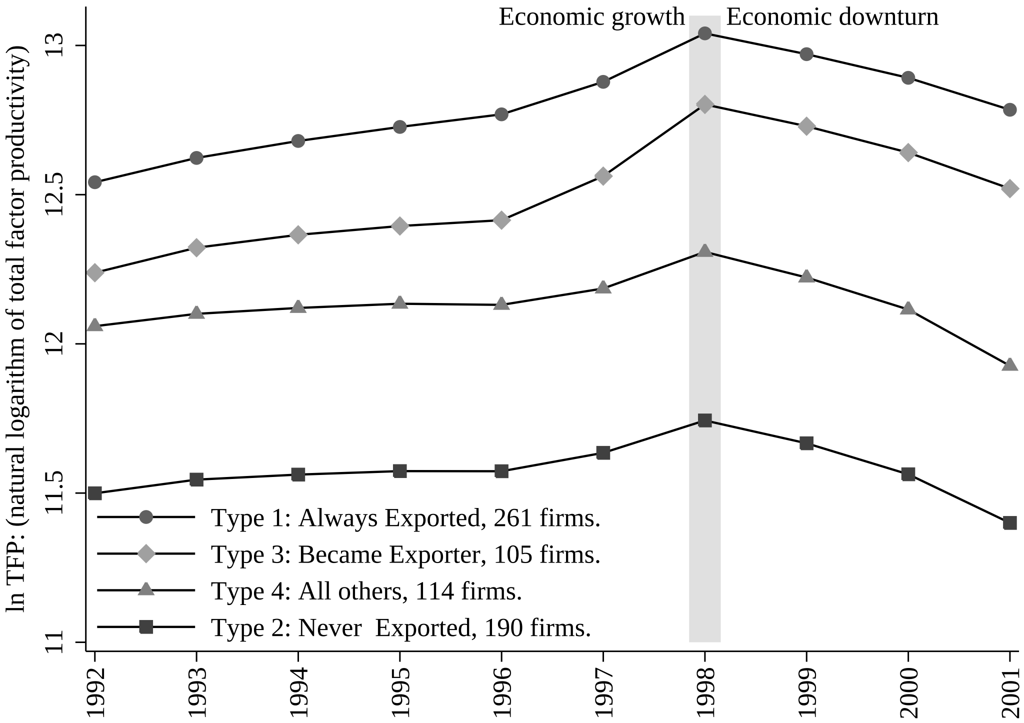

Figure 1: Log of total factor productivity (lnTFP).

Finally, Type 4 firms include all other types, including firms that became non-exporters during the sample period and those that switch in and out of exporting during the sample period. Figure 1 suggests that there is some degree of self-selection for these intermittent exporters in terms of their TFP being between those who always export (Type 1) and those firms that never export (Type 2). It is notable that the mean TFP of these intermittent exporters (Type 4) does not grow any faster than the TFP of non-exporting firms (Type 2).

3.2 Propensity Score Matching (PSM).

Propensity score matching (PSM) is a refinement on difference-in-differences (DiD) estimators because, rather than compare the outcomes of all the *treated* to all the *controls*, PSM only compares a subset of the treated that match closely the characteristics of a subset of the control. The PSM refinement is intended to overcome any *self-selection* bias that may occur in the application of DiD to a dataset where the self-selection problem has not been dealt with adequately or the dataset was not designed for the comparison at hand. The concept of PSM was first suggested by Rosenbaum and Rubin (1983, 1985) and many early implementations were made in the late 1990's by Heckman with various co-authors. For an excellent overview of propensity score matching see Blundell and Costa Dias (2000).

PSM is not a panacea for all the shortcomings of the DiD analysis on inappropriately designed datasets. Firstly, PSM is somewhat arbitrary in the choice of matching procedures. Secondly, many matching criteria are available and the conclusions can be affected by the choice of matching criteria. Thirdly, PSM may fail if the matched dataset is so small that the sample sizes makes the statistical analysis dubious. Finally, if the matching criteria are too restrictive the treated and control groups may be too similar to identify any differences, this has sometimes been compared to the *regression to the mean* problem.

Subsection 3.2.1 describes the technical details of our technique for applying PSM. Subsection 3.2.2 reports the results of a conventional PSM comparing the productivity of firms that became new exporters to firms that never exported. Subsection 3.2.3 reports the results of a non-conventional, but we hope informative, PSM comparing the productivity of firms that have always been exporters to firms that never exported.

3.2.1 Propensity Score Matching: Technique.

Our application of the propensity score matching (PSM) technique involves four steps. The first step[10] is to estimate a Probit regression for firms in 1992, where the dependent variable `Exported` indicates if a firm exported any of its product (=1) or not (=0). The explanatory variables include 'lnTFP', the 'Skill-ratio' of the workforce, the 'R&D-ratio' as a proportion of total output, 'ForeignK-ratio' the proportion of the firm's shares that are foreign-owned and also include two-digit industry dummies to control for different sub-sectoral (unobserved) shocks within a given industry. These Probit estimates are used to generate a propensity score (`pscore`) for each

[10] Carried out using the Stata module `pscore` by Becker and Ichino (2002).

firm for the whole sample period. The variable `pscore` gives the probability that the firm will have exported in 1992 given the characteristics included in the Probit regression. This first step is relatively straightforward and the results of this regression are reported in Table 4.

Sample period: 1992		
Regressand: Exported		
Regressors:	Coefficient	st.err.
lnTFP	0.392***	(0.048)
Skill_ratio	1.618	(1.042)
R&D_ratio	2.357	(1.634)
ForeignK_ratio	0.009***	(0.002)
SIC1	-0.293*	(0.162)
SIC3	-0.315	(0.198)
SIC4	-0.940***	(0.303)
SIC5	0.481	(0.330)
SIC6	-1.597***	(0.605)
SIC7	-0.524*	(0.310)
SIC8	-0.552**	(0.240)
SIC9	0.671	(0.629)
SIC11	-0.062	(0.222)
SIC12	-0.100	(0.233)
SIC13	0.121	(0.263)
SIC14	-0.178	(0.228)
SIC15	0.281	(0.193)
SIC16	-0.734	(0.879)
SIC17	-0.043	(0.242)
SIC18	-0.942**	(0.391)
SIC19	0.320	(0.344)
SIC20	-0.085	(0.230)
SIC21	-0.898**	(0.448)
SIC22	-0.542*	(0.303)
Intercept	-4.823***	(0.614)
Number of observations	1123	
Overall fit χ^2_{24}	230.37	
Log likelihood	-649.53	
Pseudo-R^2	0.1506	

Table 4: Probit results used to generate Propensity Scores.

The second step[11] involves matching firms that exported in 1992 (treated group) to those that did not (control group) using the propensity score `pscore`. The actual matching technique adopted is the *one-to-one nearest neighbor matching, without replacement* once a match has been made. A caliper setting of 0.1 is adopted, the caliper ensures all the available treated firms are used. Let the total number of matches be denoted n. Given the one-to-one matching $2n$ is the total number of matched firms. The standard approach of limiting the propensity scores to the area of common support is adopted. The final number of blocks in the PSM is five, where within each block the mean propensity score for the treated and the controls is equal. The balancing property is satisfied within each of the five blocks for the regressand 'Exported' and for each of the regressors in the Probit reported in Table 4.

The third step[12] involves comparing the total factor productivities (TFP) of the matched firms. This comparison is known as the *average treatment effect on the treated* (ATT) and is calculated by equation (4) where yearA $<$ yearB and n is the number of matched firms:

$$\begin{aligned} \mathrm{ATT}_{\text{yearA-yearB}} &= \frac{1}{n}\sum_{1}^{n}(\ln \mathrm{TFP}^{\text{treated}}_{\text{yearB}} - \ln \mathrm{TFP}^{\text{control}}_{\text{yearB}}) \\ &\quad -\frac{1}{n}\sum_{1}^{n}(\ln \mathrm{TFP}^{\text{treated}}_{\text{yearA}} - \ln \mathrm{TFP}^{\text{control}}_{\text{yearA}}) \end{aligned} \tag{4}$$

The fourth and final step[13] involves bootstrapping the ATT result to check if it is statistically different from zero. This gives an indication of whether being an exporting firm confers significant increases in TFP when compared to firms that do not export. We report confidence levels based on the bias-corrected confidence intervals.

[11] Carried out using the Stata module `psmatch2` by Leuven and Sianesi (2003).

[12] Carried out using `matchcat2`, an adaptation of the Stata implementation `matchcat` by Arnold and Javorcik (2005).

[13] This is a straightforward implementation of Stata's `bootstrap` command in the form: `bootstrap "matchcat2 LnTFP LagLnTFP switch" "r(att)", reps(200)`.

Control group: Never Exported [Type 2].

	Average Treatment effect on the Treated (ATT), see equation (4).			
Treated groups [Type 3]:	$\text{ATT}_{\text{1992-2001}}$	$\text{ATT}_{\text{1992-1996}}$	$\text{ATT}_{\text{1996-2001}}$	$2n$
All New Exporters (NE)	0.390*	0.090*	0.300**	138
	(.159)	(.075)	(.348)	
Small-Employer NE	0.344	0.091	0.445	30
	(.463)	(.207)	(.403)	
Skilled-Labor NE	0.595	0.004	0.397*	62
	(.310)	(.144)	(.245)	
High-Import NE	0.007	0.013	-.065	34
	(.550)	(.190)	(.439)	
Foreign-Owned NE	0.091	0.099	0.439	50
	(.452)	(.264)	(.467)	

***,**,* significant at the 1%, 5% and 10% levels respectively.
n is the total number of matched cases.
Standard errors in (brackets).

Table 5: ATT: New Exporters v.s. Never Exporters.

3.2.2 Propensity Score Matching (PSM): Application One. New exporters [Type 3] versus never exporters [Type 2].

In our first analysis we present a conventional PSM comparison of firms that became exporters [Type 3] to firms that never exported [Type 2] using the technique and Probit estimates described in subsection 3.2.1. The comparison is conventional insofar as we are 'matching' Type 3 firms to Type 2 firms based on their propensities scores in 1992 when both Type 2 and Type 3 firms were non-exporters. Note that we define Type 3 firms as those that became exporters during the time interval 1992-1996 and continued exporting for the rest of the period 1996-2001.

At the top of Table 5 we compare all Type 3 firms that became new exporters (*treated group*) to all Type 2 firms that never exported (*control group*). In the subsequent rows of Table 5 we restrict the sample of Type 3 firms according to various characteristics of interest: 'Small-Employer' firms employ less than 50 manual workers. 'Skilled-labour' firms hire more than 30 percent of skilled labour. 'High-Import' firms have a high reliance on imports and import more than 10 percent of their inputs. 'Foreign-Owned' firms have 10 percent or more of their share ownership in foreign hands. Given that selecting the above thresholds may be to some extent arbitrary, we set these to be quite high. We select the threshold so that the firms selected are at or above the 75 percentile of the distribution with respect to the threshold variable.[14]

We start our interpretation of the results in Table 5 by focusing on column $ATT_{1992-2001}$. The first $ATT_{1992-2001}$ for 'All New Exporters' as the *treated* group is significant at the 10 percent level. This suggests either a exporting-by-learning and/or learning-by-exporting effect. Although the magnitude of the $ATT_{1992-2001}$ estimate is also large for the 'Small-Employer New Exporters' and 'Skilled-Labor New Exporters' sub-categories in the same column, nowhere is it significant.

To explore the exporting-by-learning effects we consider more closely column $ATT_{1992-1996}$ in Table 5.[15] The strong statistical significance for the $ATT_{1992-1996}$ for all Type 3 firms means that firms becoming exporters were already more productive by 1996, although the magnitude of the ATTs is relatively small at 0.090. This supports both the exporting-by-learning hypothesis and the possibility that firms increase productivity in order to become exporters.[16] Notice as well that the ATTs in 1992-1996 are small and insignificant for the Type 3 sub-categories.

Finally, to explore the learning-by-exporting effects we consider the column $ATT_{1996-2001}$ in Table 5. The $ATT_{1996-2001}$ is large in magnitude at 0.300 and significant at the 5 percent level for the top comparison with all Type 3 firms. This gives strong support to the learning-by-exporting hypothesis. In the reminder of column $ATT_{1996-2001}$ the effect is only found to be significant for the 'Skilled-Labor New Exporters' sub-category.

These results suggest that new exporters find in their exporting experience a source of productivity gains. Part of these gains appear before ex-

[14]We have carried out sensitivity checks imposing more stringent thresholds with no substantial change in the results other than reducing the sample size. Combining threshold characteristics though interesting is not viable given the resulting very small sample sizes.

[15]The reason for not defining categories for every time interval is due to the insufficient sample size.

[16]See Hallward-Driemeier et al. (2002) for an exploration of this hypothesis.

porting actually takes place which indicates that selecting into the exporting markets may involve a conscious process where a firm gets ready to face foreign markets. This result is consistent with Alvarez and López (2005) who find conscious self-selection in Chilean firms. The only characteristic that appears to enhance learning by exporting is skilled labor intensity which is commonly associated with absorptive capacity. A first candidate for the lack of significance of other characteristics is most probably due to the small sample sizes (2n). Notwithstanding the few number of observations, it is also plausible that learning opportunities for new exporters do not require additional characteristics to learn through exporting.

We turn now to explore whether, and which, firm characteristics are relevant for those firms exporting throughout the whole period of our analysis.

3.2.3 Propensity Score Matching (PSM): Application Two. Always exporters [Type 1] versus never exporters [Type 2].

In our second analysis we propose a non-conventional PSM comparison of firms that always exported [Type 1] to firms that never exported [Type 2], again using the technique and Probit estimates described in subsection 3.2.1. The comparison is non-conventional because we are not comparing firms where the treated group and the control were both non-exporters at the start in 1992. However, the PSM procedure will match firms that are similar in their *propensity* to export. As a consequence, comparing these two types of firms may give us an indication of the effects of being an exporting firm rather than becoming one. We hope this would capture the lasting learning effects of exporting.[17] By comparing comparing exporters and non exporters, we will show which firm characteristics enhance learning by being an exporter.

In Table 6, we report results for different subgroups of the *treated group* Type 1 firms while keeping the *control group* Type 2 firms constant. At the top of Table 6 we begin by considering all firms that always exported [Type 1] as the treated group. Then we impose additional restrictions to limit the subsample of the treated group according to the same characteristics as in Table

[17] We do not know when firms became exporters before 1992 but, for comparison purposes, we associate our Type 1 firms with permanent exporters to distinguish from new exporters.

Control group: Never Exported [Type 2].				
	Average Treatment effect on the Treated (ATT), see equation (4).			
Treated groups [Type 1]:	$ATT_{1992\text{-}2001}$	$ATT_{1992\text{-}1996}$	$ATT_{1998\text{-}2001}$	$2n$
All Always Exported (AE)	0.245***	0.135**	0.041	374
	(.102)	(.045)	(.051)	
Small-Employer AE	0.561***	0.291***	0.099	68
	(.289)	(.153)	(.094)	
Skilled-Labor AE	0.383**	0.177***	0.079*	184
	(.135)	(.065)	(.053)	
High-Import AE	0.614***	0.322***	0.007	160
	(.159)	(.081)	(.072)	
Foreign-Owned AE	0.706***	0.280***	0.130*	50
	(.174)	(.086)	(.086)	
High-Export AE	0.380***	0.201**	0.099*	108
	(.184)	(.028)	(.081)	
Innovative-R&D AE	0.416*	0.252	0.080*	142
	(.254)	(.297)	(.076)	

***,**,* significant at the 1%, 5% and 10% levels respectively.
n is the total number of matched cases.
Standard errors in (brackets).

Table 6: ATT: Always Exporters v.s. Never Exporters.

5 and add the following two: 'High-Export Always Exporters' captures Type 1 firms that export a relatively high proportion of their output, the threshold defined as 15 percent. 'Innovative-R&D Always Exporters' are Type 1 firms that have made relatively high investments in R&D having spent more than 2 percent of output on R&D.

We start our analysis by considering the results for column $ATT_{1992-2001}$ in Table 6. The ATT is positive and significant in the majority of cases in this column. This suggests learning-by-exporting over the entire 1992-2001 sample period. Remember that Type 1 firms did not become exporters during this period, implying that we cannot interpret these changes as being due to exporting-by-learning effects.

We also analyze two sub-periods by considering columns $ATT_{1992-1996}$ and $ATT_{1998-2001}$ in Table 6. This gives an indication as to whether learning-by-exporting is sensitive to the business cycle.[18] 1992-1996 is a boom period and the firms that always export [Type 1] seem to do considerably better than the firms that never export [Type 2]. The one exception is the comparison for Type 1 firms that have Innovative-R&D who, as we will see, then seem to do better during the economic downturn.

1998-2001 reflects an economic downturn and although Type 1 firms do better than Type 2 firms this difference is not statistically significant. One exception is for High-Export firms. This difference may be explained by the fact that exporting firms can potentially redirect their output to foreign markets in the presence of negative domestic economic shocks.[19] As to the rest of firm characteristics, observe that the greatest rate of learning by exporting is for Foreign-Owned and High-Import firms. These results imply that previous experience in international markets is important for the extent of learning by exporting.

The fact that exporters with a relatively high rate of imports increase productivity more rapidly during the domestic boom is interesting for it suggests that contacts with international suppliers might generate a mechanism through which exporters can acquire new know-how relative to non-exporting firms. We interpret this result as an indication of a complementarity between exporting and importing in terms of knowledge appropriation.

We also find that Small-Employer exporters and exporters with Skilled-Labor learn more from their exporting activities as indicated by the large statistical significance of the ATT during 1992-1996. Taken together these results highlight the fact that learning requires fluid dissemination of knowledge. Though it is easy to argue that skilled workers allow for better appropriation of knowledge involved in exporting experience, the size effect is somewhat more surprising. On one hand, large firms are generally more structured and this would facilitate a better absorption and use of new knowledge. On the other hand, in a small firm, knowledge might be easier to disseminate. Our result suggests that the latter offsets the former. This inverse relationship between learning and firm size is consistent with micro-evidence on the

[18] Real GDP increased 9% between 1992 and 1996 and fell 2% between 1998 and 2001.
[19] Provided that shocks are not perfectly correlated between economies.

determinants of the export success achieved by *Latin American Small and Medium-Sized exporters* (SMEx). According to Milesi et al. (2007), SMEx operating in Argentina, Chile and Colombia make intensive use of technology and skilled workers and undertake a proportionally higher amount of investment in R&D.

3.3 GMM analysis.

We perform several robustness checks. We estimate Fixed and Random effects models that yield similar results.[20] In addition, we try to mitigate any problems associated with potentially endogenous regressors by performing an Arellano-Bond (1991) GMM estimation of the following type:

$$\begin{aligned}\ln \mathrm{TFP}_{i,t} &= \alpha \ln \mathrm{TFP}_{i,t-1} + \gamma \mathrm{ExpRatio}_{i,t-1} + \beta X_{i,t-1} \\ &\qquad + \sum_j \delta_j \mathrm{Time}_j + \sum_k \lambda_k \mathrm{Sector}_k + \eta_{i,t} \quad .\end{aligned}$$

where $\mathrm{lnTFP}_{i,t}$ is the natural log of TFP of firm i at time t and $\mathrm{ExpRatio}_{i,t-1}$ is the lag of exports,

The lagged vector $X_{i,t-1}$ is included in order to investigate the way firm characteristics affect the extent of learning-by-exporting. The variables within the vector $X_{i,t-1}$ are created by interacting $\mathrm{ExpRatio}_{i,t-1}$ with a vector of dummy variables indicating whether the firm is a new exporter, permanent exporter, foreign owned, highly intensive exporter, innovative or employing a relatively high skilled labor force; all defined in subsection 3.2.2. Non-interacted dummies on firm characteristics are also included in this vector.

We control for year and sector effects using Time_j and Sector_k. Finally, $\eta_{i,t}$ is the error term. Right-side variables are all lagged in order to mitigate the effect of simultaneity bias.

Table 7 reports the results.[21] Estimation 7.1 supports the existence of learning-by-exporting as the coefficient associated with exports is positive

[20] We do not report these results due to space constraints, they are available upon request.

[21] Due to space constraints and given that we are interested in the effects of learning-by-exporting, we do not report the coefficients associated with the dummies on firm characteristics.

Regressand: $\ln\text{TFP}_{i,t}$				
Regressors:	7.1	7.2	7.3	7.4
$\ln\text{TFP}_{i,t-1}$	.693***	.712***	.701***	.723***
	(.061)	(.034)	(.035)	(.032)
$\text{ExpRatio}_{i,t-1}$	027**	-.009	-.057	-.027
	(.015)	(.067)	(.064)	(.065)
$\text{ExpRatio}_{i,t-1}$×High Import		.049***	.052***	.053***
		(.019)	(.018)	(.019)
$\text{ExpRatio}_{i,t-1}$×Small Employer		.139**	.132**	.149**
		(.129)	(.061)	(.061)
$\text{ExpRatio}_{i,t-1}$×Always Exporter		-.134**		-.114***
		(.031)		(.027)
$\text{ExpRatio}_{i,t-1}$×New Exporter		.049***	.765***	
		(.010)	(.244)	
$\text{ExpRatio}_{i,t-1}$×Foreign Owned		.106***	.074**	.107***
		(.004)	(.033)	(.035)
$\text{ExpRatio}_{i,t-1}$×Skilled-Labour		.019***	.018***	.017***
		(.006)	(.006)	(.006)
$\text{ExpRatio}_{i,t-1}$×High Intensity		-.016	-.018	-.006
		(.002)	(.002)	(.029)
$\text{ExpRatio}_{i,t-1}$×Innovative-R&D		.021	.003	-.0004
		(.176)	(.013)	(.014)
Constant	4.54***	.342	1.05***	.579*
	(.758)	(.425)	(.403)	(.337)
Firm Characteristics Dummies	No	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes
AB test for AR(1)	-3.84***	-3.67***	-3.78***	-3.62***
AB test for AR(2)	-5.21***	-5.18***	-5.29***	-5.22***
Observations	4927	4927	4927	4927
Number of Groups	805	805	805	805

Standard errors in (brackets).
***,**,* significant at the 1%, 5% and 10% levels respectively.

Table 7: Generalized Methods of Moments analysis.

and significant. Estimations 7.2, 7.3 and 7.4 suggest, however, that learning-by-exporting is sensitive to firm characteristics. After controlling for them, the parameter on exports looses significance. When interacted with different firm characteristics, exporting is associated with significantly higher productivity. This is particularly true for new exporters, importers, firms that employ a relatively high proportion of skilled workers, small employers and foreign owned. We observe as well that the coefficients of small and foreign firms and importers are the greatest. This coincides with what we found with the matching estimators. Our conclusion is that most of the results obtained in the matching analysis in Section 3.2 are robust to these changes in the estimation strategy.

4 Conclusion

We find that though Argentinian firms do learn-by-exporting this is not an automatic process. Learning-by-exporting involves many aspects of the production process in which the capacity to absorb and process knowledge is critical. As well as absorptive capacity, the extent of learning by exporting depends on firm characteristics. Firms with experience in global markets, either foreign owned firms or firms using a relatively high rate of imported inputs, learn more and this result is robust. A high share of skilled workers is also consistently associated with learning-by-exporting. Finally, small firms and newly exporting firms seem to particularly benefit from exporting.

This study has evaluated what types of firms learn from their export experience. The implicit assumption behind learning-by-exporting is that exporting exposes the firm to new knowledge. As we have shown, firm characteristics play a role in the absorption and use of such knowledge. Our results offer a cautious message to policy makers. Any policy aimed at export promotion on grounds of the learning-by-exporting conjecture should target firms carefully. Not all firms increase their productivity by engaging in international markets. Neither do they all learn at the same pace. All this should be borne in mind when formulating policy, not only to target firms that benefit from exporting but also to implement measures that facilitate learning-by-exporting.

Our analysis identifies additional dimensions of learning by exporting that deserve further analysis. Learning-by-exporting appears to be influenced by the business cycle. Some firms, such as ones with a high proportion of imported inputs, do relatively better during upturns in the business cycle while other firms, such as foreign-owned ones, do relatively better during downturns in the business cycle.

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