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Does Learning by Exporting Happen? Evidence from the Automobile Industry in China

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Abstract

The concept that exporters learn from their exporting experience is a theoretical result that needs to be tested empirically. However, the literature provides mixed evidence. In this paper, to estimate productivity, an approach suggested by De Loecker is applied, which corrects for econometric and consistency problems. Using a dataset for the Chinese automobile between 1998 and 2007, no evidence of learning by exporting was found. The data also suggests explanations for why it does not support this hypothesis.

1. Introduction

One of the main arguments for an export-led growth policy is the theoretical productivity benefit from exporting—that is, the idea that plants that export have access to a wider pool of knowledge and receive technical assistance from their foreign customers (Grossman and Helpman, 1991). Trade, as Unel (2010) claims, is therefore a conduit of technology. However, empirical findings have been ambiguous. For example, Clerides et al. (1998) reported no evidence of decreasing marginal costs after export entry in Colombia and Mexico in the 1980s. This result is similar to those found regarding Taiwan and Korea by Aw et al. (2000). In contrast, accounts of productivity improvement after exporting have been documented in Canada (Baldwin and Gu, 2003), Chile (Alvarez and Lopez, 2005) and in Slovenia (De Loecker, 2007).

Keller (2009) provided an excellent review to improve investigation into technology spillover from exporting. Realizing that industry heterogeneity could bias the result, since learning is more likely to take place in high-tech industries, Keller suggested paying more attention to the industry's set-up. Following this suggestion, we chose the Chinese automobile industry for the casestudy in this paper. To our knowledge, this is the first paper that investigates learning by exporting in this industry. There are reasons why this case study is interesting. First, unlike in other sectors, learning experience is potentially an important channel for automobile manufacturers to improve their performance. Second, the growth in the automobile industry in China, especially in the first decade of the 21st century, has received considerable attention from commentators and analysts all over the world. The focus of discussion so far has largely been on the domestic market. However, exports has been outgrowing imports, with the result that China has become a net automobile exporter, as shown by Norcliffe (2006). As a result, it is important to understand how Chinese exporters are performing. Finally, China, although the biggest exporter in the world, is a relatively

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unknown case, especially since the purchase of Volvo in 2010 by Geely "defies business logic by any standard." China's exports have proven to be different from what trade theory would predict (Rodrik, 2006; Schott, 2008). There is therefore a need to find an explanation for the Chinese "miracle."

The data that we have used here has also proven to be interesting. Not only is it new data, covering the firms in the industry from 1998 to 2007, but it also provides the destination countries to which Chinese firms export. This follows the second suggestion in Keller (2009): knowing the destination of the exports could improve our analysis, since the source of any spillover is more likely to come from advanced, high income countries.

It is suggested that the mixed results we find about the learning effect result from the way performance is measured, since different conclusions can be drawn depending on how we choose to measure it (Bernard and Jensen, 1995). Clerides et al. (1998) even note that the simplifications in their estimation model could lead to negative learning. The most common measured productivity is the total factor productivity, defined as the Solow residual. Many studies have suggested ways to estimate this measure, notably Olley–Pakes (1996), Ackerberg et al. (2006) and De Loecker(2010). In this paper, we will follow their methods closely to estimate productivity.

To identify learning by exporting, the productivity of an exporter must be compared to its counterfactual. Assuming that all the plants are equally likely to export at any time since the population in the industry is small, those that do not export at the time of the study have been placed in the base group. Learning by exporting has occurred if the productivity gap between the base group and the group of exporters widens over time. Several issues with regard to the exporters' patterns need to be addressed here, however, as it might not be the case that all the exporters will learn. An export entrant, one that has recently started to export, has the highest likelihood of learning (Bernard and Jensen, 1995). Moreover, learning might take time and might also depend on the age of the plants: old plants may have already acquired the necessary expertise in the industry. Accounting for all these possibilities, we still find no evidence of learning by exporting among Chinese manufacturers. The changes in productivity between the base group and the groups of exporters are not significant enough to suggest that plants improve their productivity after participating in the export market.

The paper is organized as follows: in the next section we will introduce the data; in section 3, we discuss the way productivity is estimated and how the tests are conducted. Section 4 discusses possible explanations for our results and section 5 presents conclusions.

2. Data Manipulation and Description

The dataset we use here is from survey data collected by China's National Bureau of Statistics, which provides financial accounts of the big firms in the industry—those whose revenues were higher than 5 million Renminbi (RMB), or around US $700,000, from 1998 to 2007. By this construction, we remove the observations of firms whose revenues were less than 5 million RMB. Also plants with less than 10 employees are taken out of the sample. Table 1 presents some statistics regarding the industry: production grew from just US $37 million to more than US $3 billion (both at 1985 prices). Exports also grew impressively, from US $20 million to US $900 million. The period from 1998 to 2007 also saw an improvement in labor productivity in terms of

Table 1. Summary Statistics

	Production (US$ millions)	*Export value (US$ millions)*	*Output per worker (US$ thousands)*	*Capital (US$ millions)*
1998	377.14	19.58	19.40	12.614
1999	474.79	35.05	15.25	18.543
2000	588.75	34.61	20.53	21.115
2001	728.40	33.70	24.75	25.143
2002	1068.20	44.35	44.23	26.497
2003	1603.10	48.23	58.19	30.100
2004	2154.50	106.32	88.49	28.889
2005	1798.05	265.02	70.73	30.196
2006	2342.2	456.04	82.23	35.282
2007	3230.95	896.40	103.57	37.736

Note: The numbers are calculated from the survey data, and deflated using 1985 as the base year.

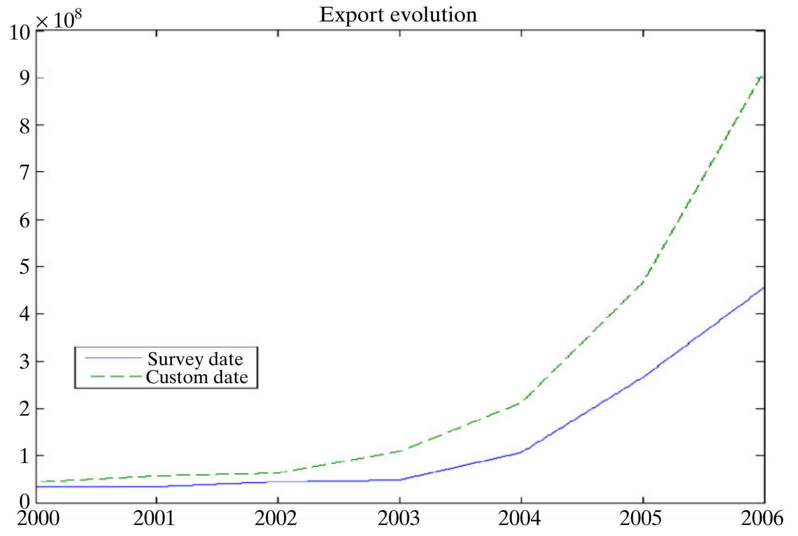

Figure 1. Export Evolution in China Automobile Industry

output per worker, calculated as the value added per worker, from US $20,000 to US $100,000. These numbers prompt the quest of whether foreign market participation really boosts the firm's productivity.

As the survey data only covers the large firms, to gain a complete picture of the exporters we use customs data that reports all the trading activities of Chinese manufacturers from 2000 to 2006. It shows which firms export to which country as well as the value of their shipments. The export activities in the two datasets are well correlated as shown in Figure 1: both data show the exports boom from 2004 to 2006. This high correlation confirms that the survey data is therefore a good representation of the exporters population in China.

In constructing the variables, labor is defined as the number of employees in the plant, multiplied by the number of hours worked. Capital stock is measured by the net value of fixed assets in a given year, deflated by the price index for investment in fixed

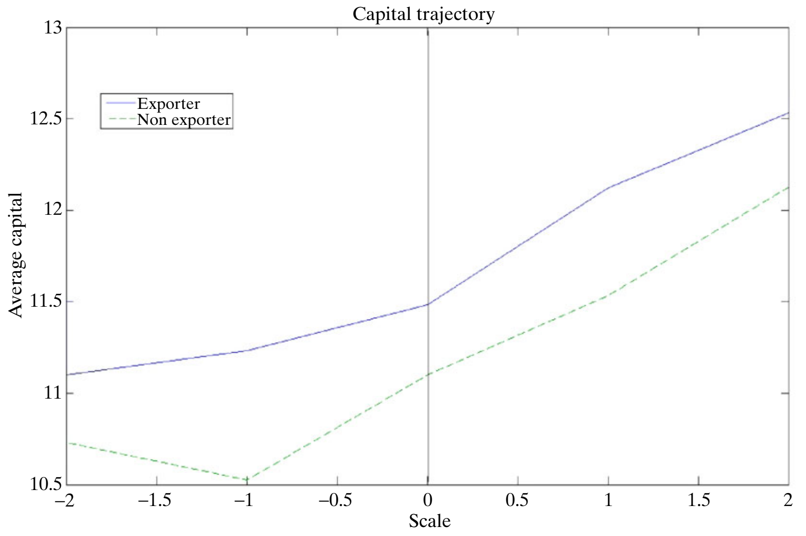

Figure 2. Capital Trajectories

assets. Investment is calculated by the perpetual inventory method $I_t = K_t - (1 - \delta)K_{t-1}$. We use the conventional 10% depreciation rate. Figure 2 shows the capital trajectory of the firms. In this figure, the scale is defined as in De Loecker (2007): for nonexporters, the scale is zero in the year 2002, which is the median year in the survey. It is suggested that if learning by exporting takes place, we should see the exporting firms accumulate capital. Figure 2 shows that capital trajectories are not very different among exporters and nonexporters. This is consistent with the export boom starting in 2004 along with the growth of the domestic market: in 2009, China surged past the USA to become the largest market in the world. This growing domestic market attracted foreign capital, which is shown in the growing numbers of foreign-invested firms. Since the main objective of foreign-invested firms is to penetrate the growing domestic market, we can see a special characteristic of the Chinese automobile industry: exporters are not necessarily more capital intensive than nonexporters. Indeed capital stock and export history are not correlated.

A new plant is presumably more likely to learn new technology than a more established one as learning may take time. The export spell in our data is on average 2 years, which is slightly less than in other countries such as the USA (Besedes and Prusa, 2006), Spain (Esteve-Pérez et al., 2013). Across countries, export duration ranges from 2 years to 5 years (Rakhman, 2011). These results put the export duration of Chinese automobile producers in the lower end. This short spell of exporters is consistent with the export turnover pattern, which is shown in Table 2. In particular, the exit rate is calculated in a certain year t as the relative number of firms that are in their final year of activity in year t. Therefore, 21.55% of the firms in 1998 would not appear in the dataset again. On average, 18% of the firms stop producing while 25% of exporters exit the foreign markets. These numbers are relatively high, compared with only 4% in Chile (Irarrazabal and Opromolla, 2006). The export entry rate is also higher than in other studies: about 27% enter the markets each year, compared with 4% in Chile (Irarrazabal and Opromolla, 2006). With the customs data including the small firms and small exporters, the turnover is even higher. In March 2006, this high turnover led the Chinese government to impose a licensing program that limited

Table 2. Industry Turnovers

	All firms		*Exporters*	
	Exit rate (%)	*Entry rate (%)*	*Exit rate (%)*	*Entry rate (%)*
1998	21.55	28.26	14.71	32.43
1999	18.48	19.67	27.03	25.64
2000	26.23	28.11	10.26	23.26
2001	22.70	22.11	6.98	20.41
2002	40.00	44.56	30.61	34.62
2003	34.20	52.94	17.31	42.42
2004	26.10	16.18	24.24	32.89
2005	19.50	20.73	14.47	22.47
2006	14.23	16.36	20.22	24.00
Average	24.78	27.66	18.43	28.68

Note: we define an exit in year *t* if the firm disappears in the following years and an entry in year *t* if the firm appears for the first time the next year. The numbers are calculated from the survey data.

the number of small exporters in order to keep the market stable. Finally, most firms export to emerging countries (eight of the top 10 export destinations are developing countries) where technology transfer and quality upgrading are less likely to occur.

The preliminary investigation above suggests that Chinese automobile manufacturers do not learn from exporting. In order to confirm this conclusion, we need to conduct a rigorous analysis, which we will describe below.

3. Empirical Strategy

The Olley–Pakes Methodology

Consider a Cobb–Douglas production function:

$$y_{jt} = \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + \omega_{jt} + \varepsilon_{jt}$$

where y_{jt} is the log of output, l_{jt} is the log of labor, k_{jt} is the log of capital stock and ω_{jt} and ε_{jt} are the shock terms. Although the last two terms represent shocks that are unobservable by the econometrician, there is a difference between them. The first shock ω_{jt} is assumed to represent the shocks that are known to, and therefore observable by, the firms. The second shock ε_{jt} is, however, unknown and unobservable to the firm.

Since a ω_{jt} shock is observable to the firm, they will use it as a parameter in their optimal input choice problem. As a result, the input choices l_{jt} and k_{jt} are correlated with ω_{jt}, which renders the estimates of their coefficients β_l and β_k biased. Olley and Pakes (1996) proposed a solution to correct this problem by distinguishing labor and capital and assuming labor is a nondynamic input that has no impact on the future profit maximization of the firm. Capital stock, however, is assumed to be predetermined and could influence future profits. More specifically, according to the perpetual inventory method, capital stock at time *t* is determined by the capital stock and investment in the previous period:

$$k_{jt} = (1-\delta)k_{jt-1} + i_{jt-1}.$$

Further, capital stock can be used to determine the optimal choice of investment in the future. Based on a dynamic optimization problem in Ericson and Pakes (1995), Olley and Pakes (1996) assume that the optimal investment strategy of the firm is as follows:

$$i_{jt} = f(k_{jt}, \omega_{jt}).$$

The firm chooses its optimal investment spending for the upcoming period based on their current capital stock and their productivity. Intuitively, a more productive firm should invest more. Therefore, they assume that the function $f(.)$ is increasing in ω_{jt} which allows them to invert f to obtain:

$$\omega_{jt} = h(i_{jt}, k_{jt}).$$

Therefore the production function can be rewritten as:

$$\begin{aligned} y_{jt} &= \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + h(i_{jt}, k_{jt}) + \varepsilon_{jt} \\ &= \beta_0 + \beta_l l_{jt} + \phi(i_{jt}, k_{jt}) + \varepsilon_{jt}. \end{aligned}$$

Since an ε_{jt} shock is assumed to be unobservable by both the econometrician and the firm, the ordinary least squares (OLS) method can be used to obtain consistent, unbiased estimates of β_0 and β_l in the first stage. The estimate of ϕ will then be used in the second stage to obtain an estimate of β_k.

In the second stage, they assume ω_{jt} follow a Markov process AR(1):

$$\omega_{jt} = g(\omega_{jt-1}) + \xi_{jt} = E(\omega_{jt}|\omega_{jt-1}) + \xi_{jt} \tag{1}$$

where ξ_{jt} is an innovation at time t, therefore is orthogonal to all the variables determined in the previous periods. Since k_{jt} is a predetermined variable, we have the following moment:

$$E(\xi_{jt}|k_{jt}) = 0$$

This moment is used to obtain an estimate of β_k. Indeed, starting from a candidate parameter β_k, they calculate the implied productivity:

$$\omega_{jt}(\beta_k) = \hat{\phi} - \beta_k k_{jt}.$$

The conditional expectation of $\omega_{jt}(\beta_k)$ can be obtained by a nonparametric estimation (e.g. kernel estimation) $E(\omega_{jt}(\beta_k)|\omega_{jt-1}(\beta_k)) = E(\omega_{jt}(\beta_k)|I_{t-1})$. The residual $\xi_{jt}(\beta_k)$ is calculated from (1). The estimate of β_k is chosen so as to minimize $\sum_{j,t} \xi_{jt}(\beta_k) k_{jt}$. The implied productivity is then given by:

$$\omega_{jt} = y_{jt} - \hat{\beta}_0 - \hat{\beta}_l l_{jt} - \hat{\beta}_k k_{jt}. \tag{2}$$

Ackeberg–Caves–Frazer Critique

The goal of the first stage in the Olley–Pakes approach is to provide the labor coefficient β_l. However it rests on the assumption that labor at time t is independent of the nonparametric function $\phi(i_{jt}, k_{jt})$. The validity of this assumption depends on how we think about the data process that generates l_{jt}. Intuitively, the firms choose input, in particular labor, based on the value of the state variables, which are ω_{jt} and k_{jt} (note that ω_{jt} is observed by the firms and k_{jt} is predetermined):

$$l_{jt} = f(\omega_{jt}, k_{jt}).$$

Investment, as we discussed above, is also a function of the state variables. As a result, we have the collinearity issue:

$$l_{jt} = f(\omega_{jt}, k_{jt}) = f(g^{-1}(i_{jt}, k_{jt}), k_{jt}).$$

Labor is now not independent of investment and capital, which prevents us from correctly estimating β_l in the first stage. To correct this problem, Ackerberg et al. (2006) proposed estimating β_l in the second stage to correct this problem. A moment is needed to determine this labor coefficient. Given that ξ_{jt} is the innovation in t, it is orthogonal to labor in $t-1$:

$$E(\xi_{jt} | l_{jt-1}) = 0.$$

This additional moment, together with the moment mentioned above, help us to estimate the parameters of interest β_l and β_k.

De Loecker Critique

Leaving aside the econometric problems mentioned above, it is still important to consider the purpose of our productivity estimates. The way we estimate productivity is not independent of the way we use the estimates, as in this case, testing learning by exporting, past exporting has to be allowed to influence productivity. In other words, it has to be included in the proxy function $\phi(.)$. Without this inclusion, we will have an inconsistency problem that could bias our analysis. To illustrate this point, De Loecker (2010) uses a simple example in which the Markov process is now as follows:

$$\omega_{jt+1} = \omega_{jt} + \gamma e_{jt} + \xi_{jt+1}$$

where is the export status. With this new Markov process, the production function can be rewritten as:

$$\begin{aligned} y_{jt+1} &= \beta_0 + \beta_l l_{jt+1} + \beta_k k_{jt+1} + \omega_{jt} + \gamma e_{jt} + \xi_{jt+1} + \varepsilon_{jt+1} \\ &= \beta_0 + \beta_l l_{jt+1} + \beta_k \Delta k_{jt+1} + \phi(i_{jt}, k_{jt}) + \gamma e_{jt} + \xi_{jt+1} + \varepsilon_{jt+1}. \end{aligned}$$

If e_{jt} is not included as an independent variable and is considered as an error term, and if it is correlated with any of the explanatory variables, in particular, the change in capital Δk_{jt+1}, then the estimate of β_k is biased. Therefore to maintain the consistency with the tests we will perform later, we need to include e_{jt} in the proxy function $\phi(.)$.

Productivity Estimation

Keeping in mind the issues mentioned above, we closely follow De Loecker's (2010) method to estimate productivity. In the first stage we run:

Table 3. Input Coefficients

	OLS	*ACF(2006)*	*De Loecker (2010)*
Labor coefficients	0.764***	0.695***	0.657***
	(0.033)	(0.057)	(0.053)
Capital coefficients	0.377***	0.394***	0.385***
	(0.022)	(0.019)	(0.018)

Note: Standard errors are reported in parentheses. *,**,*** denotes significance at 10%; 5%; and 1% respectively. OLS = ordinary least squares; ACF = Ackeberg et al.

$$y_{jt} = \phi(i_{jt}, k_{jt}, l_{jt}, e_{jt}) + \varepsilon_{jt}$$

where y_{jt}, i_{jt}, k_{jt}, l_{jt} are the logs of output, investment, capital and labor respectively. Since there are many firms that are not exporters in the dataset—in other words, there are many zeros in the export value—we use the export status as the value of e_{jt}. This first stage provides the estimate of $\phi(i_{jt}, k_{jt}, l_{jt}, e_{jt}) = \beta_l l_{jt} + \beta_k k_{jt} + h(i_{jt}, k_{jt}, e_{jt})$. In the second stage, we start from a vector of parameters (β_l, β_k) to calculate ω_{it}:

$$\omega_{jt} = \hat{\phi}(i_{jt}, k_{jt}, l_{jt}, e_{jt}) - \beta_l l_{jt} - \beta_k k_{jt}.$$

We then regress $\omega_{jt}(\beta_l, \beta_k)$ on $\omega_{jt-1}(\beta_l, \beta_k)$ using the kernel estimation. The residuals from this regression are $\xi_{jt}(\beta_l, \beta_k)$. Since capital is predetermined, the vector (l_{jt-1}, k_{jt}) belongs to the information set I_{t-1}. In other words this vector is orthogonal to any innovation in the current period, in particular $\xi_{jt}(\beta_l, \beta_k)$:

$$E\left(\xi_{jt}(\beta_l, \beta_k)\begin{pmatrix} l_{jt-1} \\ k_{jt} \end{pmatrix}\right) = 0.$$

With these moments, we can estimate the parameters of interest (β_l, β_k) using the generalized method of moments. The productivity of each plant is then determined using the equation:

$$\omega_{jt} = \hat{\phi}(i_{jt}, k_{jt}, l_{jt}, e_{jt}) - \beta_l l_{jt} - \beta_k k_{jt}$$

Table 3 reports the estimates of input coefficients. As expected, the labor coefficient is overestimated: with the OLS approach, it is estimated at 0.764, whereas with the Ackerberg et al. (ACF) and the De Loecker approaches, the estimates are 0.695 and 0.657 respectively. The estimates of capital coefficient are higher when departing from OLS, even though the changes are smaller than the labor coefficient. More important is the difference between the estimates of capital coefficient of Ackerberg et al. and De Loecker. The change is not significant. This is consistent with Figure 2: exporting does not play a significant role in boosting investment.

Testing the Learning by Exporting Hypothesis

To test the learning by exporting hypothesis, we compare the productivity trajectories of the exporters against their counterfactual, i.e. those plants that are similar

Table 4. Is the Group of Non-exporters Good for the Base Group?

	Exporters	*Nonexporters*
Output	1,662,068	245,815
Labor	5,670	810
Material	1,563,235	228,184
Capital	1,798,809	249,891
Investment	475,513	71,703
Labor per output	0.00034	0.00033
Material per output	0.94	0.93
Capital per output	1.08	1.017
Investment per output	0.286	0.291

Note: The number are simple average, calculated from the survey data.

to the exporters but do not export. Given the small number of plants in our data, we shall assume that all the plants are equally likely to export so the counterfactual will be the nonexporters. This assumption is justified by comparing some characteristics between the set of exporters and the set of nonexporters. Although the exporters are largger in size, their inputs intensities are similar to the nonexporters (see Table 4). This is also in line with Figure 2: the capital trajectories between two groups are very similar.

Moreover, since a typical exporter only stays in the export market for 2 years, we adopt an approach similar to Aw et al. (2000) to perform the productivity comparison. Our empirical strategy to test learning by exporting is shown below. We define the base group as that which contains the nonexporters at time t and $t+1$:

$$\text{Base group} = \{\text{plants} : \text{export}_t = \text{export}_{t+1} = 0\}$$

We construct the group of exporters which consists of the plants that do not export at time t but do export at time $t+1$:

$$\text{Treated group} = \{\text{plants} : \text{export}_t = 0; \text{export}_{t+1} > 0\}.$$

By construction, time t is the pre-entry and time $t+1$ is the post-entry. Learning by exporting occurs if the productivity gap between these two groups widens between time t and time $t+1$:

$$(TFP_{\text{Treatedgroup}} - TFP_{\text{Basegroup}})_{t+1} > (TFP_{\text{Treatedgroup}} - TFP_{\text{Basegroup}})_t.$$

More specifically, we run the following regression:

$$tfp_{jt} = \alpha_0 + \alpha_1 D_{jt} + f_t + u_{jt}$$

where D_{jt} is a dummy variable which is equal to 1 if the plant belongs to the treated group and 0 if the plant belongs to the base group, and f_t controls for the time fixed effect. The coefficient α_1 measures the productivity difference between the treated group and the base group. Estimates of this coefficient can be seen in Table 5. In particular, column (1) shows the productivity difference at time t, that is before the

Table 5. Average Productivity Differences

	ACF		*LP*	
	Year t (1)	*Year t* + 1 (2)	*Year t* (3)	*Year t* + 1 (4)
Exporters	0.202***	0.209***	0.204***	0.207***
	(0.061)	(0.064)	(0.066)	(0.062)
New entrants	0.225***	0.231***	0.220***	0.211***
	(0.076)	(0.080)	(0.074)	(0.082)
Established exporters	0.230***	0.239***	0.210***	0.231***
	(0.077)	(0.078)	(0.079)	(0.075)
Young exporters	0.242**	0.261**	0.180**	0.202**
	(0.103)	(0.107)	(0.103)	(0.108)

Notes: The numbers reported here are the differences in productivity between exporters and nonexporters, as explained in section 3: *,**,*** denotes significance at 10%, 5%, and 1% respectively. Exporters: the plants that do not export in year t but do export in year $t + 1$. New entrants: the plants that start exporting in year $t + 1$. Established exporters: the plants that export both in year t and in year $t + 1$. Young exporters: the plants that export in year $t + 1$ and are less than 5 years old. ACF = Ackeberg et al.; LP = Levinsohn–Petrin.

exporters entered the foreign market. Column (2) shows the results post-entry. We see that before entry, exporters are 20% more productive than nonexporters. Post-entry the gap is only 21%. The change is insignificant, implying that exporters do not significantly improve their productivity after participating in the export market.

That learning by exporting fails this simple test is possibly due to the fact that we are not looking at the patterns of exporters. Bernard and Jensen (1995) found that learning by exporting only takes place among new entrants. To examine this, we construct the new treated group as follows:

$$\text{New entrants} = \{\text{plants} : \text{export}_{j<=t} = 0; \text{export}_{t+1} > 0\}.$$

Another possibility, according to Kraay (2002), is that learning effects are more pronounced among established exporters, as learning might take time to be realized. Given that the plants export on average for only 2 years, we create the established exporters as follows:

$$\text{Established exporters} = \{\text{plants} : \text{export}_t > 0; \text{export}_{t+1} > 0\}.$$

The results in of Table 5 show that new entrants are 22.5% more productive before entry, and 23% more productive post entry. Established exporters are 23% more productive in year 1, and only 24% more productive in year 2. Again, the changes are not significant.

The final possibility we explore here is the longevity of the exporters. It might be the case that only young plants learn, as the older ones might have already acquired the expertise needed in the industry. The treated group is then:

$$\text{Young exporters} = \{\text{plants} : \text{export}_t = 0; \text{export}_{t+1} > 0; \text{age} < 5\}.$$

The estimates in of Table 5 show that young exporters are 24% more productive pre-entry, but only 26% more productive post-entry. Again no evidence of learning is seen here.

Robustness Check

The measure of productivity is crucial in this study. As an alternative to the Olley–Pakes (1996) methodology, economists also use the Levinsohn–Petrin (2003) methodology. This methodology is based on the use of intermediate inputs instead of investment, to control for the unobservable which lead to the simultaneity problems. As a result, we can use this approach as a robustness check. As shown in columns (3) and (4) of Table 5, we can see that the result still holds with this specification: there is no significant evidence that the exporters improve their productivity relative to the nonexporters, which suggests that learning by exporting is absent here. This result should not be surprising because our baseline result applies the Ackeberg et al. (2006) estimation, not that of Olley–Pakes (1996). The Ackeberg et al. (2006) approach is based on both the Olley–Pakes (1996) and Levinsohn–Petrin (2003) (see the discussion in Ackeberg et al., 2006).

4. Discussion

As the results above show no significant evidence for the learning by exporting hypothesis in China automobile industry, the data we possess here provide explanations for why we did not find any evidence for learning by exporting. For example, learning is more likely to occur if the export destinations are advanced, high-income countries (Brambilla et al., 2010) because they might require quality upgrading (Verhoogen 2008). Chinese manufacturers, however, export mostly to emerging countries where the gap in quality and technology with China is not high.

It is also possible that Chinese automobile manufacturers see exporting only as an opportunity for short-term benefits. Indeed the data shows that exports (both past and current value) are well correlated with the firm's profit, which explain the high turnover in the export market (Table 3). The high turnover prevents the plants from picking up any productivity benefits. In March 2006, the Chinese government introduced a new compulsory licensing system for all automobile exporters, which represented a new entry cost that brought more stability and encouraged exporters to seek long-term benefits.

Finally, the presence of FDI could reduce the export premium. Zhao and Zhang (2010) found evidence that FDI contributes positively to the productivity of firms. Unlike in other industries, the main objective of foreign invested firms in automobiles in China is to serve the growing domestic market. To check this channel, we run the following regression:

$$TFP_{it} - TFP_{it-1} = \beta_0 + \beta_1 Exp_{it} + \beta_2 Exp_{it} * Fr\_inv_{it} + \varepsilon_{it}$$

where Exp_{it} is the dummy which indicates whether the firm starts to export at time t and Fr_inv_{it} is the dummy which takes the value 1 if the firm has foreign capital at time $t - 1$. To eliminate errors in reporting, the threshold for foreign investment is set at 9000RMB. Results (which are omitted here) show that having received foreign capital reduced the effect of export on productivity growth. In other words, for the firms that have received foreign investment, they might have already had access to the foreign pool of knowledge. As a result, participating in the export market does not effectively help them to become more efficient.

5. Conclusion

In theory, plants that participate in export markets could have access to a wider pool of knowledge and will receive technical assistance from their foreign customers, which should mean they can improve their performance. This theoretical result needs to be verified empirically. The research consisted of two tasks: measuring performance and ascertaining whether plants do in fact perform better after participating in the export market. In this paper, we used the approach in De Loecker (2010) that corrects for the econometric problems when we estimate productivity, a measure of performance. This approach is also consistent with the tests that we conducted to identify the learning effect. These tests explored the opportunities that an exporter could have to improve its productivity. Using new data from 1998 to 2007 about Chinese automobile manufacturers, we find no evidence of learning by exporting: the changes in productivity found are not significant enough to suggest that exporters do really learn from exporting.

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