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In search of the learning-by-exporting effect: Role of economies of scale and technology

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Abstract

This paper studies the learning-by-exporting effect through which a firm increases its productivity by entering into the export market. Using Chinese firm-level data, we show that economies of scale and technology play an important role in bridging the gap between exporting and firm performance. By stratifying samples and considering causality, we find that the learning-by-exporting effect is more likely to occur for firms that produce large amounts of outputs to exploit scale economies and, at the same time, are highly capital intensive, so that they can absorb new knowledge and information from world markets.

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1. Introduction

One of the most controversial issues in international trade in the last decade has been whether the productivity of a firm increases before or after export market entry. If productivity improvement occurs before exporting, or more-productive firms start exporting, the export entry decision is referred to as self-selection. On the other hand, if productivity increases ex post or exporting enhances the firm's productivity, the result is referred to as learning by exporting. Since early works such as Bernard and Jensen (1995) and Aw and Hwang (1995), an overwhelming majority of studies support the self-selection rather than learning-by-exporting hypothesis. Wagner (2007) concludes, surveying studies on this issue, that "exporting does not necessarily improve productivity (p.67)." Melitz (2003) provides a theoretical background for the self-selection hypothesis based on his heterogeneous firm model.

So, is there no evidence, then, for learning by exporting? Conducting a meta-analysis of the learning-by-exporting hypothesis, Martins and Yang (2009) find that of 33 studies, 18 show a positive and significant learning effect, whereas 15 do not show clear-cut, significant results.[1] Although some recent studies based on micro-level (firm- or plant-level) data are consistent with the learning-by-exporting hypothesis, many controversial issues persist. First, Damijan and Kostevc (2006) find, for Slovenia, that learning by exporting is effective only in the first year of entry into the export market. Harris and Li (2008) find the same result for the UK. On the other hand, Anderson and Lööf (2009) claim the importance of exporting persistence; in other words, firms need to take time to be able to learn from exporting.[2] A second controversy, for example, concerns export intensity. Castellani (2002) and Chongvilaivan (2012) claim that the learning-by-exporting effect arises only for firms with high export intensity, while Anderson and Lööf (2009) do not provide a clear-cut answer about the relationship between export intensity and the learning effect. The third example is on export destination. An overwhelming number of studies find a positive correlation between the number of export destinations and the firm's productivity. However, as Wagner (2012) claims in his comprehensive survey, we do not know the true relationship between the characteristics of export destinations and the learning-by-exporting effect. The fourth unsolved problem is related to the estimation methodology. De Loecker (2013) points out the biased estimation of total factor productivity (TFP) commonly used in the learning-by-exporting literature. He claims that the reason a number of studies do not support learning by exporting is that the influence of past export experience is ignored, possibly causing a downward bias in the estimates. In short, it seems fair to say that we do not yet have unequivocal answers on the pros and cons of learning by exporting.

In addition to the above arguments, one of the more important yet unresolved problems concerns the premises of learning by exporting. Theoretically, learning by exporting is considered to arise mainly through two channels: new information from the world (i.e., more competitive markets) and the exploitation of economies of scale. New

[1] Martins and Yang (2009) report that their sample is not affected by publication bias.

[2] For recent surveys, see Silva, Afonso, and Africano (2012) and Ciuriak (2013).

information on technology is available through technology diffusion, while economies of scale are often observed in the globalized world. From Arrow's (1962) classical work to the recent study by Stiglitz and Greenwald (2014), the essence of learning has been recognized as a by-product of production and investment and transfer of capital goods that embody advanced technology. Through economic activities and experiences, a firm can receive from customers and competitors advanced technical assistance, professional services, managerial and marketing knowhow, production technology, and so forth.

On the other hand, exporting means producing usually much larger output for world markets, so that the firm can enjoy the benefits of scale economies. Bernard, Eaton, Jensen, and Kortum (2003) show the positive relationship between the firm's performance (productivity) and sales. Aw et al. (2001) point out the possibility of systematic bias between the firm's productivity and its output. Grossman and Helpman (1990, 1991)[3] state the importance of economies of scale as well as accumulation of knowledge capital in the global context. Entering into the world market provides exporters greater opportunities to exploit its economies of scale, allowing them to reduce average costs. A reduction in average costs improves the firm's efficiency and raises productivity.[4] Participation in international capital markets allows a firm to access physical as well as knowledge capital. Knowledge capital is a stock that a firm can accumulate though international trade.

In this paper, we study the causal relationship from the entry into export markets to the firm's performance via technology transfer and economies of scale. We assume, first, that technology transfer arises more often for firms that are endowed with physical capital or adopt capital-intensive technology, because advanced technology and knowledge are basically embodied in capital goods. Second, scale economies are more likely to be exploited by firms with large output or sales. Third, with these two assumptions, firms are more likely to benefit from exporting if they possess the above characteristics.[5]

However, few studies have considered economies of scale and capital intensity in learning by exporting. Serti and Tomasi (2008) is an important exception and is the closest to our empirical study. Using Italian manufacturing-firm-level data, they research the impact of exporting on firms' performance indicators such as productivity, sales, and capital-labor ratio (capital intensity, in their words). Note that their purpose differs from ours. They aim to test the effects of export entry on the output level, capital-labor ratio, and productivity, whereas ours is to investigate its impact on the learning outcome (productivity) in terms of output levels and technology characteristics (capital-labor ratio). Their estimation results (Table 7) summarize some interesting points. First, starting export positively and significantly affects

[3] Other theoretical ideas related to our conjectures are Krugman (1979), Evenson and Westphal (1995), and Clerides, Lach, and Tybout (1998).

[4] Silva, Afonso, and Afiricano (2012) state that the scale effect is a one-time learning-by-exporting effect and is not sustainable. However, a reduction in average costs means a change in production structure, which lasts at least for a few years.

[5] Although Alvarez and López (2005) and Máñez-Castillejo et al. (2010), for example, use the number of employees as firm size, they do not aim to test economies of scale. In our paper, we use output value, which is a more appropriate proxy for economies of scale.

the firm's productivity and sales, but not the capital-labor ratio. This means export market entry increases not only productivity but also sales. However, their results do not explain the causal relationship between scale economies (sales) and productivity. In other words, their results do not clarify how much economies of scale firms should possess to cause productivity growth. Second, the finding of no causal relationship between starting exports and capital-labor ratio growth does not necessarily mean that the capital-labor ratio is not related to productivity. One of our aims is to test if export entry by a firm with relatively higher capital-labor ratio has a greater impact on productivity.

The rest of the paper is organized as follows. Section 2 outlines the empirical methodology, including productivity measurement and causal effect detection techniques. Section 3 describes the data and firms' characteristics. Section 4 discusses the empirical results, followed by a robustness check in section 5. Finally, Section 6 concludes the study.

2. Methodology

2.1. Measuring productivity

As is common in this field, we use TFP as an output variable. To calculate TFP, we employ the index number approach instead of the semi-parametric method, which is popular in the learning-by-exporting literature. There are several TPF calculation approaches, such as a formula based on index number theory (Solow, 1957), the non-parametric approach originally developed by Farrell (1957), the instrumental variables method (Blundell and Bond, 2000), and the Olley and Pakes (1996; OP hereafter)[6] and Levinsohn and Petrin (2003; LP hereafter) semi-parametric approaches (the LP approach is a modified OP method).

Although the OP and LP semi-parametric approaches are often used in related studies because they can treat the endogeneity problem between factor inputs and unobserved productivity shocks, some weaknesses do exist. Whereas the OP method needs non-zero investment data to control for correlation between input levels and unobserved firm-specific productivity shocks in estimating the parameters of the production functions, the LP method proposes an intermediate input such as electricity to address the simultaneity problem. However, reliable investment and intermediate data are rarely available. The second problem is that large input price fluctuations across firms may not be used for non-stochastic inversion in the OP and LP procedures (Gorodnichenko, 2007). The third problem of OP and LP, particularly the latter, is related to collinearity issues raised by Ackerberg, Caves, and Frazer (2006), where the labor input may be collinear with the non-parametric terms in the second stage of the estimation in both OP and LP.[7]

Since our Chinese data set does not contain investment data or a reliable proxy for an intermediate variable, we apply the index number approach, which is relatively free from

[6] Van Biesebroeck (2007) summarizes the merits and demerits of these methods.
[7] Other issues of the OP and LP methods, such as internal inconsistency and identification of parameter problems, are addressed by De Loecker (2013).

data availability problems in comparison to the OP and LP methods. The index number approach has certain fundamental advantages over OP and LP. In the index number approach, we do not need to estimate the production function parameters, as required in the OP and LP methods. We can therefore obtain relatively robust parameter estimators. In fact, the estimated production function parameters of OP and LP are highly sensitive to variable selection, sampling periods, industry classifications, and so forth.

We therefore use the following formula, first developed by Caves, Christensen, and Diewert (1982) and extended by Good, Nadiri, and Sickless (1997) and Aw, Chen, and Roberts (2001).

$$\begin{aligned}
\ln TFP_{it} = {} & \\
& \left(\ln Y_{it} - \overline{\ln Y_t}\right) + \sum_{\tau=2}^{t}\left(\overline{\ln Y_\tau} - \overline{\ln Y_{\tau-1}}\right) \\
& - \left[\sum_{v=1}^{V}\tfrac{1}{2}\left(s_{vit} + \overline{s_{vt}}\right)\left(\ln X_{vit} - \overline{\ln X_{vt}}\right) + \sum_{\tau=2}^{t}\tfrac{1}{2}\sum_{v=1}^{V}\left(\overline{s_{v\tau}} + \overline{s_{v,\tau-1}}\right)\left(\overline{\ln X_{v\tau}} - \overline{\ln X_{v,\tau-1}}\right)\right],
\end{aligned}$$

where Y_{it} is the output of firm *i* at time *t* and X_{vit} is the quantity of input *v* corresponding to firm *i* at time *t*. s_{vit} indicates the nominal input share of input *v* of firm *i* at time *t*. Following previous literature, especially Farinas and Ruano (2005), we construct a hypothetical firm for each cross section to tackle the sampling of uneven proportions and then chain the hypothetical firms together over time to ensure that our index is transitive between firms of difference-size groups within the same industry. The bar indicates the average of the relevant quantity over the entire period. $\overline{\ln Y_\tau}$ is the reference (average) output of firm *i* at time τ in the same industry, and $\overline{\ln X_{v\tau}}$ is the reference input *v* at time τ.

The first parenthesis in the right-hand side of the equation describes the output difference between firm *i* and the hypothetical firm at time *t*. The second parenthesis indicates the chain of the hypothetical firms summed back to the base period. The rest of the right-hand side of the equation shows corresponding input quantity differences between firm *i* and the hypothetical firm at time *t* and between the aggregate input at time *t* for firm *i* relative to the hypothetical firm at the base period.

2.2 Causal effect

To evaluate the causal effect of export market entry on productivity, we rely on a combined propensity-score-matching (PSM) method. Following pioneer works such as Wagner (2002), Girma, Greenaway, and Kneller (2003), Greenaway, Gullstrand, and Kneller (2005), Girma, Kneller, and Pisu (2007), De Loecker (2007), Greenaway and Kneller (2008), we formalize the average treatment effect on the treated (ATT) as follows (Heckman et al. 1997):

$$ATT^{PSM} = E_{P(X)|T_i=1}\{E[TFP_{is}^1|START_i = 1, P(X)] - E[TFP_{is}^0|START_i = 1, P(X)]\}, \tag{1}$$

where TFP_{is}^1 and TFP_{is}^0 are outcomes representing the log of total factor productivity of firm i at time s for export market participants and nonparticipants, respectively. $START_i \in \{0,1\}$ is an indicator variable that equals unity if firm i enters the export market at time s, and zero otherwise. $P(X)$ stands for the estimated propensity score. X represents the vector of observed characteristics and is assumed to be independent of the conditional treatment assignment, $TFP_s^T, TFP_s^C \perp START_s|X_i$. This assumption, which is often referred to as the conditional independence assumption (CIA), implies that given a set of covariates X_i, potential outcomes are independent of treatment assignment.

The last term in equation (1) is not observable. We thus need to construct a counterfactual sample that has similar observable characteristics but has not entered the export market. For this purpose, we employ PSM, first developed by Rosenbaum and Rubin (1983). They suggest the use of the probability of receiving treatment (entering the export market) conditional on the observable characteristics. As suggested by Rosenbaum and Rubin, we estimate the following probability model for export entry:

$$\Pr\{START_{i,s} = 1\} = \phi\{f(\,X_{i,t})\},\ \ t < s, \tag{2}$$

where $\phi(\cdot)$ is the normal cumulative distribution function, $X_{i,t}$ represents the set of observable covariates, including year, ownership, and industry dummy variables. Based on the CIA assumption, the outcome variable must be independent of treatment conditional on the propensity score. Only covariates that simultaneously influence the participation decision and the outcome variables should be included (Caliendo and Kopeinig, 2008). Further, covariates should not be affected by participation and hence should either be fixed over time or measured before participation.

According to these criteria, we choose wage revenue, number of employees, and firm's age, all in logs, as well as year, industry, and ownership dummies, as covariates. Lagged wage revenue (in log form) is determined in the labor market and hence is considered to be unaffected by the treatment assignment. The lagged number of employees of the firm is included in the vector of covariates for three reasons: First, the number of employees represents factors of production. Second, it is not largely affected by participation. Third, since wage revenue is not a per capita variable, the number of employees controls for the size effect of wage revenue. The lagged age of a firm is predetermined and not affected by the assignment. We also include square terms of wage and age to account for the non-linearity of variables.

After constructing a counterfactual sample (control group), we employ a difference-in-difference (DID) method to estimate the impact of learning by exporting on program characteristics (Heckman et al., 1997, 1998).[8] The difference-in-difference estimate

[8] For the advantages of difference-in-difference matching over other matching methods, see, for

for each treatment firm i is calculated for two time periods as $(TFP_s^T - TFP_t^T) - \sum_{j\in C} \omega_{ij} (TFP_s^C - TFP_t^C)$, where ω_{ij} is the weight assigned to the *j*th control firm matched to treatment firm *i*. Practically, we use the following ATT model:

$$ATT^{PSM-DID} = \frac{1}{N_T}\left[\sum_{i\in T}(TFP_{is}^T - TFP_{it}^T) - \sum_{j\in C}\omega_{ij}\left(TFP_{js}^C - TFP_{jt}^C\right)\right], \quad (3)$$

where N_T is the number of treated observations and ω_{ij} is the weight, which varies depending on the estimator. We use caliper-matching estimators for the base case. In caliper matching, the weight ω_{ij} in equation (3) is set to $1/k_i$, k_i is the number of matches for $i \in T$, and 0 is assigned to all unmatched samples. A simple matching algorithm, say, nearest-neighbor matching, may be open to the risk of inferior matching, even if a match is actually the nearest neighbor. However, the caliper-matching method developed by Cochran and Rubin (1973) imposes a ceiling on the maximum propensity score distance to match a more appropriate candidate (Smith and Todd, 2005; Caliendo and Kopeinig, 2008).

As Zhao (2004) and Smith and Todd (2005), among others, note, the estimated impact is highly sensitive to the estimator chosen. Therefore, we need to check the robustness of the results. To do so, we use two different algorithms in addition, radius-matching and Gaussian kernel-matching estimators. We will explain these two matching estimators in detail in section 5.

3. Data, characteristics of firms, and covariates

3.1 Data and characteristics of firms

We use firm-level longitudinal survey data of the Chinese industrial sector, collected annually by the National Bureau of Statistics of China from 1998 to 2006. The survey, which covers all state-owned and non-state firms with sales of more than 5 million RMB per year, collects basic information on firms' characteristics such as output, value-added, sales income, ownership status, export value, and number of employees. The number of firms covered by the survey was 165,118 in 1998 and 301,931 in 2006. We select firms with 9 years of consecutive data needed for the study and drop those with missing data. In the process of creating panel data, value-term variables such as output, wages, exports, and capital are realized by using appropriate price deflators from various issues of the *China Statistical Yearbook*. We then categorize the firms into four groups according to their export status. The first group consists of non-exporters, who never export during the observed 9 years. The second group comprises export starters, who start exporting sometime in the period and continue to do so until the end of the period. The third group includes consecutive exporters, who export over the 9-year period without intermittence. The last group includes firms that stop exporting in the middle of the period or export intermittently during the period. Our

example, Smith and Todd (2005).

panel dataset consists of 17,086 firms for 9 years, resulting in 153,774 observations.

[Table 1 around here]

Table 1 shows the average values of important variables for the period 1998–2006 by export status. The log of TFP in the third column is the highest for export starters, followed by non-exporters. The difference between the two values is, however, negligible. The log of TFP for other export status types are relatively small compared to non-exporters and export starters. One of the striking differences between non-exporters and exporters is the scale-related measures of the firms. In terms of output, employees, and capital, non-exporters are, on average, smaller in scale than exporters. These three variables are the largest for consecutive exporters, among all exporter categories. The capital-labor ratio is the lowest for non-exporters and highest for consecutive exporters. Further, export starters have a higher capital-labor ratio than non-exporters. The last column of the table shows the average age by export status. Non-exporters are relatively old, 21.8 years on average, and export starters are younger, at 18.5 years on average, than other types of firms. In subsequent sections, we use non-exporters and export starters for experiments of causality from exporting to performance.

3.2 Choice of covariates

We first show the characteristics of the variables used in the empirical study and then present the empirical results. Table 2 summarizes the main variables. "Treat" is the treatment indicator; treat = 1 means firms are export starters, and treat = 0 stands for non-exporters. Therefore, we use only non-exporter and export-starter samples for further experiments. The vector of pretreatment variables or covariates includes the number of employees, wage rate, and age. To account for non-linearity, square terms of wage and age are also included. Except for age and the square term of age, all covariates are transformed into natural log form.

[Table 2 around here]

Caliendo and Kopeinig (2008) discuss the practical guidelines for the choice of covariates. They argue that covariates should simultaneously influence the participation decision and the outcome variable (productivity in this paper), and should either be fixed or measured before participation. In other words, covariates should be unaffected by participation or the anticipation of it. We include, therefore, a lagged number of employees, lagged wage rate, lagged firm's age, square term of lagged age, and three dummy variables that represent, respectively, unobserved industry differences, ownership structure, and macro shock for each year. The lagged number of employees is included to account for the difference in the factor resources of firms[9] and is affected in the short run merely by the

[9] Alvarez and Lopez (2005) and Máñez-Castillejo et al. (2010) find, for Chile and Spain, respectively, that productivity varies according to the number of employees.

export decision.[10] The wage rate is determined in the labor market and is unaffected by participation. Age is included because it is predetermined and unaffected by participation. Square terms of lagged wage and age are included to capture the non-linear relationship between the export decision and the two variables. Industry[11] and ownership dummies are fixed over time and are measured before participation, whereas the year dummy captures unobserved common macro shocks.

To check the validity of the created counterfactual group, we test the condition $X \perp START|\Pr\{START = 1|X\}$ following Rosenbaum and Rubin (1983). Our potential covariates include the number of employees, the wage rate and its square term, and age and its square term, in line with Rosenbaum and Rubin (1985) and Smith and Todd (2005). To assess the appropriateness of the matched covariates, we use the balance test, which is based on standardized differences in the sample mean.[12] Although the balance test is common in the propensity-score-matching literature, the threshold point is chosen in an arbitrary manner. Our rule of evaluation is as follows: If the bias in covariates between the treated and controlled groups is not different from zero at the 1% significance level in the *t*-test, we use the matched covariate to estimate the ATTs. On the other hand, if there is more than one variable that cannot satisfy this condition, we report it accordingly just for reference.

4. Empirical results

4.1. Overall result

The first step of ATT evaluation is to estimate the participation equation. Pooling the treated and controlled groups, we estimate the probit model of program participation. Table 3 reports the probit estimation result of equation (2). The dependent variable is the binary treatment, which is one if the firm exports and zero otherwise. All coefficients in the probit estimation are highly significant, meaning that the covariates in our model influence the firm's participation decision.[13] We find that the relationship between wage rate and export decision, as well as between age and export decision, is non-linear, indicating that the higher the wage rate, and the older the firm, the more likely it is to participate in the export market. Moreover, the relationship is exponential.

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[10] Capital can also be considered a candidate for covariates. However, participation in the world market facilitates the firm's finance, which violates the above assumption. Furthermore, capital is not significantly correlated with the participation decision.

[11] Greenaway and Kneller (2007) were the first to point out that productivity varies across industries.

[12] For a discussion on the importance of balance tests and the limitation of the standardized difference *t*-test, see Hansen and Bowers (2008) and Imai, King, and Stuart (2008).

[13] There is, however, a tidbit argument on this point: Khandker, Koolwal, and Samad (2010) note that statistical significance is not very informative since the participation equation is not a determinant model and causality is not of much interest at this stage.

[Table 3 around here]

Using this score, we next estimate the ATT with PSM-DID. ATT under PSM-DID is the difference in the average effects between the treated (export-starter) and control (non-exporter) groups. In equation (3), the first term in the right side bracket indicates the sum of TFP changes of export starters, and the second term in the bracket is the sum of estimated (counterfactual) units from the control group, obtained by using the propensity score from the previous probit estimation and caliper-matching estimator. Table 4 reports the ATTs (i.e., the effects of starting exports) of the matched sample results of PSM-DID from equation (3) on the log of TFP by the caliper-matching estimator.

The second column of the table represents the average outcome if the unit is treated ($E[TFP_{is}^{1}|START_i = 1]$), while the third column represents the estimates of counterfactual average outcome ($E[TFP_{is}^{0}|START_i = 1]$). The fourth column is the mean difference between the second and third columns, and is our main concern. We estimate three-period productivities: $dtfp_t$ stands for the outcome in the year when the firm starts exporting, $dtfp_{t+1}$ is the outcome one year after exporting, and so on. We set the tolerance rate for maximum distance at 0.01. It is noteworthy that the longer the period after export entry, the greater the average treated outcomes. The differences between the treated and controlled groups, i.e., ATTs, for three periods are 0.0126, 0.0436, and 0.0140 respectively. However, judging from the low *t*-statistics, the null hypothesis that the mean difference is statistically different from zero cannot be rejected even at the 5% significance level. In other words, we find no strong evidence of learning by exporting during the observed period.

[Table 4 around here]

4.2. Economies of scale and technology

In this subsection, we consider the role of output size and the capital-labor ratio in the learning process. As discussed in the introduction, the learning effect is based on two premises: theoretical economies of scale and transfer of knowledge capital.[14] Table 5 shows the characteristics of sample units classified into four groups by output level and capital-labor ratio, in addition to export-starter and non-exporter groups. The following points are noteworthy. First, for both export starters and non-exporters, the output averages in the top 20% are respectively, 14.4 and 9.4 times those of the lower 80% of firms. On the other hand, although the average capital-labor ratio is higher in the top 20% than in the lower 80% for

[14] These two factors are not included in propensity score estimation. The number of employees, which is included in probit estimation, is regarded as the resource factor of a firm rather than an indicator of economies of scale. Note also that the covariates in our probit model are related to exporting, but not necessarily to productivity, directly, although we assume that output size and the capital-labor ratio are correlated with productivity (not necessarily with export behavior).

both export starters and non-exporters, the differences are lower than the average output differences. Second, the average output of export starters is larger than that of non-exporters, particularly in the top 20% of firms. Third, the average capital-labor ratio differences between export starters and non-exporters, however, are not so large. In fact, the non-exporters' average capital-labor ratio in the lower 80% is 145.5, whereas the export starters' average is 143.1. These findings suggest that output size may be correlated with the export decision, whereas the capital-labor ratio is not strongly correlated with that decision. These first-glance observations suggest the importance of sample stratification and indicate that output and capital-labor ratio stratification may affect the outcome differently.

[Table 5 around here]

We now consider the firms' characteristics from different aspects based on exports. Table 6 calculates the mean export-output share of export starters. Export shares of the top 20% in terms of output as well as capital-labor ratio are lower than those of the bottom 80%. The negative relationship between output and export share may be explained by the fact that the export-output share is a declining function of output. However, the negative relationship between the export-output share and the capital-labor ratio is more difficult to explain. One possible explanation is a positive correlation between output size and the capital-labor ratio. However, the correlation ratio is only 0.223, which is not unduly high. Another possible explanation is that China is relatively abundant in labor and hence exports more labor-intensive than capital-intensive goods. Whatever the reason, the complex relationships between output size, capital-labor ratio, and firm performance via export seem to be important enough to merit serious consideration.

[Table 6 around here]

4.3 Estimation results of the stratified sample

We next turn to ATT estimation using the stratified sample. The sample is broken down into five categories according to output level and capital-labor ratio, each category covering 20% of firms. In order to break down the sample, we calculate arithmetic means of output and the capital-labor ratio for each non-exporter firm over the observed period (9 years), as well as mean values before exporting for each export starter. If the learning effect increases the after-export output or capital-labor ratio of export starters, the mean of export starters may be biased upward. We then break down the sample according to this mean order. The estimation results based on this matched sample are reported in Table 7. ATTs with caliper-matching estimators[15] are calculated for three periods as in Table 4.[16]

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[15] We set the tolerance level at 0.01.

[16] Since the results of the propensity score and balance tests are lengthy, they are not reported here, because of space considerations. The information is available upon request. A balancing test is applied

All covariates in each categorized sample pass the balancing test at the 1% significance level. The mean difference and its corresponding *t*-statistic show a significant positive effect for large-output (top 20%) firms two years after exporting and for high-capital-labor-ratio firms (top 20%) one year after exporting. On the other hand, we find no strong evidence of learning by exporting for firms in the bottom 80%, either by output or capital-labor ratio. This result suggests that economies of scale and the capital-labor ratio are both important for learning from exporting. In other words, the larger the output level, or the higher the capital-labor ratio, the more likely the firm can learn from exporting as the theory predicts. It is also noteworthy that firms may need some time to receive the positive leaning effects even if they have large output or high capital-labor ratios.

[Table 7 around here]

The next question should be, Are large output and/or high capital-labor ratio sufficient conditions for receiving learning effects? To examine this, we estimate ATTs in combinations of less than 20% of output and less than 20% of capital-labor ratio, less than 20% of output and between 20% and 40% of capital-labor ratio, and so forth. Totally, 25 cases are examined. What we aim to investigate here is whether a relatively small-size firm with a high capital-labor ratio or relatively capital-scarce but large-output firms can learn from exporting. The basic statistics are as follows: The number of firms in the top 20% range in terms of either output or capital-labor ratio is 1,901, of whom 637 are export starters as against 486 export-starters in the top 20% in terms of capital-labor ratio (see Table 5). Whereas 808 firms rank among the top 20% in terms of either output or capital-labor ratio, 315 do so in terms of both output and capital-labor ratio.

Table 8 presents caliper-matching ATT estimates in 25 combinations. All combinations satisfy the balance condition of covariates between the treated and matched groups at the 1% significance level. The capital-labor ratio ranges are presented across columns, and the output levels across rows. The table shows that ATTs that are significant at the 5% level can be found in large-output and relatively high-capital-labor ratio regions. Significant effects are found in the {80%≤X<100% and 60%≤Y<80%} and {80%≤X and 80%≤Y<100%} combinations, where X and Y stand for output and capital-labor ratio, respectively. This implies that firms with large output *and* higher capital-labor ratio are relatively more likely to increase productivity by learning from exporting.

[Table 8 around here]

5. Robustness check

In this section, we check the robustness of the previous results. We use two additional matching estimators. The counterfactuals in the previous caliper-matching

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in each case, and if it does not pass the test at the 1% level, we report the result accordingly.

experiments were chosen only from comparison groups within the caliper, and the appropriate tolerance rate in caliper matching was not known a priori. To overcome these shortcomings, Dehejia and Wahba (2002) developed radius matching, which uses information on not only the nearest neighbors but also all comparison members within the caliper with replacement. The second estimator we use for the robustness check is the Gaussian kernel-matching estimator. The kernel-matching estimator uses weighted averages of almost all samples in the control group, and hence has a smaller variance (Caliendo and Kopeinig, 2008). The kernel-matching estimator has the following weights in equation (3):[17]

$$\omega_{ij} = \frac{G\left(\frac{\hat{p}_j - \hat{p}_i}{a_n}\right)}{\sum_{j \in C} G\left(\frac{\hat{p}_j - \hat{p}_i}{a_n}\right)},$$

where $G(\cdot)$ is a Gaussian kernel function, $\hat{p}_j$ $(\hat{p}_i)$ is the estimated propensity score for $j \in C$ $(i \in T)$, and a_n is a bandwidth parameter. We allow both estimators to replace a subset of covariates. To maintain consistency between the three different estimators and to test the robustness rigorously, we use the same five covariates for the estimation.

Matched sample ATTs of radius and kernel-matching estimates for the effect of starting export on $dtfp_t$, $dtfp_{t+1}$, and $dtfp_{t+2}$ for the overall sample are shown in Table 9. The covariates of the radius-matching estimator satisfy our balancing test, but no covariates of kernel matching satisfy our 1% balance requirement. Therefore, we report the kernel-matching result only for reference. The radius-matching estimator produces the same result. In other words, the ATTs are not significant for all periods, at the 5% level, indicating no causal effect between exporting and productivity.

[Table 9 around here]

We next show the results of stratified data by output and capital-labor ratio. Table 10 reports the ATT for two matching estimators. Again, the kernel-matching estimator does not satisfy our balance test requirement, but we report it just for reference. With radius-matching estimators, the estimated ATTs are positive and significant (at 1%) for firms with high (top 20%) output or capital-labor ratio. There are no statistically significant ATTs in the bottom 80% group. This result is exactly the same as that of the caliper-matching estimator. The results of the kernel-matching estimator and the other two estimators show the same trends. In other words, it is statistically rare for firms with relatively smaller output or lower capital-labor ratio (those that constitute the bottom 80%) to learn from exporting. Regarding the timing of the effect, significant ATTs appear in the second and third periods after exporting, which seems to support Anderson and Lööf's (2009)[18] idea that persistent activity

[17] See Heckman, Ichimura, and Todd (1997), Smith and Todd (2005), and Morgan and Winship (2015) for a general unified representation of various matching estimators.
[18] However, this contradicts the finding by Damijan and Kostevc (2006) as well as Harris and Li

is required to learn from exporting.

[Table 10 around here]

We turn to test the premises of economies of scale and technology. Tables 11 and 12 are analogous to Table 8. Table 11 reports the results of radius-matching estimators in 25 categories based on output and capital-labor ratio. All covariates satisfy our balancing requirement. As in Table 8, the following is an important feature of the significant results: a combination of a large output and a high capital-labor ratio leads to positive and significant ATT. However, the results are slightly different from those in Table 8. A combination of large output and medium capital-labor ratio {80%≤X<10% and 40%≤Y<60%} shows a significant effect at the 5% level. This implies that a large-output firm is likely to enjoy the learning effect even with a medium capital-labor ratio.

[Table 11 around here]

Table 12 reports the ATTs of the kernel-matching estimator.[19] Although 2 out of the 25 combinations, {0≤X<20, 0≤Y<20} and {0≤X<20, 20≤Y<40}, do not satisfy the balancing requirements, the other 23 combinations satisfy the conditions at the 1% significance level. The table reveals that firms with positive and significant ATT generally appear in both large-output and high-capital-labor-ratio ranges but not in the large-output and medium-capital-labor-ratio combination in the range of {80≤X<100, 40≤Y<60}. Unlike other matching estimators, a different kernel-matching estimator shows that the {60≤X<80, 80≤Y<100} combination also has positive and significant ATT. No combinations of small-output and low-capital-labor-ratio firms produce positive learning-by-exporting effects similar to the other two estimators' results. Examining ATTs that are significant at the 1% level, we find that only firms in the top 20% in terms of both output and capital-labor ratio have positive learning effects.

[Table 12 around here]

Combining the results of the three different estimators, we robustly conclude that firms with both large output and high capital-labor ratio are most likely to learn from exporting. We infer from the results that compared to a small firm, a relatively large-output firm can more easily access world markets and exploit their scale economies. The findings on capital-labor ratio suggest that the essence of learning by exporting lies in capital—new technology and labor-saving machines, for example, which embody new information and product know-how.

(2008) that the effect is higher in the year of export entry.

[19] We set a bandwidth of 0.08 and restrict the common support condition within 95% of the sample. According to Smith and Todd (2005), however, estimates are not sensitive to the bandwidth level.

6. Conclusions

With a careful treatment of the causality-of-learning effect and a robust productivity measurement, we revealed important findings, summarized as follows. 1. Learning by exporting is not a general phenomenon. 2. Firms in our Chinese sample are rich in variation in terms of output, factor endowment (capital-labor ratio), and export-output ratio. 3. Firms with a large output or high capital-labor ratio are more likely to learn from exporting. 4. However, neither large output nor high capital-labor ratio is by itself a sufficient condition for productivity upgrading. 5. Only firms that have both features, that is, large output and high capital-labor ratio, are likely to learn from exporting.

Not only are our findings the first in the related literature but, more importantly, they provide guidelines for both policy makers and researchers. For policy makers (and firm owners), our findings suggest that their export promotion efforts might be pointless if they push firms to export without explicitly considering their output size and resources. For researchers, it is important to acknowledge that export promotion policies are not always effective. In other words, firms need to satisfy relatively severe conditions to enjoy learning effects, and the number of firms able to do so is limited. Therefore, policy makers should identify firms with large output and abundant capital to promote learning by exporting. However, we should note that the top 20% range for both output and capital-labor ratio comprises 904 firms, accounting for 9.5% of the total sample of 9,509 firms. Of the top 904 firms, 297 are export starters, representing about 3.1% of the total sample. We found evidence of learning by exporting, but the number of firms likely to enjoy the learning effect from exporting may not be large.

We identified the latent conditions for firms to successfully learn by starting exports, but the sources of economies of scale and the process of advanced-technology transfer remain unexplained. Identifying the process of knowledge capital transfer is particularly important for constructive development policies, pointing to the need of wide-ranging empirical and theoretical studies. Specifically, we need to examine whether, and how, advanced technology or knowledge diffuses from exporters to non-exporters in order to find the missing pieces in the learning-by-exporting puzzle.

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Table 1: Characteristics of Key Variables by Export Status
(1998–2006 Average)

	No. Obs.	No. Firms	ln(TFP)	Output (in 1000s of RMB)	Exports (in 1000s of RMB)	Employees (no. of persons)	Capital (in 1000s of RMB	Capital-Labor Ratio	Age (years)
Non-exporters	67842	7538	1.23574	70463	0	272	63815	249.86	21.84
	44.1%		(0.82654)	(232023)	0	(639)	(230187)	(587.36)	(11.93)
Export Starters	17739	1971	1.30817	160707	18631	515	159487	289.53	18.53
	11.5%		(0.80532)	(557747)	(64412)	(1628)	(675511)	(421.28)	(10.85)
Consecutive Exporters	56898	6322	1.17807	277772	96401	764	284572	358.10	20.42
	37.0%		(0.70408)	(1524084)	(632074)	(2917)	(1749497)	(5484.09)	(12.39)
Intermittent Exporters	11295	1255	1.18011	124719	3173	424	126166	321.37	20.20
	7.3%		(0.77316)	(456761)	(28207)	(1021)	(449302)	(1157.47)	(11.87)
Total	153774	17086	1.21532	165509	38607	494	163708	303.46	20.81
	100.0%		(0.77762)	(1003520)	(389479)	(1929.76)	(1132201)	(3376.55)	(12.00)

Note: Standard errors are in parentheses.
Export status: Non-exporters: have never exported in the period, Export Starters: started exporting in the period, Consecutive Exporters: export throughout period, Intermittent Exporters: stop in the middle of the period.

Table 2: Summary Statistics of Variables

Variables	No. Obs.	Mean	Std. Dev.	Min	Max
treat	85581	0.2073	0.4054	0	1
ln(emp(t-1))	76072	5.1046	1.0399	0	10.8017
ln(wage(t-1))	76072	7.2624	1.2197	0.0419	14.1703
ln(wage(t-1))-sq	76072	54.2306	18.3439	0.0018	200.7967
age(t-1)	76072	20.6919	11.6961	3	109
age(t-1)-sq	76072	564.9494	749.5880	9	11881

Note: The sample includes non-exporters and export starters only.

Table 3: Propensity Score Estimation Export Market Entry (Probit Estimation)

	Coefficient	Std. Err.	t-value
ln(emp(t-1))	0.071580	0.02004	3.57
ln(wage(t-1))	-0.298218	0.06596	-4.52
ln(wage(t-1))-sq	0.026435	0.00439	6.02
age(t-1)	-0.028140	0.00312	-9.03
age(t-1)-sq	0.000310	0.00005	6.87
Number of obs	54661		
LR chi-sq test	1573.27		
Pseudo R-sq	0.0929		
p>chi-sq	0.0000		

Note: The dependent variable is the binary export choice: 1 for starting export, 0 otherwise. Firm ownership, industry, and year dummies are included. Robust standard errors are in parentheses. All coefficients are statistically significant at 1% in the *z*-test. See the text for the definitions of variables.

Table 4: ATT (PSM-DID) of Export Entry on Productivity
(Caliper Matching)

Variable	Treated	Controls	Difference	*t*-statistics
$dltfp_t$	0.05834	0.04575	0.01260	0.55
$dltfp_{t+1}$	0.11557	0.07194	0.04363	1.71
$dltfp_{t+2}$	0.15987	0.14591	0.01396	0.49

Note: ATT = average treatment effect on the treated, PSM = propensity score matching, DID = difference in difference. All estimates are based on the matched sample. *t*-statistics are calculated from the standardized difference in sample means. All covariates in caliper matching satisfy the balancing requirement. The critical points of the t-statistics are 2.576 and 1.960 at the 1% and 5% significance levels, respectively.

Table 5: Characteristics of Firms (in 1000s of RMB) in Stratified Sample

		Export Starters (n =1971)			Non Exporters (n = 7538)		
		No. Firms	Mean	Std. Dev.	No. Firms	Mean	Std. Dev.
Output	Lower 80%	1334	37699.1	23048.0	6274	30305.7	22228.1
	Top 20%	637	542331.8	1289122.0	1264	285483.9	505663.3
Capital-Labor Ratio	Lower 80%	1485	143.1	85.2	6123	145.5	81.6
	Top 20%	486	865.8	978.6	1415	708.3	579.0

Table 6: Export/Output Share of Export Starters in Stratified Sample

		Export Share of Export Starters		
		No. Firms	Mean	Std. Dev.
Output	Lower 80%	1334	0.2499	0.3530
	Top 20%	637	0.1611	0.2645
Capital-Labor Ratio	Lower 80%	1485	0.2428	0.3474
	Top 20%	486	0.1550	0.2571

Table 7: ATT of Export Entry on Productivity
(Caliper Matching)

		Output		Capital-Labor Ratio	
Range		Difference	t-stat	Difference	t-stat
0%≤Z<20%	dltfpt	0.019439	0.35	0.067351	1.39
	dltfpt+1	0.060550	0.90	0.033240	0.63
	dltfpt+2	0.081048	1.11	0.097892	1.67
20%≤Z<40%	dltfpt	0.040314	0.76	0.020078	0.39
	dltfpt+1	0.078948	1.23	-0.001228	-0.02
	dltfpt+2	0.062959	0.88	-0.068211	-1.04
40%≤Z<60%	dltfpt	0.039972	0.69	0.031170	0.56
	dltfpt+1	0.034400	0.52	0.047067	0.70
	dltfpt+2	0.000014	0.00	0.027055	0.39
60%≤Z<80%	dltfpt	0.005643	0.11	-0.004888	-0.09
	dltfpt+1	-0.017788	-0.30	-0.021262	-0.35
	dltfpt+2	0.029695	0.47	-0.056178	-0.86
80%≤Z<100%	dltfpt	0.046903	1.23	0.024332	0.54
	dltfpt+1	0.067675	1.51	0.140545	2.80**
	dltfpt+2	0.115044	2.18*	0.155798	2.86**

Note: ATT= average treatment effect on the treated. *Z* indicates output or capital-labor ratio. All estimates are based on the matched sample. *t*-statistics are calculated from the standardized difference in sample means. ** and * represent the 1% and 5% significance levels, respectively. Balancing tests for all cases satisfy our criteria for caliper-matching estimators.

Table 8: ATT of Export Entry on Productivity by Percentile of Capital-Labor Ratio and Output (Caliper Matching)

		0%≤X<20%		20%≤X<40%		40%≤X<60%		60%≤X<80%		80%≤X<100%	
Range		Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
0%≤Y<20%	$dltfp_t$	0.010150	0.13	0.063499	0.70	0.034999	0.28	-0.045191	-0.28	-0.281216	-1.76
	$dltfp_{t+1}$	-0.078989	-0.83	-0.072670	-0.69	0.082596	0.57	-0.128465	-0.67	-0.039078	-0.19
	$dltfp_{t+2}$	-0.017250	-0.15	-0.158147	-1.48	0.143189	0.80	0.174020	0.91	-0.129228	-0.62
20%≤Y<40%	$dltfp_t$	-0.032013	-0.24	-0.032350	-0.29	-0.058891	-0.63	0.032960	0.31	0.089928	0.75
	$dltfp_{t+1}$	-0.046616	-0.32	-0.117923	-0.77	0.002066	0.02	-0.057657	-0.42	0.194479	1.30
	$dltfp_{t+2}$	-0.156071	-1.09	0.112338	0.79	-0.209270	-1.78	-0.137893	-0.81	0.080494	0.55
40%≤Y<60%	$dltfp_t$	-0.142001	-0.76	-0.005232	-0.04	0.008193	0.07	0.017578	0.14	0.036993	0.37
	$dltfp_{t+1}$	0.331257	1.49	0.224440	1.81	0.138339	0.92	0.135753	0.92	0.022524	0.14
	$dltfp_{t+2}$	0.006936	0.03	0.244795	1.75	0.132394	0.71	0.190899	1.32	0.244477	1.53
60%≤Y<80%	$dltfp_t$	-0.099412	-0.58	0.086967	0.52	-0.012124	-0.11	-0.003890	-0.04	0.224936	2.77**
	$dltfp_{t+1}$	-0.301235	-1.19	-0.019438	-0.11	0.180639	1.28	0.039726	0.35	0.216962	2.17*
	$dltfp_{t+2}$	-0.368960	-1.39	0.191745	0.87	0.193289	1.36	0.025141	0.21	0.046355	0.47
80%≤Y<100%	$dltfp_t$	-0.044989	-0.22	-0.235340	-1.30	-0.149786	-0.95	0.007500	0.06	0.063296	1.10
	$dltfp_{t+1}$	-0.043456	-0.18	-0.084748	-0.34	-0.155501	-0.82	0.115854	0.96	0.117003	1.81
	$dltfp_{t+2}$	0.367907	1.10	0.201478	0.83	-0.040872	-0.22	0.251857	1.64	0.173620	2.18*

Note: ATT= average treatment effect on the treated. X and Y indicate output and capital-labor ratio, respectively. Matched sample estimates are shown. ** and * represent the 1% and 5% significance levels, respectively. All covariates in all combinations satisfy our balancing condition (see text).

Table 9 ATT (PSM-DID) of Export Entry on Productivity
(Radius and Kernel Matching)

Variables	Treated	Controls	Difference	*t*-statistics
Radius Matching				
$dltfp_t$	0.05834	0.04209	0.01625	1.02
$dltfp_{t+1}$	0.11557	0.08206	0.03351	1.82
$dltfp_{t+2}$	0.15987	0.13362	0.02625	1.31
Kernel Matching				
Variables	Treated	Controls	Difference	*t*-statistics
$dltfp_t$	0.05854	0.04388	0.01466	0.97
$dltfp_{t+1}$	0.11233	0.09396	0.01837	1.02
$dltfp_{t+2}$	0.16482	0.14817	0.01665	0.86

Note: ATT = average treatment effect on the treated, PSM = propensity score matching, DID = difference in difference. All estimates are based on the matched sample. *t*-statistics are calculated from the standardized difference in sample means. All covariates in radius matching satisfy the balancing requirement, while no covariates in kernel matching satisfy the balancing requirement. The critical points of the t-statistics are 2.576 and 1.960 at the 1% and 5% significance levels, respectively.

Table 10: ATT of Export Entry on Productivity
(Radius and Kernel Matching)

		Radius Matching				Kernel Matching			
		Output		Capital-Labor ratio		Output		Capital-Labor Ratio	
Range		Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
0%≤Z<20%	dltfpt	0.016862	0.43	0.029509	0.80	0.022880	0.63	0.028814	0.89
	dltfpt+1	0.024155	0.53	0.031257	0.72	0.013305	0.31	0.014722	0.37
	dltfpt+2	0.003921	0.08	0.055851	1.18	-0.001911	-0.04	0.020976	0.49
20%≤Z<40%	dltfpt	0.042587	1.12	-0.014078	-0.40	0.040341	1.07	-0.014458	-0.42
	dltfpt+1	0.088553	1.89	-0.022109	-0.56	0.087108	1.89	-0.037691	-0.99
	dltfpt+2	0.075674	1.65	-0.064352	-1.42	0.073415	1.63	-0.090154	-2.08
40%≤Z<60%	dltfpt	0.024267	0.59	0.009529	0.24	-0.015034	-0.43	0.002201	0.06
	dltfpt+1	0.073742	1.64	0.079317	1.62	0.050437	1.25	0.046980	0.96
	dltfpt+2	0.011382	0.23	0.072621	1.46	-0.016202	-0.36	0.016499	0.34
60%≤Z<80%	dltfpt	-0.001276	-0.03	-0.008818	-0.23	0.003537	0.10	-0.015232	-0.41
	dltfpt+1	-0.005153	-0.12	-0.003686	-0.09	0.002633	0.06	-0.016301	-0.40
	dltfpt+2	0.040500	0.85	-0.011540	-0.26	0.031160	0.68	-0.009687	-0.22
80%≤Z<100%	dltfpt	0.052071	1.87	0.042131	1.30	0.057118	2.11*	0.056216	1.83
	dltfpt+1	0.067444	2.06*	0.096201	2.57*	0.067677	2.10*	0.080605	2.26*
	dltfpt+2	0.108446	2.96**	0.138834	3.31**	0.109497	3.03**	0.130593	3.25**

Note: ATT = average treatment effect on the treated. *Z* indicates output or capital-labor ratio. All estimates are based on the matched sample. *t*-statistics are calculated from the standardized difference in sample means. ** and * represent the 1% and 5% significance levels, respectively. Balancing tests for all cases satisfy our criteria for radius matching estimators, but not all covariates of the kernel-matching estimator satisfy the balancing condition. The bandwidth is 0.08, and the common support condition is set for 95% of the sample for the kernel-matching estimator.

Table 11: ATT of Export Entry on Productivity by Percentile of Capital-Labor Ratio and Output (Radius Matching)

		0%≤X<20%		20%≤X<40%		40%≤X<60%		60%≤X<80%		80%≤X<100%	
Range		Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
0%≤Y<20%	$dltfp_t$	0.019822	0.34	0.059528	0.97	-0.032392	-0.34	0.102156	0.83	-0.078429	-0.71
	$dltfp_{t+1}$	0.021595	0.33	0.010949	0.14	-0.007812	-0.07	0.101689	0.69	-0.056912	-0.45
	$dltfp_{t+2}$	0.085544	1.05	-0.019475	-0.25	0.035750	0.28	0.159374	1.03	0.115371	0.81
20%≤Y<40%	$dltfp_t$	0.048300	0.61	-0.023584	-0.26	-0.010628	-0.17	-0.048570	-0.57	0.104883	1.17
	$dltfp_{t+1}$	0.040999	0.42	0.030949	0.32	0.012801	0.21	-0.137902	-1.28	0.056526	0.63
	$dltfp_{t+2}$	-0.085778	-0.85	0.100767	0.95	-0.099167	-1.29	-0.041494	-0.34	0.074667	0.65
40%≤Y<60%	$dltfp_t$	-0.022028	-0.23	0.017660	0.19	-0.009083	-0.09	0.043525	0.46	0.009726	0.12
	$dltfp_{t+1}$	0.231613	1.50	0.131149	1.52	0.218428	1.78	0.006859	0.07	0.055382	0.50
	$dltfp_{t+2}$	0.063167	0.45	0.105517	1.20	0.127032	0.96	0.031115	0.29	0.224864	2.12*
60%≤Y<80%	$dltfp_t$	-0.347541	-2.09	0.054833	0.38	0.026650	0.30	0.005551	0.08	0.112262	1.86
	$dltfp_{t+1}$	-0.162434	-0.83	0.057905	0.38	0.160138	1.36	0.039281	0.56	0.022904	0.32
	$dltfp_{t+2}$	-0.197015	-1.11	0.235728	1.44	0.132351	1.23	0.035256	0.46	-0.045499	-0.61
80%≤Y<100%	$dltfp_t$	0.069276	0.56	0.116252	0.92	0.015172	0.12	0.033106	0.46	0.075831	1.74
	$dltfp_{t+1}$	-0.073257	-0.57	0.111707	0.67	0.116955	0.90	0.032701	0.35	0.146321	2.91**
	$dltfp_{t+2}$	-0.025668	-0.15	0.221307	1.33	0.097403	0.69	0.141827	1.56	0.209868	3.59**

Note: ATT = average treatment effect on the treated. X and Y indicate output and capital-labor ratio, respectively. Matched sample estimates are shown. ** and * represent the 1% and 5% significance levels, respectively. All covariates in all combinations satisfy our balancing condition (see text).

Table 12: ATT of Export Entry on Productivity by Percentile of Capital-Labor Ratio when Output>80%
(Kernel Matching)

		0%≤X<20%		20%≤X<40%		40%≤X<60%		60%≤X<80%		80%≤X<100%	
Range		Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
0%≤Y<20%	$dltfp_t$	0.026046	0.49	0.060135	1.02	-0.016733	-0.22	0.101023	0.86	-0.033096	-0.32
	$dltfp_{t+1}$	-0.009479	-0.16	0.008928	0.12	0.043398	0.51	0.093267	0.66	-0.015477	-0.13
	$dltfp_{t+2}$	0.017814	0.24	-0.027290	-0.36	0.066391	0.65	0.102748	0.69	0.149291	1.13
20%≤Y<40%	$dltfp_t$	0.041247	0.58	0.048409	0.49	-0.018483	-0.31	-0.083380	-1.01	0.052666	0.60
	$dltfp_{t+1}$	0.028545	0.33	0.084057	0.79	0.014301	0.25	-0.159325	-1.53	0.026615	0.33
	$dltfp_{t+2}$	-0.144022	-1.54	0.119625	1.10	-0.131034	-1.77	-0.133875	-1.13	0.011268	0.11
40%≤Y<60%	$dltfp_t$	0.021417	0.22	-0.003419	-0.04	0.013938	0.15	0.068605	0.76	0.018717	0.24
	$dltfp_{t+1}$	0.246590	1.57	0.168255	1.15	0.124763	1.10	0.012044	0.13	0.060270	0.56
	$dltfp_{t+2}$	0.107531	0.77	0.088138	1.07	0.015280	0.13	0.008736	0.09	0.211581	2.05*
60%≤Y<80%	$dltfp_t$	-0.324547	-2.08	0.070529	0.51	-0.046428	-0.60	0.005485	0.08	0.075627	1.37
	$dltfp_{t+1}$	-0.216477	-1.18	0.125692	0.89	0.081088	0.76	0.043991	0.68	0.004265	0.07
	$dltfp_{t+2}$	-0.195357	-1.21	0.387723	1.56	0.019780	0.21	0.023990	0.34	-0.043062	-0.63
80%≤Y<100%	$dltfp_t$	0.089888	0.77	0.088848	0.75	-0.011306	-0.09	-0.002176	-0.03	0.077670	1.94
	$dltfp_{t+1}$	-0.035385	-0.30	0.090809	0.57	0.124439	0.98	0.023855	0.27	0.139849	3.02**
	$dltfp_{t+2}$	-0.079949	-0.51	0.231326	1.47	0.088350	0.65	0.164316	1.97*	0.190349	3.49**

Note: ATT= average treatment effect on the treated. X and Y indicate output and capital-labor ratio, respectively. Matched sample estimates are shown. ** and * represent the 1% and 5% significance levels, respectively. The Gaussian kernel function is used as the weight. The bandwidth is 0.08, and the common support condition is set for 95% of the sample. All cases satisfy our balancing criterion (see text) except for the following combinations: {0≤X<20, 0≤Y<20} and {20≤X<40, 0≤Y<20}.